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Review of Air-Fuel Ratio Prediction and Control Methods

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ABSTRACT— ***Air pollution is one of main challenging issues nowadays that researchers have been trying to address. The emissions of vehicle engine exhausts are responsible for 50 percent of air pollution. Different types of emissions emit from vehicles including carbon monoxide, hydrocarbons, NOX, and so on. There is a tendency to develop strategies of engine control which work in a fast way. Accomplishing this task will result in a decrease in emissions which coupled with the fuel composition can bring about the best performance of the vehicle engine. Controlling the Air-Fuel Ratio (AFR) is necessary, because the AFR has an enormous impact on the effectiveness of the fuel and reduction of emissions. This paper is aimed at reviewing the recent studies on the prediction and control of the AFR, as a bulk of research works with different approaches, was conducted in this area. These approaches include both classical and modern methods, namely Artificial Neural Networks (ANN), Fuzzy Logic, and Neuro-Fuzzy Systems are described in this paper. The strength and the weakness of individual approaches will be discussed at length.***

Keywords— Air-fuel ratio, Artificial Neural Networks, Fuzzy Logic

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1.INTRODUCTION

Prediction is regarded as a significant part in constructing real world systems' models particularly in engineering, trying to predict the future responses. One of the implicit purposes of attaining prediction is controlling such systems. The controlling of processes needs the application of a predictor embedded in the control structure. In addition, over the past few years, many researchers have been attracted to the area of delay systems' control. It is argued that delays cause instabilities in the function of control systems. Generally, delays may appear as a result of the control input computation, transport phenomena, time-consuming process of information in measurement devices, and so on.

A high level of uncertainty may decrease the usefulness and accuracy of prediction, where alternative approaches are required to support to control the achievement of favourable results. To improve the prediction accuracy, additional information must be applied. This additional information should be the result of knowledge of how typically a system operates internally, considering all the integral feedback loops, as well as the external factors influencing it. The consequent feedback effects will create highly non-linear responses [35].

To build models for making prediction in the real world systems, any causal properties (i.e., properties which link cause and effect) derived from knowledge associated with the system, need to be used. To do so, observable delays between external causal factors as well as their influences on system response are sought [52].

There is a tendency to develop engine control strategies which work in a fast manner. Accomplishing this task will lead to a decrease in emissions along with composition of fuel, resulting in maintaining the best performance and function of the engine. To this end, a number of factors including engine speed, engine torque, air intake, spark timing, fuel injection timing, AFR, etc. should be controlled. The AFR has a great effect on effectiveness of the fuel and the decrease of emissions compared to all other engine control factors [37].

2.AIR-FUEL RATIO

As fuel enters the engine of vehicle it requires air to be burnt in the engine combustion chamber, which happens in the system of fuel injection system, mixing a certain quantity of air with the given fuel in an internal combustion engine. There is a ratio required and desired between the air-fuel mixtures known as the perfect or stoichiometric ratio. Usually, the perfect ratio equals 14.7:1 which depends on the amount of hydrogen and carbon found in a certain amount of fuel, since different fuels have diverse perfect ratios. A mixture which has less amount of air compared to the perfect ratio is known as a rich mixture. Conversely, when the air is more in comparison with the perfect ratio it is known as a lean mixture.

In the rich mixture, an amount of fuel will be left over following the combustion that causes the power of the vehicle to increase, the fuel economy to reduce, the emissions of CO and hydrocarbon in the air to increase, the catalytic converter a device responsible for reducing the toxic emissions originated from an internal combustion engine to overheat. The overheating may lead to melting of the catalyst that can block inside of it partially or completely.

In the lean mixture, redundant oxygen is left that causes the fuel efficiency to increase, and the nitrogen-oxide emissions to increase. Also, the engine is damaged and its performance is reduced.

The oxygen sensor (or O2 sensor) regulates the air-fuel mixture, responsible for giving feedback to the vehicle engine control unit (ECU) controlling the air-fuel ratio.

