EvoPOL: a framework for optimising social regulation policies

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Abstract

Purpose – This paper aims to propose a novel computational framework called EvoPOL (EVOlving POLicies) to support governmental policy analysis in restricting recruitment of smokers. EvoPOL is a fuzzy inference-based decision support system that uses an evolutionary algorithm (EA) to optimize the if-then rules and its parameters. The performance of the proposed method is compared with a fuzzy inference method adapted using neural network learning technique (neuro-fuzzy).

Design/methodology/approach – EA is a population-based adaptive method, which may be used to solve optimization problems, based on the genetic processes of biological organisms. The Takagi-Sugeno fuzzy decision support system was developed based on three sub-systems: fuzzification, fuzzy knowledge base (if-then rules) and defuzzification. The fine-tuning of the fuzzy rule base and membership function parameters is achieved by using an EA.

Findings – 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 the error values on the test sets have improved considerably. Hence, when policy makers require more accuracy EvoPOL seems to be a good solution.

Originality/value – When policy makers require more accuracy EvoPOL seems to be a good solution. For complicated decision support systems involving more input variables, EvoPOL would be an excellent candidate for framing if-then rules with precise decision scores that could help the government representatives as to what extent to concentrate on available social regulation measures in restricting the recruitment of smokers.

Keywords Cybernetics, Programming and algorithm theory, Fuzzy control, Knowledge management

Paper type Research paper

1. 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 (Bachman *et al.*, 1977). Ill-health effects are too remote to be of concern (Winstanley *et al.*, 1995). Recruitment of minors as smokers is different from the "rational addiction" of established adult smokers (Becker and Murphy, 1988), and decisions by adults to continue or cease smoking (Beauchesne, 1998). Early commencement of smoking is closely linked to both long-term smoking and heavy smoking (Tutt *et al.*, 2000).

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Access to cigarettes is a major factor in the high levels of smoking among minors (Winstanley *et al.*, 1995).

The extent of social regulation of the community has effects 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 has been studied. 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 (Coghill and Petrovic-Lazarevic, 2002).

Two types of models were applied to support knowledge management in social regulation (Coghill and Petrovic-Lazarevic, 2002; Petrovic-Lazarevic *et al.*, 2002). That is, a fuzzy inference system (FIS) (Yen and Lanagari, 1999) with variables defined as membership functions (MFs) expressing explicit expert systems knowledge in the form of fuzzy *if-then* rules with mechanism of reasoning in humanly understandable terms. 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 MFs for both input and output variables and the parameters of the learning algorithms.

In this paper, we propose an evolutionary algorithm (EA) to optimize the fuzzy *if-then* policies and the MF parameters. In this respect the paper is divided as follows: Section 2 defines what has been done in terms of modeling in order to support governmental policy analysis in restricting recruitment of smokers. In Section 3, we summarize our previous work using neuro-fuzzy systems (Petrovic-Lazarevic *et al.*, 2003). Section 4 deals with the modeling of the problem using EAs followed by experimentation set-up and results in Section 5. Some conclusions are also provided towards the end.

2. 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 (De Boer and Walbeek, 1999). 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 (Zouros *et al.*, 2005) such as fuzzy logic, and neural networks learning methods.

Knowledge, described as natural language (spoken language) or using symbolic terms (Tran and Zahid, 2000), 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 (Wiener, 2004). But it is also related to ethics and core values of the society. Social networks and problem solving are associated with 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 judgment – is difficult to codify. But since it is expressed mainly through linguistic information it can be stored with a help of FIS and could be further optimized using some learning methods.

3. What is known?

3.1 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 (compliance rate by retailers' obedience), 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 (Coghill and Petrovic-Lazarevic, 2002).

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.

3.2 Neuro-fuzzy models

Neuro-fuzzy systems make use of linguistic knowledge of FIS 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 FISs are tested with tobacco smoking enforcement efforts (Petrovic-Lazarevic *et al.*, 2003). 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 FIS 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 MFs 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 EA-based learning technique to optimize the fuzzy rule base and MFs based on a hierarchical search process.

4. Problem solution

EAs 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 (Tran *et al.*, 2002). 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 (Cordon and Herrera, 1997). 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:

(1) base line condition (compliance rate by retailers' obedience);

(2) maximum enforcement according to protocol; and

(3) enforcement community education (no retailer education).

We used a grid partitioning algorithm to determine the initial rulebase. We later have to decide the optimal number of rules, representation of the antecedent and consequent parts. 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 shows such a chromosome structure representation with m rules.

We used the angular coding method proposed by Cordon and Herrera (1997) 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 $\alpha_i = \arctan p_i$. 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. 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.

