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**SELF LEARNING NEURO-FUZZY MODELING USING HYBRID  
GENETIC PROBABILISTIC APPROACH FOR ENGINE  
AIR/FUEL RATIO PREDICTION**



**DOCTOR OF PHILOSOPHY  
UNIVERSITI UTARA MALAYSIA  
2017**



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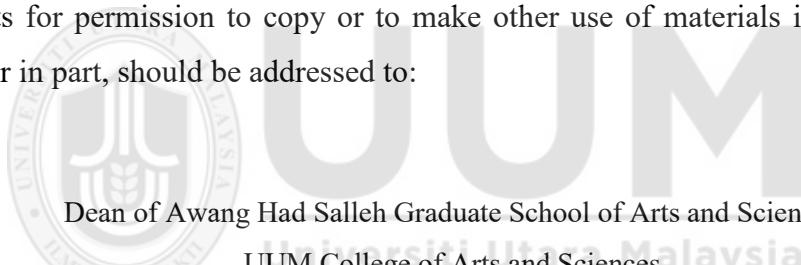
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## **Abstrak**

Pembelajaran Mesin merupakan pembinaan model yang boleh mempelajari dan membuat ramalan berasaskan data. Pengekstrakan peraturan dari dunia data sebenar, kebiasaannya dicemari oleh bunyi, kekabur dan ketidakpastian. Sistem Neuro-Kabur (NFS) yang diketahui dalam meramal prestasi, mempunyai kesukaran dalam menentukan bilangan peraturan yang sesuai dan bilangan fungsi keahlian bagi setiap peraturan. Penambahbaikan hibrid Algoritma Genetik Pengelasan Bayesian Kabur (GA-FBC) dicadangkan untuk membantu NFS dalam mengekstrak peraturan. Pemilihan ciri dilakukan di dalam tahap peraturan bagi menyelesaikan masalah FBC yang bergantung pada kekerapan ciri yang terarah pada pengabaian corak kelas kecil. Dalam keadaan dunia sebenar masalah multi-objektif seperti ramalan nisbah Udara / Minyak (AFR) telah diguna pakai. GA-FBC menggunakan maklumat bersama entropi, yang mengambilkira perkaitan di antara sifat-sifat ciri dan sifat-sifat kelas. Fungsi kecergasan adalah dicadangkan untuk menangani masalah pelbagai objektif tanpa pemberat dengan menggunakan kaedah komposisi baru. Model ini telah dibuat perbandingan dengan algoritma pembelajaran yang lain seperti algoritma Pengelompokan Kabur C-Min, (FCM) dan algoritma Pecahan Grid. Ketepatan ramalan dan kerumitan dalam Sistem Kabur Berasaskan Peraturan (FRBS) termasuk bilangan peraturan dan bilangan syarat pada setiap peraturan telah diambilkira sebagai syarat penilaian. Perbandingan juga dibuat dengan GA-FBC yang asal bergantung kepada kekerapan yang tiada dalam Maklumat Bersama (MI). Keputusan pengujian menggunakan set data AFR menunjukkan bahawa model baharu ini dapat membawa kepada penurunan bilangan atribut dalam peraturan dan boleh meningkatkan prestasi berbanding model lain. Kajian ini membolehkan berlakunya penjanaan sendiri FRBS daripada data sebenar. GA-FBC boleh digunakan sebagai satu arah baru dalam penyelidikan pembelajaran mesin. Kajian ini menyumbang dalam mengawal pelepasan asap kenderaan bagi membantu mengurangkan punca pencemaran untuk menghasilkan persekitaran yang lebih hijau.

**Kata kunci:** Algoritma Genetik, Pengelasan Bayesian Kabur, Pemilihan ciri, Pengekstrakan peraturan, Maklumat Bersama Entropi