The reason for the requirement of O2 sensor in the engine is that because the amount of oxygen that the vehicle engine is able to pull in, determines the fuel mixture's relative richness and leanness. This is dependent on many factors including air temperature, barometric pressure, airflow, engine coolant temperature, throttle position, engine load, and so on. The most vital reason is that the engine control unit is not capable of measuring and compensating for every potential factor. Besides the O2 sensor issue, one of the problems is the transfer delays of the oxygen sensor which requires time to transport voltage of the signal to the ECU. Hence, this big time delay between the ECU controlling action and O2 sensor measurement accounts for the problem of quick fluctuation in the AFR, affecting the performance of the AFR control loop. In addition, O2 sensor turns out to be less active because of an increase of pollutants coming from normal combustion.

The AFR is a key index which affects the emission reduction as well as gasoline engine's fuel efficiency. This needs a quick prediction of the AFR to obtain the required engine control. Accordingly, it is very significant to have a control over the ratio to keep it in close proximity to its perfect value. In both the transient state and steady state of engine operation, the AFR must be controlled. Controlling the vehicle engine in steady state of operation is easy to apply, because in addition to all the air-induction, fuel dynamics vanishes as the system is under steady state. Nevertheless, when intake air pressure, the throttle position, and engine speed are instantly changing, the engine will mainly be operating in a transient state where mostly the engine is operated [43].

The prediction and controlling of AFR will bring about controlling vehicle emissions which will help reduce one of the greatest sources of environmental pollution and minimize the hazard of costly damage done to the engine as well as guarantee peak engine performance. Addressing the issues of high cost and performance of O2 sensor can be done by substituting it with a virtual sensor, consequently enhancing fuel efficiency and making a contribution to fuel economy. Normally, the final goal of engine producers is to attain an improved engine control without using additional sensory devices, i.e., without other costs. Thus, under such conditions, virtual-sensor techniques appear to be preferred.

There are a lot of approaches dealing with AFR prediction and control and other nearby engineering applications, including classical and modern approaches, where classical approach involves the ECU which represents the engine's nonlinear conduct in real-time utilizing three-dimensional mapping (or 3-D maps) through look-up tables, whereas the modern approach removes the huge numbers of look-up tables. The application of modern methods like Artificial Intelligence technologies (AI) is widely accepted since they offer an alternative method to solve complicated and ill-defined problems. These kinds of technologies have the following features: they can learn from examples; they are error tolerant since they can handle incomplete and noisy data, they can handle nonlinear problems, and when trained they can carry out prediction and control rapidly. More clarification and explanations will be provided in the subsequent sections.

3. CLASSICAL APPROACHES

The main disadvantage of classical approach is that it requires certain amount of time to determine the values necessary to achieve optimal engine performance. This process is called the ECU calibration [39]. Engine calibration is applied from the optimized data tables along with functions accumulated in the ECU. Likewise, the calibration process tries to determine the premium settings for vehicle engine and accordingly it should be performed very quickly at the lowest cost. But it is a time consuming and iterative process achieved through numerous engine measurements cycles.

Many of the controllers of production fuel-injection work on the basis of open-loop feed-forward control which employs a look-up table with PID (i.e., proportional–integral–derivative) or PI (i.e., proportional plus integral) feedback control. Such process of creating the table is arduous because the process of calibration and tuning requires a great deal of effort and time.

The main issue of PID control is that this system is a sort of feedback system which has constant parameters and has no direct knowledge and information of the process, and consequently the overall performance will be reactive and compromising. A system controlled by A PI is less reactive to real (or non-noise) data and also provides comparatively quick alterations in state. Consequently, the system will be more sluggish in reaching a set-point and also slower to react to perturbations in comparison with a well-tuned PID system. Mentioning a number of studies in this field that was applied for the control of AFR, Ebrahimi, et al. [6] used filtered PID controller, Franceshi, et al. [15] used adaptive PID controller, and di Gaeta, et al. [1] introduced a feed-forward controller, inner feedback PI model-based controller, and Smith predictor.

Other linear control methods that have been employed, including the method of Linear-quadratic-Gaussian (LQG), have little benefit because they require the output magnitude data, whilst the control system is non-linear and the output of sensor is nearly binary [37]. Tan [11] used LQG controller for AFR control.

