PREDICTION OF COLD START HYDROCARBON EMISSIONS OF AIR COOLED TWO WHEELER SPARK IGNITION ENGINES BY SIMPLE FUZZY LOGIC SIMULATION

by

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The cold start hydrocarbon emission from the increasing population of two wheelers in countries like India is one of the research issues to be addressed. This work describes the prediction of cold start hydrocarbon emissions from air cooled spark ignition engines through fuzzy logic technique. Hydrocarbon emissions were experimentally measured from test engines of different cubic capacity, at different lubricating oil temperature and at different idling speeds with and without secondary air supply in exhaust. The experimental data were used as input for modeling average hydrocarbon emissions for 180 seconds counted from cold start and warm start of gasoline bike engines. In fuzzy logic simulation, member functions were assigned for input variables (cubic capacity and idling rpm) and output variables (average hydrocarbon emission for first 180 seconds at cold start and warm start). The knowledge based rules were adopted from the analyzed experimental data and separate simulations were carried out for predicting hydrocarbon emissions from engines equipped with and without secondary air supply. The simulation yielded the average hydrocarbon emissions of air cooled gasoline engine for a set of given input data with accuracy over 90%.

Key words: *spark ignition engine, cold start, hydrocarbon emissions, simulation, fuzzy logic*

Introduction

Cold start is defined as the starting of the engine after a minimum stop time of 8 hours or more. Hydrocarbon (HC) emissions are produced in large amount during cold start of spark ignition (SI) engine during the first 3-4 minutes of engine running due to poor vaporization, flame quenching, wall wetting, misfiring, incomplete combustion, lubrication oil dilution with liquid and fuel vapor, inlet and exhaust valve leakage, and crevice storage [1]. The factors which affect the engine-out HC emissions are the air-fuel ratio, spark timing, speed, load, and cylinder wall temperature. About 90% of the total emission of a vehicle during a short trip is mainly from the first 2 to 3 minutes of its cold start. New emission regulations and vehicle certification tests have placed increasing demands on the minimization of HC emissions from the vehicle during cold start conditions.

The cold start HC emission of an engine is greatly influenced by the ambient temperature and the results [2] show that the decrease in atmospheric temperature leads to an increase in cold start HC emissions. The cold start emissions are generally observed after a engine stop time

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of 8-12 hours but the experimental investigations confirm that the HC emission are also influenced by the shorter stop periods of 0.5, 1, 2, and 4 hours [3].

The cold start HC emissions can be reduced by different techniques. HC absorber like zeolite used in the exhaust manifold absorbs HC during cold start period and oxidizes it during the warm running conditions [4, 5]. Selective catalytic reduction, when used before the catalytic convertor unit, reduces the harmful NO_x emissions to yield oxygen for oxidizing HC in the main convertor [6]. Three way catalytic convertors consisting of ceramic or metallic substrate wash-coated with metals like platinum, palladium, and rhodium, convert the HC and CO emissions to H_2O and CO_2 and reduce NO_x to N_2 and O_2 [7, 8]. External air supply in exhaust manifold oxidizes the unburnt HC and CO emissions during cold start operations. Phase change materials are used to preheat the engine coolant and there by cylinder wall, which in turn increases the start up temperature of the engine at cold start, reducing cold start emissions [9, 10].

The soft computing techniques like fuzzy logic, artificial neural network (ANN), neuro-fuzzy techniques are used widely to predict performance parameters of various systems. It is difficult to model a process if it is highly non-linear with limited input data. Studies show that an efficient fuzzy model consisting of a number of fuzzy implications, each of them, in an IF-THEN form can be logically related to get the desired results even with limited experimental data [11]. The neuro-fuzzy modeling framework is used to discover the knowledge from the data and represent it in the form of rules. A real world problem such as prediction of chemical composition of ashes has been addressed using this model [12].

The emission and performance characteristics of an engine, by varying the timing of inlet valve opening have been studied from the experiments and the data were used for training the artificial neural network (ANN). The developed fuzzy expert system (FES) was realized for the prediction of HC emissions, engine power and engine torque. The intermediate values which were not performed on the experiment set but obtained from the developed system were found to be fitting with the experimental results [13] and a similar approach has been followed in this paper.

Neuro fuzzy modeling has been done for flue gas emissions from power plant [14] and neuro-fuzzy modeling technique was found to give higher accuracy in predicting the CO_2 production rate than the combined approach of neural network modeling and sensitivity analysis [15]. Flexible Fuzzy Inference Systems (FLEXFIS) approach has been applied for building up fuzzy NO_x prediction models, which estimates the consequent parameters of Takagi-Sugeno fuzzy systems. The predictive power of the fuzzy NO_x prediction models has been compared with that one achieved by physical-oriented models based on high-dimensional engine data recorded during steady-state and dynamic engine states [16].

The emission models control the design parameters and performance of the vehicle to meet the emission standards. However these low order models typically make certain assumptions about the engine with constant temperature operation. But the cold start operation of the engine becomes more critical and the constant temperature assumption turns to be a limiting factor [17]. Estimating emissions from road traffic is a permanent task, which needs frequent updates, via well-designed programmes, including both experiments and simulations [18].