The rule base and the MF parameters could be formulated as an evolutionary search wherein the knowledge base, MFs (quantity and shape), parameters of the MFs, etc. is evolved at different time scales as shown in Figure 4 (Abraham and Nath, 2000).

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

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

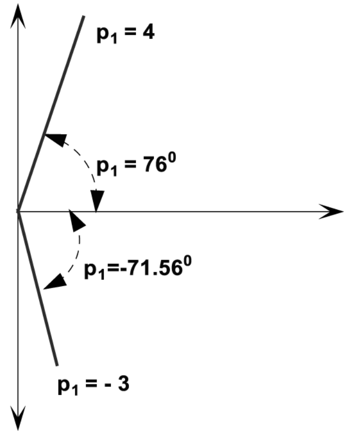

Figure 2.
Angular coding technique of the rule consequent parameters of Takagi-Sugeno FIS

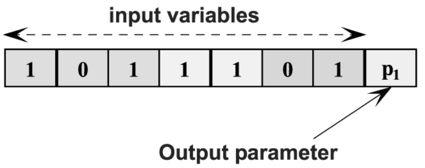

Figure 3.
Chromosome representation of a fuzzy rule

5. Experimentation set-up and test results

A 2-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 18 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 to seek higher levels of compliance. 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

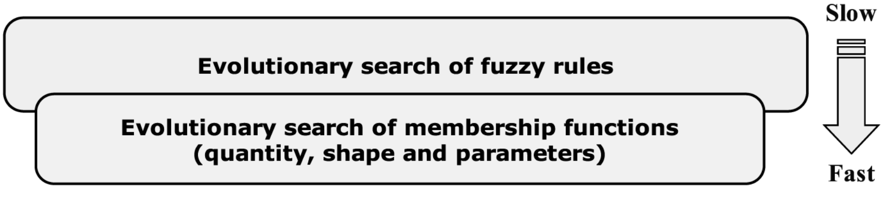

Figure 4.
EvoPOL framework for optimization of FIS

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 I. For each LGA, 70 percent of the data were extracted randomly and used for training the EvoPOL and building up the FIS. Remaining 30 percent 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 optimized by the EA.

To limit the search space of the EA, we restricted to two Gaussian MFs for each input variables and the MF parameters were encoded as shown in Figure 3. We used the direct encoding technique and the settings for the EA are depicted in Table II. The parameter settings were finalized after a few trial and error approaches. Experiments were repeated 3 times and the average RMSE values of the decision scores are reported.

Figure 5 shows how EvoPOL converged as the algorithm continued its global search for the best solutions. Figures 6-11 show the fine-tuning of MFs for the three different inputs for LGA1. Figure 12 shows the developed Takagi-Sugeno FIS after 30 generations of EvoPOL learning. We were not able to reduce the number of rules (eight rules). Owing to space restrictions, the graphical results of other five LGA's are not depicted in this paper. The empirical results for all the six LGA's are depicted in Table III. The efficiency mentioned in Table III is calculated as follows with RMSE that stands for root means squared error:

$$\text{Efficiency} = \frac{\text{RMSE}_{\text{Test set}}(\text{NF}) - \text{RMSE}_{\text{Test set}}(\text{EvoPOL})}{\text{RMSE}_{\text{Test set}}(\text{NF})} \times 100$$

Baseline condition	Maximum enforcement	Enforcement community education	Output
Occasional	Sufficient	Good	Do not change rules
Frequent smokers	Insufficient	Acceptable	Change some rules
Established smokers	–	Bad	Change all rules

Table I. Variables that influence the government smoking restriction policy

Population size	30
Maximum no of generations	50
Fuzzy inference system	Takagi Sugeno
Rule antecedent MFs	2 MFs per input variable
Rule consequent parameters	Parameterized Gaussian angular coding
Ranked-based selection	0.50
Elitism (percent)	5
Starting mutation rate	0.40