Sliding mode control (SMC) technique [13] was proposed to solve this problem. This method has an analytic design and also is compatible with the binary nature of the O2 sensor signal. Some researchers have denoted the use of this method for controlling the AFR in their research works, such as, Shiao and Moskwa [54] utilized sliding observers, Puleston, et al. [31] utilized dynamic sliding mode for AFR and speed control, Yoon and Sunwoo [32] used an adaptive sliding control algorithm depending on the oxygen sensor measurements in order to reach an exhaust emissions reduction, Pfeiffer and Hedrick [24] used multiple-surface sliding control for AFR and speed control, Choi and Hedrick [38] used a sliding mode strategy to develop a control algorithm for observer-based fuel injection, and Wang and Yu [46] improved previous algorithms by combining the second-order sliding mode with an RBF neural network. However, despite many advantages, this method suffers from the issue of huge amplitude chattering attributed to an inevitable measurement time-delay.

4.MODERN APPROACHES

The most promising and capable controllers work in line with modern control concepts which tackle the nonlinear parts of the challenging problem. ANN along with fuzzy systems are eye-catching in this field for their capability in predicting and controlling of nonlinear problems.

4.1 Artificial Neural Networks

An ANN, inspired by biological human nervous system, operates based on mainly interconnected simple elements, which operate together as a function of network. To this end, no prior knowledge is presumed; however, data, records, observations, and measurements, are taken into account. ANN research is associated with learning from data to imitate linear and nonlinear biological capability in problem solving. Normally, a neural network is composed of several neurons, and information is transmitted via links (connections) known as the weights. There are two kinds of parameters in a neuron, namely input parameters and output parameters. Also, it has an activation function. Most commonly the neural network consisted of an input layer, an output layer, and a hidden layer. The learning rules manage the change in the weight matrix of the network. There are two categories of learning: supervised learning and unsupervised learning. Accordingly, supervised learning employs the data set containing input vectors as well as corresponding output vectors in order to train the network, whereas unsupervised learning is dependent on the local information along with internal control embedded in the network. According to [5], there are two diverse kinds of NN structures, feed-forward networks and recurrent networks. There is at least one feedback loop in a recurrent neural network (RNN).

NNs normally work based on a distributed knowledge representation. They also can make a concise representation of nonlinear and complex concepts. Furthermore, it is possible to directly acquire knowledge from experience such that they can process noisy and inconsistent data. Similarly, NNs calculate the most reasonable output in relation to each input and also they can adapt to unstable and mostly unknown environments. They provide parallel computation, strong error tolerance ability and are able to appreciate the simulation designed for a model of human thinking. The capabilities of learning and generalization allow neural networks to address nonlinear and time variant issues, even under noisy circumstances more effectively. NN-bound solutions do not utilize the system's mathematical modelling; however, their disadvantage is that they rely on data-intensive training algorithms, where there is little opportunity for integrating available and discrete knowledge. Running into local culmination is effortless. The noticeable disadvantage is that it is difficult to explain the behaviour of the neural nets due to the distributed knowledge representation [27].

Much research study has been conducted in the area of prediction and controlling of the AFR through using neural networks. Correspondingly, Howlett, et al. [33] developed a Multi-Layer Perceptron (MLP) network depending on the spark plug, also Howlett, et al. [34] upgraded engine control by integrating neural nets and other intelligent-system methods into the ECU. In a related study, Thompson, et al. [17] presented a method in which a system working based on NN can be employed to predict fuel consumption, emission and engine performance. Frith, et al. [2] used a method to estimate and control AFR via a system of multiple NN modelling. Multi-Layer Perceptron (MLP) architectures have been utilized with the process dynamics which is represented in the input parameters of model. Engine system's variable time constant aspects were accommodated by using input parameters in relation to the ANN model considered as a combination of delayed, filtered sample data values. Likewise, Richter, et al. [49] employed a MLP neural nets for estimating values of the O2 sensor. Data was comprised of 42 factors to train the net such as the oxygen sensor, air flow rate, engine speed, torque, and so on. Over 2,300 topologies of MLP neural nets were trained by utilizing the entire universe of data along with subset of the universe. Traver, et al. [28] applied a NN for a virtual real-time transient NOX sensor. Alippi,et al. [8] employed a NN controller to obtain the minimum value of engine emissions. Hill and Lung [40] developed an off-line trained NN controller that used engine speed and intake manifold pressure as an input to the model to control the fuel of several engines. Manzie, et al. [10] introduced a RBF network for fuel injection control, the method needed no priori knowledge about the engine system and had good mapping capabilities. Zhai and Yu [55] used two RBF networks to control the AFR by estimating the air flow rate and desired fuel injection rate during different throttle transients. An inverse fuel injection dynamics was also applied to achieve more precise improvements. Subramaniam, et al. [29] described the use of virtual sensor based MLP NN instead of the NOX sensor. The model used to predict the NOX concentration depending on engine speed, EGR, AFR, and load information and achieved good results during steady state conditions. Lenz and Schroeder [51] presented a feed-forward NN for AFR control during transient operation of engine.