Hence, modeling and prediction of HC emissions has become very essential in the process of developing low emission vehicle. The current work deals with the prediction of harmful HC emissions under cold start and warm start at different idling speeds of gasoline bike engines using fuzzy logic simulation. Bike engines of different engine capacity, with and without air supply at the exhaust port, were tested. The obtained HC emission data were analyzed and used to formulate the fuzzy logic simulation.

Factors affecting cold start HC emissions

Secondary air supply

Secondary air supply is commonly found in modern motor bikes which use "air suction valve" (ASV). This valve constantly supplies fresh air, sucked through a diaphragm unit into the exhaust pipe to reduce HC and CO emission by oxidation. The ASV has three openings. One is connected to the intake pipe vacuum, another is connected to the exhaust pipe and the third is open to the atmosphere through air filter in the suction unit. When a negative pulse is induced in the exhaust, a portion of air from the engine suction side enters the exhaust pipe through the diaphragm unit actuated by pressure difference between inlet and exhaust pipes. This fresh air is utilized to oxidize the CO and HC in the exhaust. In the present work, motor bikes with and without ASV were tested for cold start and warm start HC emissions.

Idling speed

Cold start HC emissions are considerably affected by the idling speed of the engine. The idling speed is set by adjusting the volume control screw in the carburetor to vary the quantity of air-fuel mixture entering into the engine cylinder. As spark ignition engines are quantity governed engines, higher volume of air-fuel mixture increases the engine speed. As the speed increases, the time available for heat transfer through cylinder walls is reduced resulting in overall temperature rise inside the engine cylinder. This leads to better vaporization of air-fuel mixture and better combustion reducing unburnt hydrocarbon emissions. In the current work, for each motor bike, the range of idling speed was recommended idling rpm ± 300 rpm.

Engine capacity

As the engine displacement volume is increased, more quantity of air-fuel mixture is used inside the engine cylinder to develop more power. This increases the chances of poor vaporization, flame quenching and higher crevice storage volume. As a result, the unburnt HC emissions in the exhaust increase proportionately. Though combustion chamber shape and geometry (S/D ratio) affect formation of HC emissions, they are not considered in the present work as all the engines tested were air cooled, single cylinder engines with lower capacity (100-150 cm^3).

Lubricating oil temperature

Cold start HC emissions are mainly due to the lower temperature of engine components. The cylinder wall temperature is increased by higher lubricating oil temperatures and this reduces the possibilities of poor vaporization and incomplete combustion, resulting in lower HC emissions. Hence, engines started at warm conditions produce less HC emissions compared to cold start. In the current work, experiments were conducted at different lubricating oil temperatures.

Experimental set-up

The experimental setup consisted of test bike, two wheeler chassis dynamometer, engine speed sensor, exhaust gas analyzer, and computer interface as shown in fig. 1. Test bike was mounted on the chassis dynamometer and experiments were carried out to measure the exhaust gas emissions using the exhaust gas analyzer of specifications shown in tab. 1. The Indian driving cycle was followed to drive the test bike on chassis dynamometer. Exhaust emissions were measured for the first 180 seconds of the engine running at cold and warm starts. Exhaust analyzer was interfaced to a computer to record the exhaust emissions for every 2 seconds.

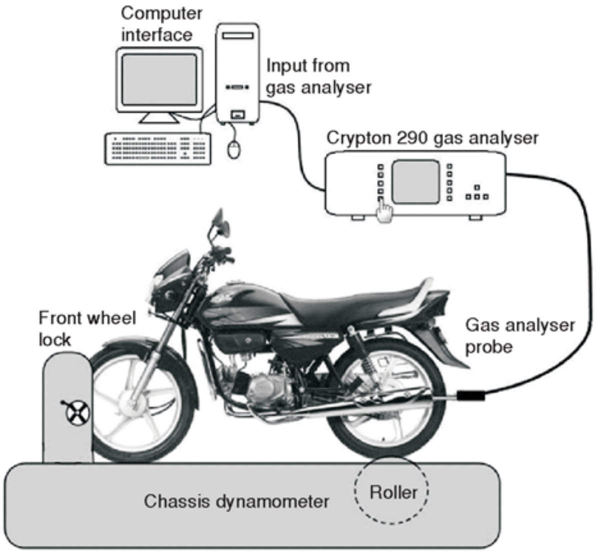


Figure 1. Experimental set-up

Among various exhaust gas emissions, HC emissions were emitted in relatively larger quantities at cold start and therefore only HC emissions are considered in the current work. The variations of HC emissions with design variables (engine cubic capacity (CC)/displacement volume, secondary air supply) and operating variables (idling speed, lubricating oil temperature) were analyzed and the data were used for simulation.

The HC emissions were found to be influenced by engaging choke/ /starting system or multiple starting attempts at starting. Hence maximum care was given to start the engine in the first attempt. All the test runs were carried out at an ambient temperature of 30 ± 0.5 °C.