## Abstract

Machine Learning is concerned in constructing models which can learn and make predictions based on data. Rule extraction from real world data that are usually tainted with noise, ambiguity, and uncertainty, automatically requires feature selection. Neuro-Fuzzy system (NFS) which is known with its prediction performance has the difficulty in determining the proper number of rules and the number of membership functions for each rule. An enhanced hybrid Genetic Algorithm based Fuzzy Bayesian classifier (GA-FBC) was proposed to help the NFS in the rule extraction. Feature selection was performed in the rule level overcoming the problems of the FBC which depends on the frequency of the features leading to ignore the patterns of small classes. As dealing with a real world problem such as the Air/Fuel Ratio (AFR) prediction, a multi-objective problem is adopted. The GA-FBC uses mutual information entropy, which considers the relevance between feature attributes and class attributes. A fitness function is proposed to deal with multi-objective problem without weight using a new composition method. The model was compared to other learning algorithms for NFS such as Fuzzy c-means (FCM) and grid partition algorithm. Predictive accuracy and the complexity of the Fuzzy Rule Base System (FRBS) including number of rules and number of terms in each rule were taken as terms of evaluation. It was also compared to the original GA-FBC depending on the frequency not on Mutual Information (MI). Experimental results using Air/Fuel Ratio (AFR) data sets show that the new model participates in decreasing the average number of attributes in the rule and sometimes in increasing the average performance compared to other models. This work facilitates in achieving a self-generating FRBS from real data. The GA-FBC can be used as a new direction in machine learning research. This research contributes in controlling automobile emissions in helping the reduction of one of the most causes of pollution to produce greener environment.

**Keywords:** Genetic Algorithms, Fuzzy Bayesian classifier, Rule extraction, Feature selection, Mutual Information Entropy.

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## List of Abbreviations

|        |   |
|--------|---|
| AFR    | Air/Fuel Ratio                                    |
| ANFIS  | Adaptive Network – based Fuzzy Inference System   |
| BC     | Bayesian Classifier                               |
| BN     | Bayesian Network                                  |
| CLT    | Coolant Engine Temperature                        |
| DB     | Data Base   |
| DTGA   | Decision Tree and Genetic Algorithm               |
| ECU    | Engine Control unit                               |
| FBC    | Fuzzy Bayesian Classifier                         |
| FCM    | Fuzzy c-means                                     |
| FIS    | Fuzzy Inference System                            |
| FRBS   | Fuzzy Rule Base System                            |
| FS     | Fuzzy Systems                                     |
| GA     | Genetic Algorithms                                |
| GA-FBC | Genetic Algorithm based Fuzzy Bayesian Classifier |
| GFS    | Genetic fuzzy System                              |
| IRL    | Iterative Rule Learning                           |
| KB     | Knowledge Base                                    |
| KNN    | K-Nearest Neighbour                               |
| LDC    | Linear Discriminant Classifier                    |
| MAP    | Manifold Air Pressure                             |
| MAT    | Manifold Air Temperature                          |
| MF     | Membership Function                               |
| MIFS   | Mutual Information Feature Selection              |
| MOEA   | Multi-objective Evolutionary Algorithm            |
| MOEFS  | Multi-objective Evolutionary Fuzzy System         |
| MI     | Mutual Information                                |
| MIM    | Mutual Information Maximisation                   |
| MLP    | Multi-Layer Perceptron                            |
| NFS    | Neuro-Fuzzy System                                |
| NN     | Neural Network                                    |
| PW     | Pulse Width – Injection Opening Time              |
| QDC    | Quadratic Discriminant Classifier                 |
| RB     | Rule Base   |
| RBFN   | Radial Basis Function Network                     |
| RMSE   | Root Mean Square Error                            |
| RPM    | Revolution per Minute - Engine Speed              |
| TPS    | Throttle Position                                 |

# **CHAPTER ONE**

## **INTRODUCTION**

Developing systems or computer programs with self-learning capabilities is one of the most difficult feats in the field of computer science. Machine learning focuses on the development of computer programs that can teach themselves to grow and change when exposed to new data.

Machine learning is not only based on algorithms which enable programs or machines to analyse data and learn from it but is also influenced by the representation of knowledge obtained in the learning process. A learning system is usually capable of informing its user of the learning it has acquired. Therefore, a user, in addition to learning about the problem of interest, can also ascertain if the representation of knowledge within the learning system is accurate and credible.

Induction is a frequently used methodology for learning systems. This implies that a learning algorithm processes samples that can lead to an accurate output for any set of input data. Learning algorithm samples that are based on real life data are generally corrupted with noise, indistinctness, imprecision, uncertainty, incompleteness, or vagueness.

Many a time, it is necessary that the learning model is readable by humans. Rule sets are one of the most understandable kinds of models in this regard. In this thesis, the different learning models in the form of rule sets are discussed.

Linguistic rules or fuzzy rules are defined as “if-then” rules that use linguistic expressions (for example, “if  $x$  is small, then  $y$  is approximately zero”). Fuzzy

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