Renewable and Sustainable Energy Reviews 90 (2018) 665–686

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

A review on the application of response surface method and artificial neural network in engine performance and exhaust emissions characteristics in alternative fuel

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ARTICLE INFO

Keywords:
Response surface methodology
Artificial neural network
Alternative fuel
Internal combustion engine

ABSTRACT

Alternative fuel is one of the widely used fuel substitutions for both petrol and diesel in the field of internal combustion engine. The increase in the demand for alternative fuel is currently driven by the requirement of decreasing engine fuel consumption and fulfilling the stringent engine exhaust emissions pollutant regulations. In order to effectively tackle the aforementioned concerns, it appears that through engine experimental analysis alone for both engine performance and exhaust emissions is insufficient. Recently, the need for engine modelling based on statistical and machine learning methodologies through response surface and artificial neural network technique, respectively, are non-trivial to provide a better decision support analysis. Therefore, the present study reviews the extent to which the application of these methods in various alternative fuel in both spark and compression ignition engine to investigate their viability. The paper also describes herein the ways to determine the accuracy and the significance of model fitting for both methodologies. It was demonstrated from the review that most of the research yield favourable results of engine modelling prediction for both of the methods. It can be concluded the comparison between predicted and experimental results provided a high degree of determination coefficient indicating that the model could predict the model efficiency with reasonable accuracy.

1. Introduction

The industrial revolution, which took place in between the late 18th and early 19th century, was a period at which the global energy consumption started to increase dramatically [1]. These frequent energy consumption are due to the rapid increase of population growth and economic development [2]. Fig. 1 presents the projection of the energy consumption until 2035. Petroleum fuel is the largest contributor empowering the global economy. It is almost certain that fossil fuel will acquire approximately 60% of the growth in energy which accounts for almost 80% of total energy supply in 2035. This scenario is expected to continue further in the future [3]. The central area that is responsible for the never-ending energy utilization from the fossilised fuel is the transportation sector, with transport, contribute to almost two-thirds of the usage. The abundance use of this type of energy had led to the adverse effects towards the climatic change of the earth. This is due to the fact that combustion of this fuel produces anthropogenic emissions particularly carbon dioxide (CO_2), which is the major cause of both

Abbreviations: AFR, air fuel-ratio; ANN, artificial neural network; AI, artificial intelligence; bTDC, before top dead centre; BDC, bottom dead centre; BMEP, brake mean effective pressure; BSFC, brake specific fuel consumption; BTE, brake thermal efficiency; BVP, butanol volume percentage; CI, compression ignition; CO, carbon monoxide; CO_2, carbon dioxide; COV, coefficient of variation; DA, direction accuracy; DLS, damped least-squares; ECI-multi, electronically controlled multi-point fuel injection; EU, european union; FF, feedforward; FIT, fuel injection timing; FIP, fuel injection pressure; G100, gasoline; GBu5, 5% 2-butanol + 95 gasoline; GBu10, 10% 2-butanol + 90% gasoline; GBu15, 15% 2-butanol + 85% gasoline; GNA, Gauss–Newton algorithm; GHG, greenhouse gasses; H_nOME, honne oil methyl ester; IMEP, indicated mean effective pressure; HC, unburned hydrocarbon; HCCI, homogenous charge compression ignition engine; KGE, Kling–Gupta efficiency; LR, linear regression; LHV, lower heating value; Logsig, hyperbolic log-sigmoid; MAPE, mean absolute percentage error; CAD HRRmax, location of heat release rate; CAD P_{max}, location of maximum pressure; CuHRR, cumulative heat release rate; CI, compression ignition; MLP, multilayer perceptron; MSE, mean square error; MSRE, mean square root error; NO_x, nitrogen oxides; PME, peanut methyl ester; ppm, parts per million; purelin, linear function; RBF, radial basis function; RSM, response surface method; RSE, relative standard error; RMSE, root mean square error; rpm, revolutions per minute; SI, spark ignition; SHL, single hidden layer; SOHC, single overhead camshaft; Tansig, hyperbolic tangent sigmoid; TDC, top dead centre; THL, two hidden layer; trainbfg, quasi-Newton backpropagation; trainrp, resilient backpropagation; trainscg, scaled conjugate gradient; traingdx, gradient descent momentum; UN, united nation; WCO, waste cooking oil; WTO, wide throttle open; NSE, Nash–Sutcliffe coefficient of efficiency; *n*-butanol, primary butyl alcohol; 2-butanol, secondary butyl alcohol

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https://doi.org/10.1016/j.rser.2018.03.095
Received 5 June 2017; Received in revised form 25 November 2017; Accepted 31 March 2018
1364-0321/

Nomenclature

°CA	degree of crank angle
AP_e	average effective pressure
$CH_3CH_2CH_2CH_2OH$	n-butanol
$CH_3CH_2CHOHCH_3$	2-butanol
$C_nH_{2n+1}OH$	alcohol structure formula
CH_3OH	methanol structure formula
C_2H_5OH	ethanol
C_3H_7OH	propanol
C_4H_9OH	butanol
$(CH_3)_2CH_2CHOH$	iso-butanol
$(CH_3)_3COH$	tert-butanol
P_e	effective power
P_{max}	maximum pressure
N m	Newton metre
R	correlation coefficient
R^2	coefficient of determination
Te_x	exhaust gas temperature
rpm	revolutions per minute
–OH	hydroxyl group