Table1. Specifications of exhaust gas analyzer (Crypton 290 series)

Parameters	Range	Accuracy/performance	Resolution
CO	0 to 10% by vol.	±0.06% CO	0.01% vol.
HC	0 to 10,000 ppm by vol.	±12 ppm HC	1 ppm vol.
CO_2	0 to 20% by vol.	±0.5% CO_2	0.1% vol.
O_2	0 to 25% by vol.	±0.1% O_2	0.01% vol.
rpm	0 to 10,000 rpm	±10 rpm	1 rpm

Experimental data analysis

Variation of HC emissions with time

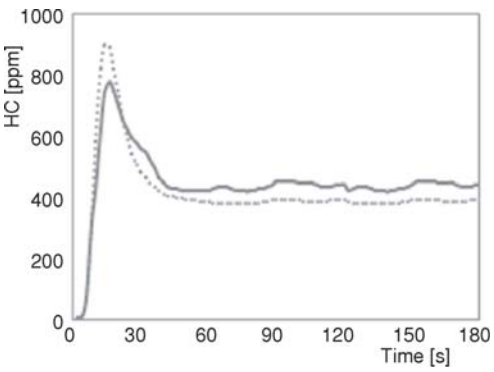


Figure 2. Variation of HC emissions with time

Tests were conducted at a minimum interval of 8 hours, if same bike was used for testing, to measure cold-start emissions. To ensure the repeatability, the experiments were conducted twice at each condition and the average was taken for simulation.

The variation of HC emissions with time for 100 cm^3 bike engine without secondary air supply at cold start running at recommended idling speed of 1200 rpm, in two trials, is shown in fig. 2. It was found that the HC emissions were stable after a time period of first 60 seconds. As the cold start emissions are reported to be higher for the first 3-4 minutes, observations were recorded for first 180 seconds and the average value was used for simulation.

Variations of average HC emissions with engine lubricating oil temperature

To study the variation of average HC emissions with lubricating oil temperature, the vehicle was driven repeatedly through the Indian driving cycle shown in fig. 3. The oil temperature was measured periodically at the completion of each driving cycle.

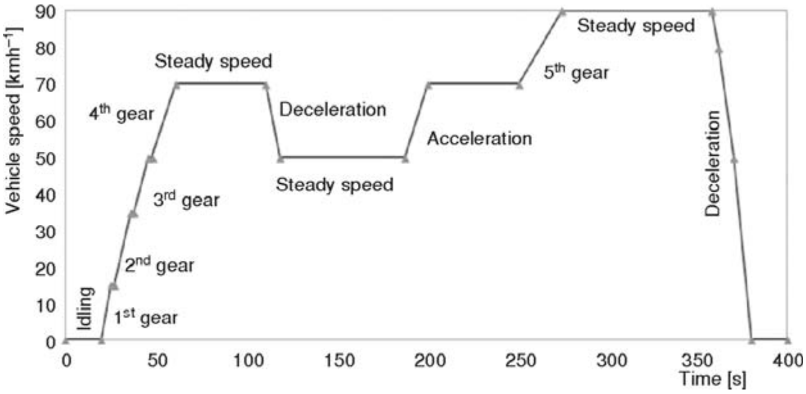


Figure 3. Indian driving cycle

Two bike engines equipped with and without secondary air supply were tested at recommended idling speeds to study the variation of average HC emissions with lubricating oil temperature. For the engine without air supply, HC emissions were found to decrease significantly till lubricating oil temperature reached 44 °C and from 44 °C to 70 °C, it was almost constant as shown in fig. 4. But, for a bike engine with secondary air supply, minimum variations in HC emissions were found above the oil temperature of 50 °C, as shown in fig. 5.

In the current work, the cut off lubricating oil temperature is taken as 44 °C and 50 °C for engines equipped without and with air supply, respectively. In this paper the term warm start refers to starting of the engine above the cut off lubricating oil temperature.

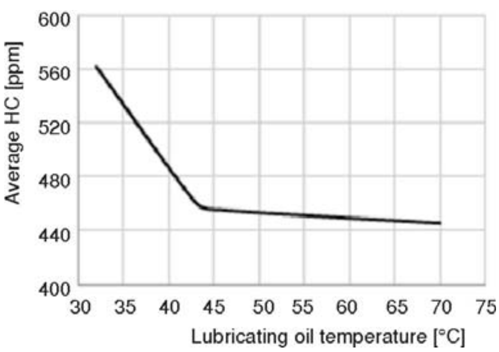


Figure 4. Average HC without air supply

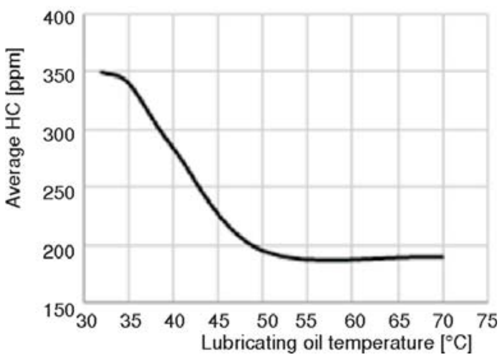


Figure 5. Average HC with air supply

Variations of average HC emissions with idling speed, cubic capacity and secondary air supply

Experiments were conducted in bikes with and without secondary air supply, at a range of idling speeds (recommended idling rpm ± 300) in steps of 100 rpm. The average HC in ppm (parts per million) emitted from bikes of 100 cm^3, 110 cm^3, and 150 cm^3 engines at different idling speeds (800, 1200, and 1500 rpm), with and without secondary air supply at cold and warm start are shown in figs. 6 to 11 as samples.