Also other types of NNs were used for AFR control, such as, Lee, et al. [48] developed a new estimator for the AFR during cold start using a feed-forward Generalized Regression Neural Network (GRNN). Parameters like coolant temperature and exhaust gas temperature were used for the AFR estimation. Shiraishi, et al. [19] applied a Cerebellar Model Articulation Controller (CMAC) neural network.

The usefulness of NNs has been proven for the purpose of modelling nonlinear dynamic systems through introducing feedback connections in computational structure recursively. Zhang, et al. [56] presented an AFR estimation methodology via a recurrent neural network (RNN), and it could predict AFR a few steps ahead of reasonable accuracy. To validate the RNN model, they used the following techniques: estimation of the mean square error of generalization and visualization of its capability and ability to predict. Also, the single-factor method was employed to conduct data analysis. Similarly, Arsie, et al. [20] used a RNN model to simulate AFR dynamics. In this state, a trial and error analysis was carried out to choose the best RNN acting as a compromise and cooperation between the network dimension and the generalization error. Beltrami, et al. [9] introduced a study showing the simulation feasibility of utilizing a recurrent neural network for the control of AFR, the network used Levenberg-Marquardt method for training. Arise, et al. [21] introduced a work showing the experimental identification and validation of RNN models which was used for both forward and inverse dynamics of AFR to achieve a satisfying accuracy of estimation and control. Park, et al. [42] used a RBF neural network controller based on feedback error training method for AFR control. The controller's performance was measured during transient conditions.

For related studies employing adaptive neural networks in this field, Wang and Yu [44] used an adaptive neural network trained by RLS method. As mentioned, the model reaches better results for modeling the AFR dynamics than traditional PI controller, also another related study, Wang and Yu [45] used an adaptive neural network for AFR control based on a radial basis function (RBF) network. The network was trained by recursive k-means and recursive least-squares algorithms. Weins, et al. [50] presented a preliminary experimental verification of an adaptive AFR controller using a generalized neural network. The model was able of achieving a high AFR control precision and eliminating the time-consuming calibration process. Also, neural networks were employed with combination with other linear methods.

Mentioning a number of studies in this field, Ju-Biao [53] introduced a combined model that can overcome the transportation delay of the AFR signal. The model included a modified Elman neural network and PI controller that was able to achieve the AFR prediction in real-time and keeping the AFR value during the range ±3 of transient operating states. Wang and Lu [47] employed a RBF network for the control of dynamic sliding mode control AFR, the network was trained using Lyapunov. Blomqvist, et al. [12] presented an evaluation of various control strategies for AFR during transient conditions. The control strategies included feedback PI control, feed-forward control based inverse modeling applying both ANN and linear models, and feed-forward control based indirect inverse modeling applying ANN models. The latter confirmed better performance than others.