Table II. Parameter settings for EA

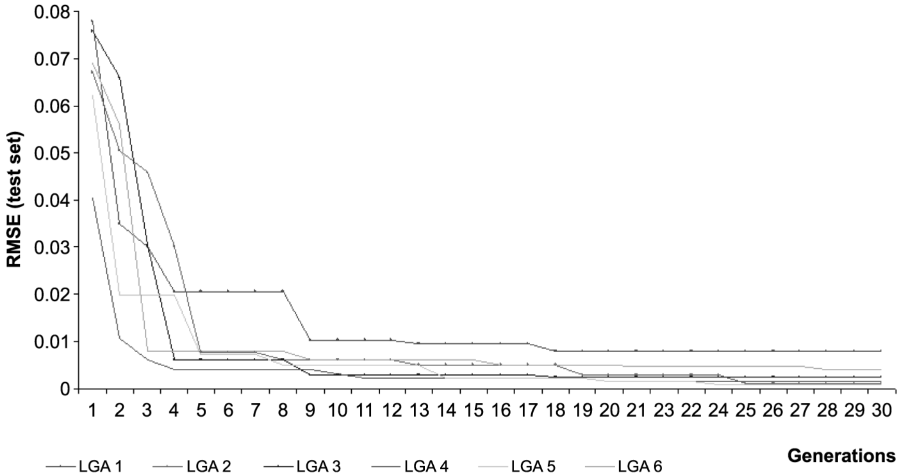

Figure 5.
EvoPOL convergence after 30 generations for the six LGAs

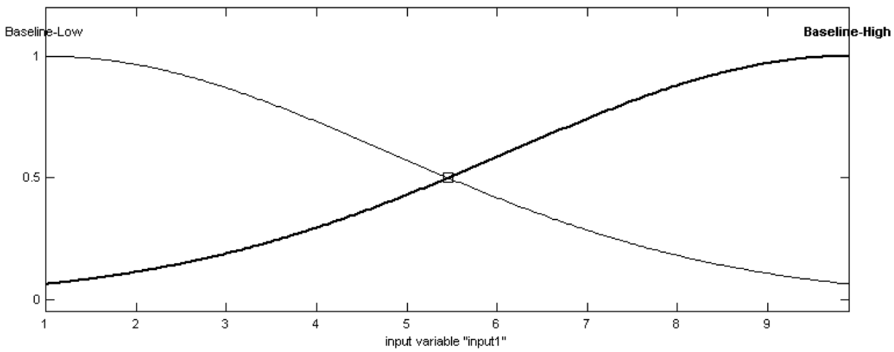

Figure 6.
LGA1, input 1: MFs before EvoPOL learning

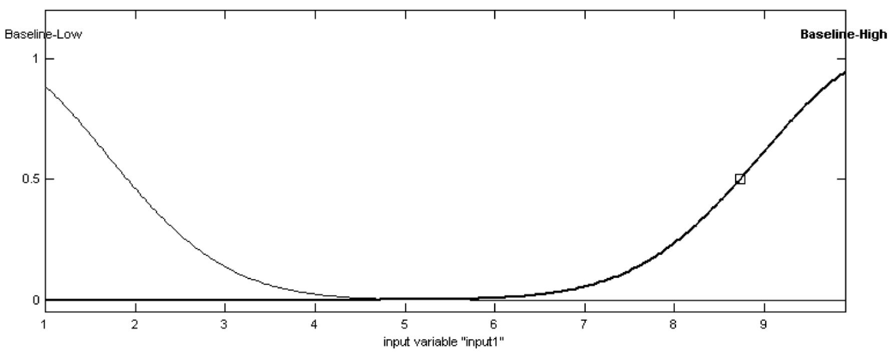

Figure 7.
LGA1, input 1: MFs after EvoPOL learning

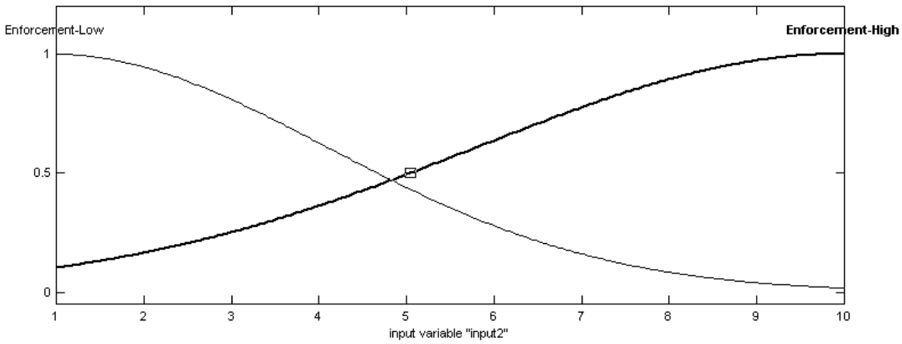

Figure 8.
LGA1, input 2: MFs before EvoPOL learning

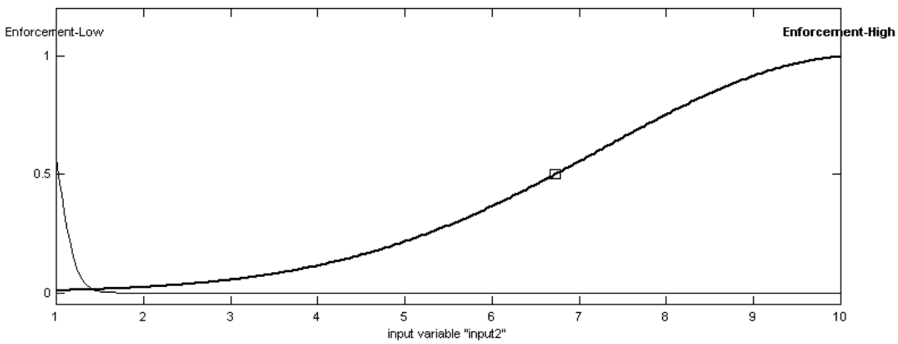

Figure 9.
LGA1, input 2: MFs after EvoPOL learning

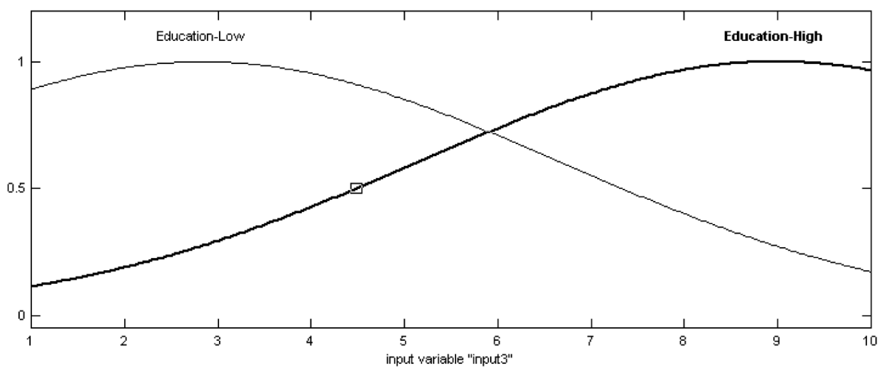

Figure 10.
LGA1, input 3: MFs before EvoPOL learning

6. 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.