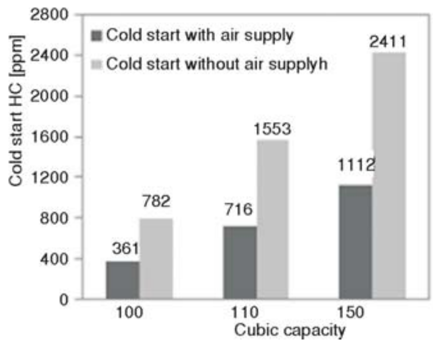


Figure 6. Cold start HC *vs.* CC at 800 rpm

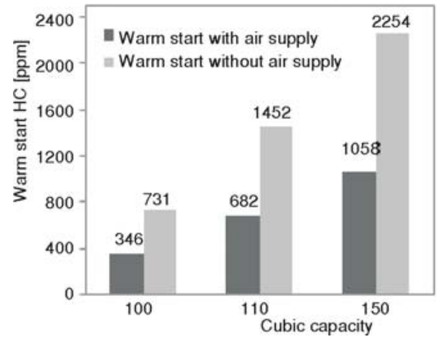


Figure 7. Warm start HC *vs.* CC at 800 rpm

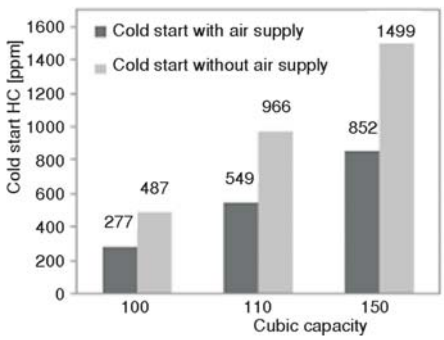


Figure 8. Cold start HC *vs.* CC at 1200 rpm

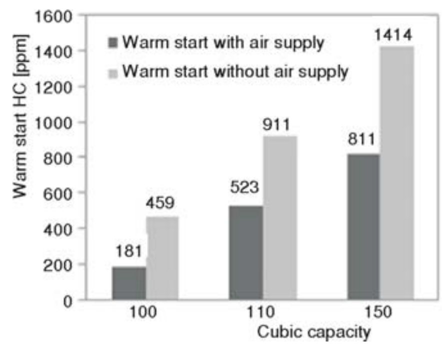


Figure 9. Warm start HC *vs.* CC at 1200 rpm

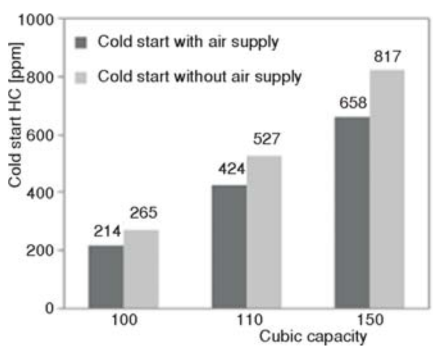


Figure 10. Cold start HC *vs.* CC at 1500 rpm

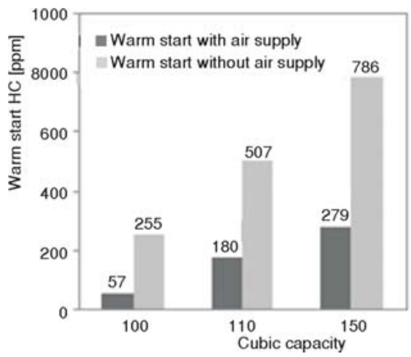


Figure 11. Warm start HC *vs.* CC at 1500 rpm

From the experiments, the trends in HC emissions with the considered variables (CC, idling speed, lubricating oil temperature, secondary air supply) were observed and are listed below.

- For a particular engine, as the idling speed of the engine increased, the average HC emitted reduced significantly.
- The warm start HC emissions were less compared to the cold start HC emissions for an engine at particular idling speed.
- HC emissions without secondary air supply were higher than that with secondary air supply for engines of same cubic capacity at particular idling speed.
- Generally, as the cubic capacity increased, the average HC emissions increased proportionately.

These relationships were used to formulate knowledge based rules for the fuzzy logic simulation in this paper.

Data for fuzzy logic simulation

HC emissions experimentally measured from 100 cm^3, 110 cm^3, and 150 cm^3 engines at a particular idling speed under cold and warm start were plotted against CC values. The equation of the curve joining the experimental data points was obtained. Similarly, equations were obtained from the experimental cold and warm start HC values at 900 to 1500 rpm with an increment of 100 rpm for 100, 110, and 150 cm^3 engines with and without secondary air supply. Cold and warm start HC emissions were calculated for the other CC (105 cm^3, 115 cm^3, 120 cm^3, 125 cm^3, 130 cm^3, 135 cm^3, 140 cm^3, and 145 cm^3) engines from these equations. These data were used to define the member functions in the fuzzy logic simulation. For sample, equation of the curve joining the experimental cold start HC with secondary air supply at 1500 rpm is shown in figure 12. In the equation, x denotes the CC of the engine and y denotes the HC emission in ppm by volume.