4.2 Fuzzy Logic

Fuzzy logic, as a soft computing technique, is employed to solve extremely complex problems and issues when it is too difficult or impossible to develop a mathematical model, due to nonlinearity, imprecise measurement information and time varying behaviour. Fuzzy logic techniques provide approximate solutions robustly to engineering problems that are too complicated or ill-defined to produce analytical solutions, and are challenging, for example, their boundaries are not hard and crisp, and data is inconsistent, incomplete, ambiguous, and imprecise. Concerning real world problems and issues, two kinds of uncertainty, namely, probabilistic uncertainty and possibilistic (i.e., vague & imprecise) uncertainty need to be addressed. Information is generally collected in two forms, including numerical and linguistic data. Numerical data is obtained from sensor measurements, while linguistic data is received from human experts and operators. As the sensors use simplified mathematical models, and also provide measurements according to past operations, such sensor measurements are not useful to accurately encompass future simulations. Besides, when human beings convey their skill through linguistic rules, some data is lost in the process of communication. Consequently, neither numerical data nor linguistic data is sufficient to represent and solve real-world engineering problems and issues. Therefore, the main idea is to utilize numerical as well as linguistic data via fuzzy logic in order to provide approximate solutions for tackling complex engineering problems [36].

Fuzzy logic involves fuzzy inference, fuzzification, and defuzzification. The process of fuzzification is transforming crisp input variable to linguistic variable. This transformation is appreciated by function memberships, defining a range of value along with a degree of membership. Simply, the fuzzy inference does the mapping of input linguistic variables on output linguistic variables based on fuzzy rules system. Also, this phase contains the rule outputs aggregation. Aggregation is considered as the process of unifying all rules outputs. In the defuzzification phase, regularly the weighted values associated with the output linguistic variable gained as a consequence of fuzzy inference must be transformed and changed to crisp variables [25][30].

Several research studies were conducted on AFR control in the past. Correspondingly, Lee, et al. [39] introduced an intelligent system employed to organize the fuel injection systems of small spark-ignition internal-combustion engines during engine's steady state operation. A fuzzy approach was exhibited used for reaching rapid and appropriate calibrations of the ECU. Bose and Kumar [7] demonstrated a technique of fuzzy logic modelling utilized to predicate emissions of engine in a diesel vehicle engine via combustion information obtained from in-cylinder pressure variables, with no mathematical model to correlate the emissions with information of combustion. To verify the fuzzy logic model experimentally, a regression analysis was employed. Likewise, the fuzzy system was evaluated and tested during both the steady state and transient state of the engine performance. Ghaffari, et al. [3] presented a method of controlling the AFR of a vehicle spark-ignition engine by means of adaptive fuzzy control. Also, a method of proportional integral-derivative (PID) tuning was discussed by employing an adaptive fuzzy system designed for formulating the correlation between the controller's gains and the response of target output. A Mamdani-type fuzzy inference system has been utilized for the Fuzzy-PID controller. An experiment was conducted in the steady and transient states of the engine operation. Consequently, the AFR control performance was significantly better compared to a conventional PID controller. Lauber, et al. [23] presented a nonlinear AFR controller by establishing a TS fuzzy model. Copp, et al. [14] introduced a comparison between two models trying to predict the air flow rate into the engine. The dynamic fuzzy model gave better results when compared with PID controller, the former was capable of reducing the transient deviations in AFR which is consequent to load and speed disturbance.

Due to nonlinear features of the AFR control problem, an adaptive control using self-tuning regulator was applied by Al-Olimat, et al. [26]. It used fuzzy logic to evaluate the model's parameters depending on the throttle angle, fuel pulse width and equivalent ratio as inputs. Shamdani, et al. [4] applied fuzzy controller. Nam, et al. [41] developed a predictive fuzzy-sliding model applied for fuel-injection control, due to its capabilities in dealing the incomplete and the delay issue of the oxygen sensor and also its usability for nonlinear engine models. Also, Haj Bagheri, et al. [22] and Vosooghi, et al. [18] employed fuzzy logic systems to obtain the fuel injection system regulation of SI engines.

Although it is easy to design fuzzy logic, it has some critical problems. When the complexity of the system augments, it would be a challenging issue to determine the proper set of rules along with membership functions in order to explain the system behaviour. Hence, a great amount of time is required to accurately tune the membership function as well as adjust the rules in order to find a good solution, which is associated with the fact that training fuzzy systems appears to be impossible. In addition, the generalization capabilities of fuzzy logic are poor in comparison with neural networks [27].

4.3 Neuro-Fuzzy Systems

To overcome the disadvantages of neural networks and fuzzy systems, a combination of the fuzzy system and the neural networks is used which is called neuro-fuzzy computing systems. These systems employs the modeling of uncertain and linguistic, human like reasoning of fuzzy systems and the robust computing abilities of neural networks. There were a number of studies that included using neuro-fuzzy systems for AFR modeling and control.