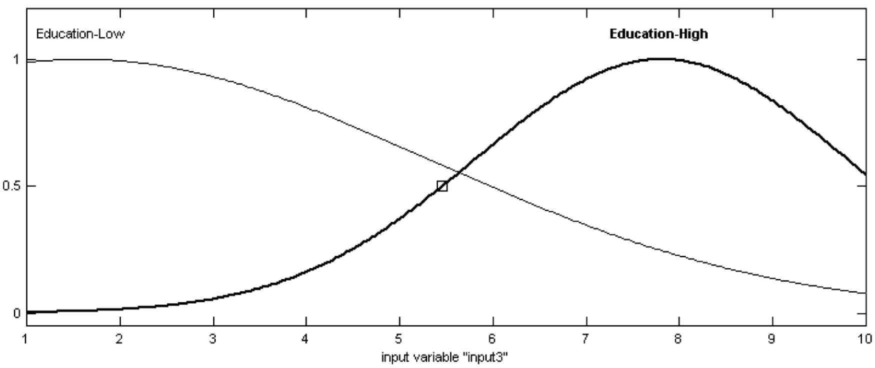

Figure 11.
LGA1, input 3: MFs after EvoPOL learning

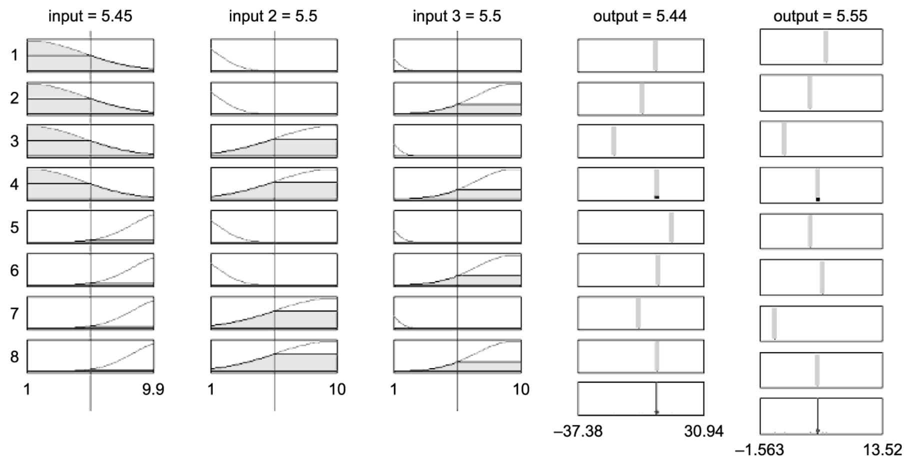

Figure 12.
Developed Takagi-Sugeno FIS using EvoPOL

Table III.
Comparison of EvoPOL and ANFIS

	EvoPOL		ANFIS (NF)		
		RMSE			
LGA	Train	Test	Train	Test	Efficiency (percent)
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

It is interesting to note that we were not able to reduce the number of fuzzy rules (eight 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 EAs 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 (Abraham, 2002) 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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