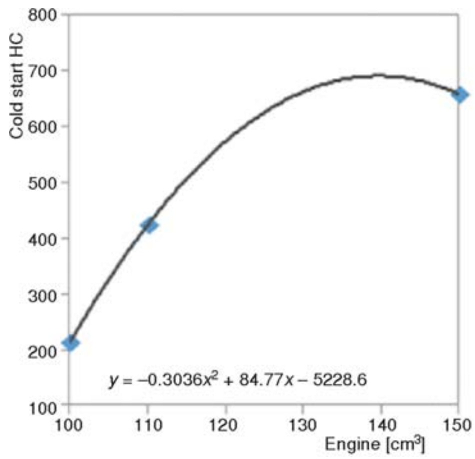


Figure 12. Curve fitting for cold start HC with secondary air supply at 1500 rpm

Fuzzy logic simulation

The fuzzy logic enables to set smooth boundary allowing partial membership, unlike the crisp boolean set which allows only 0 or 1 value. Fuzzy logic simulation is done in three main steps, *i. e.*, fuzzification, adopting knowledge based rules, and defuzzification of the data. In this study, Mamdani controller was used along with the triangular member functions for fuzzification of the data. The Mamdani approach was used since output is used as member function.

The HC emissions from bikes with and without secondary air supply were simulated separately using MATLAB software. The input variables were the engine cubic capacity, idling rpm of the bike engine. The output variables were the average cold start and warm start HC. The structure of developed fuzzy expert system is shown in fig. 13.

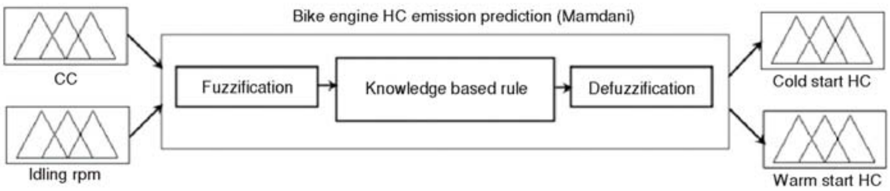


Figure 13. Fuzzy logic simulation for bikes with and without secondary air supply

Fuzzification

The crisp values obtained from experiments and curve fitting were taken as the input and output variable for the fuzzy logic. These crisp values were fuzzified to the membership values and degrees. The linguistic expression for CC (let X) of the engine was determined as L1, … L4, M1,… M4, H1, … H3 with triangular member functions as given in column 1 of tab. 2 (Sample equations for member functions – input variable – CC). Here, $\mu_{CC}(X)$ is the membership degree and X is a member of CC fuzzy set. Similarly sample equations for member functions of output variable are given in column 2.

Table 2. Sample equations for member functions – input and output variables

Sample equations for member functions – input variable CC	Sample equations for member functions – output variable – cold start HC with secondary air supply
$\mu_{L1}(X)=\begin{Bmatrix} 0;\ \text{otherwise} \\ \dfrac{105-x}{5}X;\ 100\le X\le 105 \end{Bmatrix}$	$\mu_{L1}(X)=\begin{Bmatrix} 0;\ \text{otherwise} \\ \dfrac{250-X}{50};\ 200\le X\le 250 \end{Bmatrix}$
$\mu_{L2}(X)=\begin{Bmatrix} 0;\ X\le 100 \\ \dfrac{X-100}{5};\ 100\le X\le 105 \\ \dfrac{110-X}{5};\ 105< X<110 \\ 0;\ X\ge 110 \end{Bmatrix}$	$\mu_{L2}(X)=\begin{Bmatrix} 0;\ X\le 200 \\ \dfrac{X-200}{50};\ 200\le X\le 250 \\ \dfrac{300-X}{50};\ 250< X<300 \\ 0;\ X\ge 300 \end{Bmatrix}$
$\mu_{M3}(X)=\begin{Bmatrix} 0;\ X\le 125 \\ \dfrac{X-125}{5};\ 125< X<130 \\ \dfrac{135-X}{5};\ 130< X<135 \\ 0;\ X\ge 135 \end{Bmatrix}$	$\mu_{L3}(X)=\begin{Bmatrix} 0;\ X\le 250 \\ \dfrac{X-250}{50};\ 250< X<300 \\ \dfrac{350-X}{50};\ 300< X<350 \\ 0;\ X\ge 350 \end{Bmatrix}$
$\mu_{H3}(X)=\begin{Bmatrix} 0;\ \text{otherwise} \\ \dfrac{X-145}{5};\ 145\le X\le 150 \end{Bmatrix}$	$\mu_{H7}(X)=\begin{Bmatrix} 0;\ \text{otherwise} \\ \dfrac{X-1150}{50};\ 1150\le X\le 1200 \end{Bmatrix}$

The input variables (CC and idling rpm) were kept constants for simulating HC emissions of bikes with and without secondary air supply. The experimental data from the test bikes were fuzzified using the triangular member functions for input variables as shown in figs. 14 and 15. The output variables (cold start and warm start HC) for bikes without secondary air supply were fuzzified as shown in figs. 16. For bikes with secondary air supply, the output variables were fuzzified as shown in figs. 17 and 18.