Exists a number of studies in the field of neuro-fuzzy computing for control, Weige, et al. [58] combined fuzzy neural network with PI controller to control the AFR of a lean-burn compressed natural gas. The model was tested during transient operating conditions. Liu and Zhou [57] used fuzzy neural network to control AFR under transient conditions. Barghi and Safavi [16] applied a Recurrent Neuro-Fuzzy Network (RNFN) as an intelligent approach for AFR modeling and predictive control.

5.CONCLUSION

This paper reviews some recent research works on the prediction and controlling of the AFR in relation to a gasoline engine. To this end, a number of research studies based on different approaches such as classical approaches namely PI and PID controllers, look-up tables, SMC, and LQG, and modern approaches such as ANN and Fuzzy logic were discussed. The most promising and capable controllers function based on the concepts of modern control, addressing the nonlinear sides of the problems and also promotes accuracy as well as enhances faster response.

REFERENCES

[1] A. di Gaeta, U. Montanaro, and V. Giglio, "Model-based control of the air fuel ratio for gasoline direct injection engines via advanced co-simulation: an approach to reduce the development cycle of engine control systems" *Journal of Dynamic Systems, Measurement, and Control,* vol. 133, pp. 061006, 2011.

[2] A. Frith, C. Gent, and A. Beaumont, "Adaptive control of gasoline engine air-fuel ratio using artificial neural networks" 1995.

[3] A. Ghaffari, A. H. Shamekhi, A. Saki, and E. Kamrani, "Adaptive Fuzzy Control for Air-Fuel Ratio of Automobile Spark Ignition Engine" Proceedings of World Academy of Science: Engineering & Technology, vol. 48, 2008.

[4] A. H. Shamdani, A. H. Shamekhi, M. Ziabasharhagh, and C. Aghanajafi, "Air-to-Fuel Ratio Control of a Turbocharged Diesel Engine Equipped with EGR using Fuzzy Logic Controller" Training, vol. 2014, pp. 04-07, 2007.

[5] A. Ukil, Intelligent systems and signal processing in power engineering: Springer, 2007.

[6] B. Ebrahimi, R. Tafreshi, H. Masudi, M. Franchek, J. Mohammadpour, and K. Grigoriadis, "A parameter -varying filtered PID strategy for air–fuel ratio control of spark ignition engines" Control Engineering Practice, vol. 20, pp. 805-815, 2012.

[7] B. K. Bose, "Expert system, fuzzy logic, and neural network applications in power electronics and motion control" Proceedings of the IEEE, vol. 82, pp. 1303-1323, 1994.

[8] C. Alippi, C. De Russis, V. Piuri, "A fine control of the air-to-fuel ratio with recurrent neural networks", Proceedings of Instrumentation and Measurement Technology Conference, IEEE, pp. 924-929, 1998.

[9] C. Beltrami, Y. Chamaillard, G. Millerioux, P. Higelin, and G. Bloch, "AFR control in SI engine with neural prediction of cylinder air mass" ,Proceedings of American Control Conference, pp. 1404-1409, 2003.

[10] C. Manzie, M. Palaniswami, H. Watson, "Gaussian networks for fuel injection control", Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, vol. 215, pp. 1053-1068, 2001.

[11] C. W. Tan, "Modeling and control of an engine fuel injection system," Universiti Teknologi Malaysia, Faculty of Electrical Engineering, 2009.

[12] D. Blomqvist, S. Byttner, T. Rögnvaldsson, U. Holmberg, "Different strategies for transient control of the air - fuel ratio in a SI engine", SAE transactions: journal of fuels and lubricants, 2000.

[13] D. Cho, J. K. Hedrick, "Sliding mode fuel-injection controller: Its advantages", Journal of Dynamic Systems, Measurement, and Control, vol. 113, pp. 537-541, 1991.

[14] D. Copp, K. Burnham, F. Lockett, "Model comparison for feedforward air/fuel ratio control", 1998.