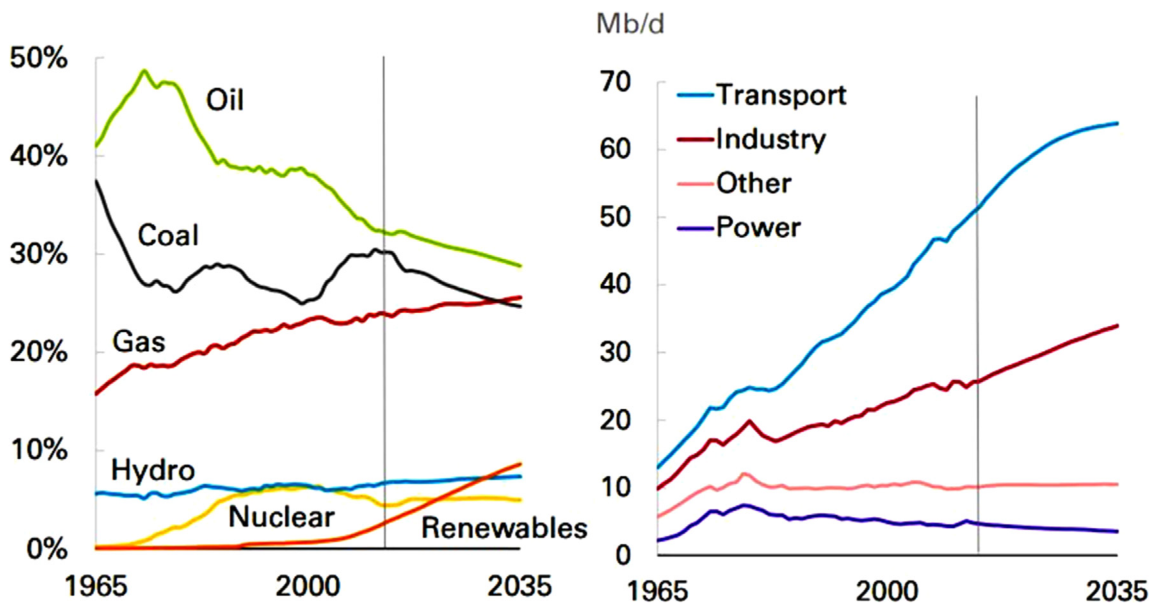

Fig. 1. Global energy consumption [6].

atmospheric pollution and the deterioration of human health. This issue has been brought up globally, and the reduction of CO2 emissions are mandated through stringent emissions legislation. The European Union (EU) members have pledged to use 10% and 20% of renewable energy for energy supply and transportation fuel, respectively [4]. In 2009, United Nations (UN) agencies set a target of US $100 billion fund expenditure to mitigate the global climate change during the climate summit in Copenhagen [5].

In view of this energy crisis, alternative renewable fuels are seen as a possible solution to be embraced throughout each corner of the world as a source of fuel substitution for fossilised fuels. This is primarily owed to their potential for improving engine pollutant emissions for transportation vehicles [7–9]; however, the research for availability, quality, and suitability of alternative fuels to be mixed with conventional fuel is still ongoing. Recently, researchers have proven that alternative fuels, e.g., alcohols, biodiesel, hydrogen, compressed natural gas (CNG) and liquefied petroleum gas (LPG) are potential substitutes for the conventional fuel in spark ignition (SI) and compression ignition (CI) engine [8,10–12]. Notwithstanding the need of the experimental work, in order to achieve a better understanding towards the engine behaviour operating by the alternative fuels, recently there has been an increasing interest in using the various methods to model the engine performance and exhaust emissions [13]. Perhaps one the most serious advantage of this modelling is that it minimises the processing time and cost, by reducing the reliance on the need for experimental works [14].

Application of response surface methodology (RSM) and artificial neural network (ANN) are fast becoming essential and widely used techniques in solving many industrial problems [15]. This method also is considered as effective and economical for examining single and combined factors of experiment variables that lead to output responses [16]. Both of the modelling methodology have been well reviewed in other engineering fields namely analytical chemistry [17], energy applications [18], food industry [19] and process and product optimisation [20], system design [21], solar [22], cooling system [23] and catalyst [24]. In reviewing the literature, it was discovered that there is an absence of a review that caters the aforementioned methodologies with respect to alternative fuels and engine performance and exhaust emissions behaviour. Due to the advantages offered by both of the modelling methodologies to solve complex and non-linear problems in the field of internal combustion engine (ICE) using alternative fuels toward engine performance and exhaust emissions, this study systematically review the application of RSM and ANN in internal combustion engine with regards to the engine performance and exhaust emissions. Moreover, the aforementioned methodologies are selected as they are able to provide a correlation between the input and the output responses of the experimental studies.

2. Theory and methodology of RSM and ANN

2.1. RSM

Response surface methodology was initially developed by Box during the 50 s [25]. RSM comprises of a group of mathematical and statistical approach in which the response of interest relies on several significant variables, and the aim of the method is to model and optimise this response [26]. In order to achieve this objective, linear or