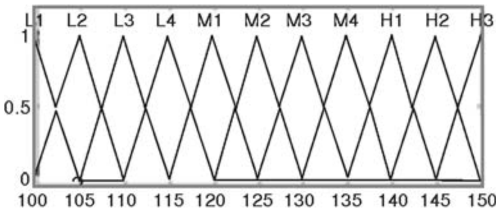


Figure 14. Input variable – CC

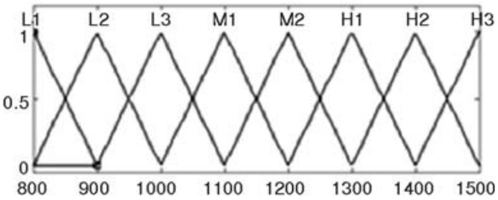


Figure 15. Input variable – rpm

Figure 16. Output variable – cold/warm start HC (without secondary air supply)

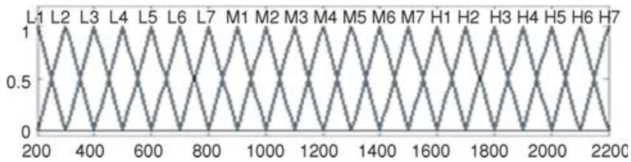


Figure 17. Output variable – cold start HC (with secondary air supply)

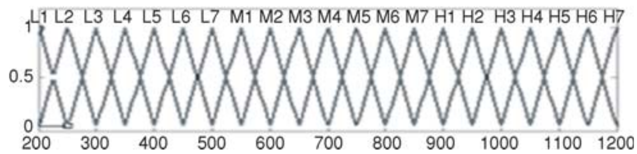
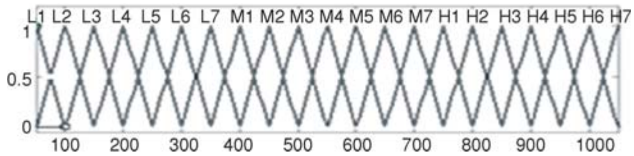


Figure 18. Output variable – warm start HC (with secondary air supply)



Knowledge based rules

Based on the experimental observations and the HC emission influencing factors analysis the crisp values are fuzzified with human expert and the IF -THEN rules were applied to the linguistic values such as extremely low (L1), lowest (L2), low (L3) almost low (L4), under medium (M1), medium (M2), over medium (M3), upper medium (M4), almost high (H1), higher (H2), highest (H3) for CC. The similar rules were applied for all the other input and output variables. Eighty eight knowledge based rules (11 cm^3 × 8 rpm) were specified based on the observations from the experimental data. The data used for formulating knowledge based rules for simulation of cold and warm start HC emissions without secondary air supply are given in tabs. 3 and 4 for sample.

The rules were applied separately for simulating HC emissions for bikes with and without secondary air supply. The data for cold and warm start HC without secondary air supply are shown in tabs. 3 and 4, respectively. When input data are entered, one or more than one rule can be fired and the output is defuzzified to a crisp value. For example, from tabs. 3 and 4, "IF CC is M4 and rpm is H1, THEN Cold start HC is M5 and warm start HC is M4".

Table 3. Data for cold start HC without secondary air supply

mf		L1	L2	L3	M1	M2	H1	H2	H3
		800	900	1000	1100	1200	1300	1400	1500
L1	100	L7	L6	L5	L5	L4	L3	L2	L2
L2	105	M2	M1	L7	L7	L6	L5	L4	L4
L3	110	M7	M6	M5	M3	M2	L7	L6	L4
L4	115	H1	M7	M6	M4	M3	M1	L7	L5
M1	120	H2	H1	M7	M5	M4	M2	M1	L6
M2	125	H3	H2	H1	M6	M5	M3	M2	L7
M3	130	H4	H3	H2	M7	M6	M4	M3	M1
M4	135	H5	H4	H3	H1	M7	M5	M3	M1
H1	140	H6	H5	H4	H2	M7	M5	M3	M1
H2	145	H7	H6	H5	H2	M7	M5	M3	M1
H3	150	H7	H7	H5	H2	M7	M5	M3	M1

Table 4. Data for warm start HC without secondary air supply

mf		L1	L2	L3	M1	M2	H1	H2	H3
		800	900	1000	1100	1200	1300	1400	1500
L1	100	L6	L6	L5	L4	L4	L3	L2	L1
L2	105	M3	M2	M1	L7	L6	L5	L4	L3
L3	110	M6	M5	M4	M2	M1	L7	L5	L4
L4	115	M7	M6	M5	M3	M2	M1	L6	L5
M1	120	H1	M7	M6	M4	M3	M2	L7	L6
M2	125	H2	H1	M7	M5	M4	M3	M1	L7
M3	130	H3	H2	H1	M6	M5	M4	M2	L7
M4	135	H4	H3	H2	M7	M6	M4	M2	L7
H1	140	H5	H4	H3	H1	M6	M4	M2	L7
H2	145	H6	H5	H3	M1	M6	M4	M2	L7
H3	150	H7	H5	H3	M1	M6	M4	M2	L7

Defuzzification

The centroid method was used for the defuzzification as expressed in eq. 1. Here "AND" method was chosen with minimum implication and maximum aggregation:

$$X^* = \frac{\int_v \mu_B(X) X \mathrm{d}X}{\int_v \mu_B(X) \mathrm{d}X} \tag{1}$$

Here $\int_v$ is the conventional integral symbol and this centroid defuzzification determines X^* point as the middle of the area where membership function and the cover field intersects. Thus the fuzzified data is again converted to crisp values by defuzzification. The resulting surface plots are shown in figs. 19 to 22.