[15] E. Franceschi, K. R. Muske, J. C. P. Jones, I. Makki, "An adaptive delay-compensated PID air fuel ratio controller", Training, vol. 2013, pp. 10-14, 2007.

[16] F. Barghi, A. A. Safavi, "Experimental validation of recurrent Neuro-Fuzzy Networks for AFR estimation and control in SI engines", in Computational Intelligence for Measurement Systems and Applications (CIMSA), IEEE International Conference , pp. 1-6, 2011.

[17] G. Thompson, C. Atkinson, N. Clark, T. Long, E. Hanzevack, "Technical Note: Neural network modelling of the emissions and performance of a heavy-duty diesel engine", Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, vol. 214, pp. 111-126, 2000.

[18] G. Vosooghi, M. H. Saeedi, M. Miri, "Air to Fuel Ratio Control in Internal Combustion Engines with fuzzy, Integral and Fuzzy-Integral Controllers" Proceeding of the Third International Conference on Internal Combustion Engines, Tehran, Iran, 2004.

[19] H. Shiraishi, S. L. Ipri, D.-I. Cho, "CMAC neural network controller for fuel-injection systems", Control Systems Technology, IEEE Transactions on, vol. 3, pp. 32-38, 1995.

[20] I. Arsie, C. Pianese, M. Sorrentino, "A procedure to enhance identification of recurrent neural networks for simulating air–fuel ratio dynamics in SI engines", Engineering Applications of Artificial Intelligence, vol. 19, pp. 65-77, 2006.

[21] I. Arsie, S. Di Iorio, C. Pianese, G. Rizzo, M. Sorrentino, "Recurrent neural networks for air-fuel ratio estimation and control in spark-ignited engines", Proceedings of the 17th IFAC World Congress, Seoul, July, pp. 6-11, 2008.

[22] J. Haj Bagheri, A. Alasti, A. Safi Khani, "Fuzzy control of air to fuel ratio of the internal combustion engine with manifold pressure observer", Proceeding of the Third International Conference on Internal Combustion Engines, 2004.

[23] J. Lauber, T.-M. Guerra, M. Dambrine, "Air-fuel ratio control in a gasoline engine", International Journal of Systems Science, vol. 42, pp. 277-286, 2011.

[24] J. M. Pfeiffer J. K. Hedrick, "Nonlinear algorithms for simultaneous speed tracking and air-fuel ratio control in an automobile engine", SAE transactions, vol. 108, pp. 783-788, 1999.

[25] K. M. Passino, S. Yurkovich, M. Reinfrank, Fuzzy control, vol. 42: Citeseer, 1998.

[26] K. S. Al-Olimat, A. A. Ghandakly, M. M. Jamali, "Adaptive air-fuel ratio control of an SI engine using fuzzy logic parameters evaluation", SAE Technical Paper, 2000.

[27] L. C. Jain, N. Martin, Fusion of neural networks, fuzzy systems and genetic algorithms: industrial applications, vol.