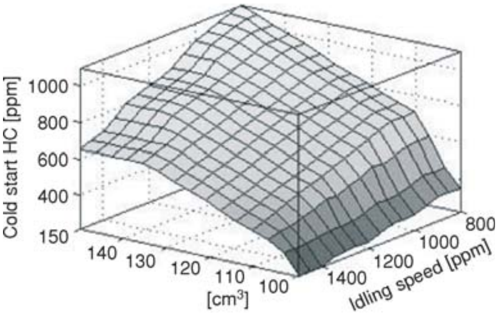


Figure 19. Cold start HC with air supply

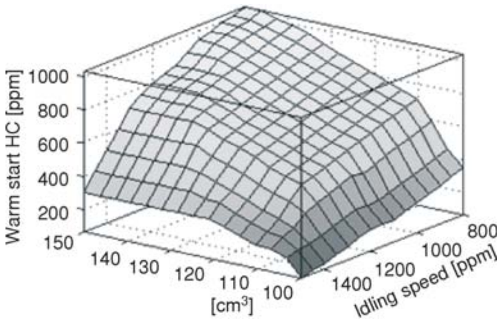


Figure 20. Warm start HC with air supply

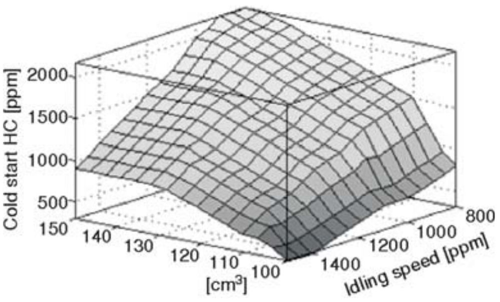


Figure 21. Cold start HC without air supply

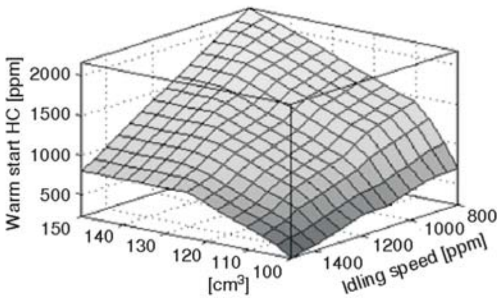


Figure 22. Warm start HC without air supply

Results and discussion

As the simulation was done based on experimental data from 100, 110, and 150 cm^3 engines, a motor bike powered by 125 cm^3 engine was considered for validation of the simulated results. This 125 cm^3 bike was equipped with no secondary air supply system and was tested for cold start and warm start HC emissions. Experiments were conducted at different idling speeds under cold and warm start and average HC emissions were measured. HC emissions were simulated from developed fuzzy expert system for the same experimental conditions. Experimental and simulated data are compared in fig. 23 (cold start HC) and fig. 24 (warm start HC), respec-

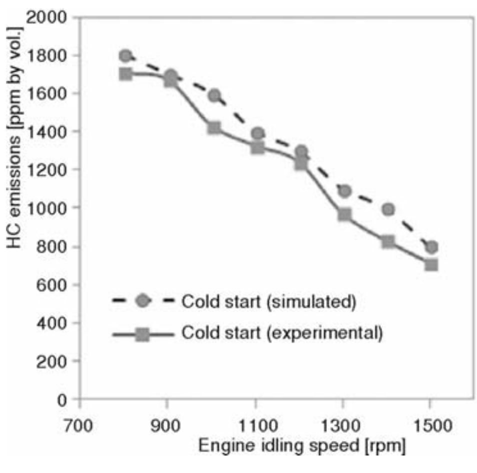


Figure 23. Cold start HC of 125 cm^3 bike

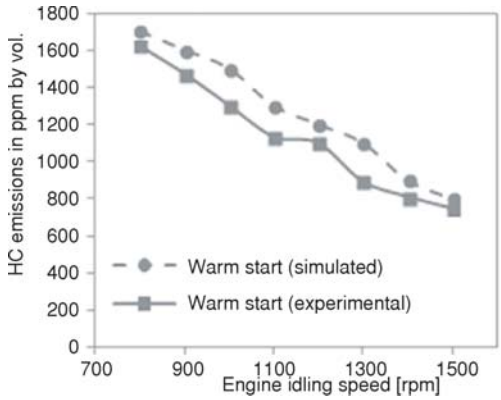


Figure 24. Warm start HC of 125 cm^3 bike

tively. The deviations of the experimental values from the simulated ones are less than 10%.

The developed fuzzy logic model can be used to predict the HC emission of any air cooled motor bike engine with engine cubic capacity between 100-150 cm^3 running at any idling speed in the range of 800 -1500 rpm. The cubic capacity of the engine for motor bikes can vary depending on the designer's perspective and idling speed may change according to the usage and tuning of the engine during service periods. This makes fuzzy as the best choice for modeling the system. With the help of the developed simulation model, it will be possible to obtain the HC emissions of current and future bike engines.