4: CRC press, 1998.
[28] M. L. Traver, R. J. Atkinson, C. M. Atkinson, "Neural network-based diesel engine emissions prediction using in-cylinder combustion pressure", SAE transactions, vol. 108, pp. 1166-1180, 1999.
[29] M. N. Subramaniam, D. Tomazic, M. Tatur, M. Laermann, "An artificial neural network-based approach for virtual NOx Sensing", SAE paper, pp. 01-0753, 2008.
[30] M. Negnevitsky, Artificial intelligence: a guide to intelligent systems: Pearson Education, 2005.
[31] P. Puleston, G. Monsees, S. Spurgeon, "Air-fuel ratio and speed control for low emission vehicles based on sliding mode techniques", Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering, vol. 216, pp. 117-124, 2002.
[32] P. Yoon and M. Sunwoo, "An adaptive sliding mode controller for air-fuel ratio control of spark ignition engines," Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, vol. 215, pp. 305-315, 2001.
[33] R. J. Howlett, S. D. Walters, P. A. Howson, I. Park, "Air-fuel ratio measurement in an internal combustion engine using a neural network," in Advances in Vehicle Control and Safety (International Conference), AVCS, 1998.
[34] R. J. Howlett, M. de Zoysa, S. Walters, "Monitoring internal combustion engines by neural network based virtual sensing", Recent Advances in Artificial Neural Networks Design and Applications, pp. 291-318, 2000.
[35] R. Lozano, P. Castillo, A. Dzul, "Modeling and control of mini-flying machines", Springer Verlag London, 2005.
[36] R.-N. Singh, W. H. Bailey, "Fuzzy logic applications to multisensor-multitarget correlation," Aerospace and Electronic Systems, IEEE Trans, vol. 33, pp. 752-769, 1997.
[37] S.B. Choi, M. Won, J. Hedrick, "Fuel-injection control of SI engines", in Decision and Control, Proceedings of the 33rd IEEE Conference, vol. 2, pp. 1609-1614, 1994.
[38] S.B. Choi, M. Won, J. Hedrick," An observer-based controller design method for improving air/fuel characteristics of spark ignition engines", Control Systems Technology, IEEE Trans, vol. 6(3), pp. 325-334, 1998.
[39] S. H. Lee, R. Howlett, S. Walters, "Engine fuel injection control using fuzzy logic", Intelligent Sistems & Signal Processing Laboratories, 2004.
[40] S. Hill, B. Lung, "The application of neural controls to ford and dodge pickup trucks running on natural gas", Technical Report 11305-4C02, Saskatchewan Research Council, Saskatoon, 2003.
[41] S. Nam, M. Lee, W. Yoo, "Predictive sliding control with fuzzy logic for fuel-injected automotive engines", Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering, vol. 206, pp. 237-244, 1992.
[42] S. Park, M. Yoon, M. Sunwoo, "Feedback Error Learning Neural Networks for Air-To-Fuel Ratio Control in SI Engines", 2003.
[43] S. S. Kamat, H. Javaherian, V. V. Diwanji, J. G. Smith, K. Madhavan, "Virtual air-fuel ratio sensors for engine control and diagnostics", American Control Conference, 2006.
[44] S.-W. Wang, D.-L. Yu, "Adaptive air-fuel ratio control with MLP network", International Journal of Automation and Computing, vol. 2, pp. 125-133, 2005.
[45] S. Wang, D. Yu, J. Gomm, G. Page, S. Douglas, "Adaptive neural network model based predictive control for air–fuel ratio of SI engines", Engineering Applications of Artificial Intelligence, vol. 19, pp. 189-200, 2006.
[46] S. Wang, D. Yu, "A new development of internal combustion engine air-fuel ratio control with second-order sliding mode", Journal of Dynamic Systems, Measurement, and Control, vol. 129, pp. 757-766, 2007.
[47] S. Wang, D. Yu, "Adaptive RBF network for parameter estimation and stable air–fuel ratio control", Neural Networks, vol. 21, pp. 102-112, 2008.
[48] T. Lee, C. Bae, S. V. Bohac, D. N. Assanis, "Estimation of Air Fuel Ratio of a SI Engine from Exhaust Gas Temperature at Cold Start Condition", SAE paper, p. 1667, 2002.
[49] T. Richter, A. F. Oliveira, and I. N. da Silva, "Virtual oxygen sensor implementation using artificial neural networks," in Technological Developments in Education and Automation, ed: Springer, 2010, pp. 219-224.
[50] T. Wiens, R. Burton, G. Schoenau, M. Sulatisky, S. Hill, B. Lung, "Preliminary experimental verification of an intelligent fuel air ratio controller", Power Electronics, vol. 2013, pp. 04-08, 2007.
[51] U. Lenz, D. Schroeder, "Transient Air-Fuel Ratio Control Using Artificial Intelligence", Training, vol. 2014, pp. 03-03, 1998.
[52] W. C. Cave, Prediction Theory for Control Systems: Prediction Systems, Inc., Spring Lake, NJ, 1-12, 2010.
[53] Y. Ju-Biao, "Research on transient air fuel ratio control of gasoline engines," in Information Technology and Applications, pp. 610-613, 2009.
[54] Y. Shiao, J. J. Moskwa, "Model-based cylinder-by-cylinder air-fuel ratio control for SI engines using sliding observers", in Control Applications, 1996., Proceedings of the 1996 IEEE International Conference, pp. 347-354, 1996.