Conclusions

The variations of hydrocarbon emissions of air cooled motor bike engines during cold start and warm start were studied with engines of different swept volume (CC), at different idling speeds and at different lubricating oil temperatures. It was found that cold start average HC emissions were significantly higher than warm start HC emissions. With the increase in engine capacity, increase in HC emission was observed at cold and warm start. This confirms that the magnitude of displacement volume of bike engines needs to be compromised for meeting the emission standards. With increase in idling speed, the cold start and warm start HC emissions reduced considerably.

Motor bikes with engine capacity of 100 cm^3, 110 cm^3, and 150 cm^3 were considered for testing. Cold/warm start HC emissions at different idling speeds (800-1500) were measured. The data for HC emissions of intermediate CC engines were obtained by curve fitting and were used in the simulation. Mamdani approach was used as fuzzy interface mechanism for the current simulation. Triangular member functions and centroid method were used for fuzzification and defuzzification, respectively. The knowledge based rules were applied based on the observations from the experimental results with and rule as minimum. Three dimensional surface plots from the simulation consolidated the average HC emissions at different CC and idling speed for bike engines with and without secondary air supply.

The results obtained from the simulation were compared with the experimental ones for 125 cm^3 engine at different idling speeds and the values were very closely fitting. This simulation technique reduces the overall cost, manpower, and time for measuring the HC emission with sophisticated equipments. At an ambient temperature of 30 ± 0.5 °C, this model could be used to predict HC emissions in cold start and warm start of single cylinder, air cooled motor bike engines in 100 cm^3-150 cm^3 capacity range, with or without secondary air supply.

References

[1] Heywood, J. B., *Internal Combustion Engine Fundamentals*, McGraw-Hill Publications, New York, USA, 1998
[2] Weilenmann, M., *et al.*, Cold-Start Emissions of Modern Passenger Cars at Different Low Ambient Temperatures and Their Evolution over Vehicle Legislation Categories, *Atmospheric Environment, 43* (2009), 15, pp. 2419-2429

[3] Favez, J. Y., *et al*., Cold Start Extra Emissions as a Function of Engine Stop Time: Evolution over the Last 10 Years, *Atmospheric Environment, 43* (2009), 5, pp. 996-1007
[4] Park, J. H., *et al*., A Fast and Quantitative Assay for Developing Zeolite Type Hydrocarbon Trap Catalyst, *Microporous and Mesoporous Materials, 101* (2007), 1-2, pp. 264-270
[5] Yeon. T. H., *et al*., Adsorption and Desorption Characteristics of Hydrocarbons in Multi-Layered, Hydrocarbon Traps, *Microporous and Mesoporous Materials, 119* (2009), 1-3, pp. 349-355
[6] Miao, Y., *et al*., Study of SCR Cold-Start by Energy Method, *Chemical Engineering Journal, 155* (2009), 1-2, pp. 260-265
[7] Twigg, M. V., Roles of Catalytic Oxidation in Control of Vehicle Exhaust Emissions, *Catalysis Today*, *117* (2006), 4, pp. 407-418
[8] Twigg, M. V., Progress and Future Challenges in Controlling Automotive Exhaust Gas Emissions, *Applied Catalysis B, Environmental, 70* (2007), 1-4, pp. 2-15
[9] Farid, M. M., *et al*., A Review on Phase Change Energy Storage: Materials and Applications, *Energy Conversion and Management, 45* (2004), 9-10, pp. 1597-1615
[10] Gumus, M., Reducing Cold-Start Emission from Internal Combustion Engines by Means of Thermal Energy Storage System, *Applied Thermal Engineering, 29* (2009), 4, pp. 652-660
[11] Lou, H. H., Huang, Y. L., Fuzzy-Logic-Based Process Modeling Using Limited Experimental Data, *Engineering Applications of Artificial Intelligence, 13* (2000), 2, pp. 121-135
[12] Castellano, G., *et al*., Knowledge Discovery by a Neuro-Fuzzy Modeling Framework, *Fuzzy Sets and Systems, 149* (2005), 1, pp. 187-207
[13] Tasdemir, S., *et al*., Artificial Neural Network and Fuzzy Expert System Comparison for Prediction of Performance and Emission Parameters on a Gasoline Engine, *Expert Systems with Applications, 38* (2011), 11, pp. 13912-13923
[14] Ikonen, E., *et al*., U., Neuro-Fuzzy Modelling of Power Plant Flue-Gas Emissions, *Engineering Applications of Artificial Intelligence, 13* (2000), 6, pp. 705-717
[15] Zhou, Q., *et al*., Modeling of the Carbon Dioxide Capture Process System Using Machine Intelligence Approaches, *Engineering Applications of Artificial Intelligence, 24* (2011), 4, pp. 673-685
[16] Lughofer, E., *et al.*, Identifying Static and Dynamic Prediction Models for NO_x Emissions with Evolving Fuzzy Systems, *Applied Soft Computing, 11* (2011), 2, pp. 2487-2500
[17] Keynejad, F., Manzie, C., Cold Start Modeling of Spark Ignition Engines, *Control Engineering Practice, 19* (2011), 8, pp. 912-925
[18] Ntziachristos, L., Samaras, Z., An Empirical Method for Predicting Exhaust Emissions of Regulated Pollutants from Future Vehicle Technologies, *Atmospheric Environment, 35* (2001), 11, pp. 1985-1999

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