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An ensemble neuro-fuzzy radial basis network with self-adaptive swarm based supervisor and negative correlation for modeling automotive engine coldstart hydrocarbon emissions: A soft solution to a crucial automotive problem

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ABSTRACT

In this paper, the authors propose a novel intelligent framework to identify the exhaust gas temperature (T_{exh}) and the engine-out hydrocarbon emission (HC_{raw}) during the coldstart operation of an automotive engine. These are two key variables affecting the cumulative tailpipe emissions (HC_{cum}) over the coldstart phase, which is the number one emission-related problem for today's spark-ignited (SI) engine vehicles. The coldstart operation is regarded as a highly nonlinear, transient and uncertain phenomenon. The proposed identifier integrates different soft computational strategies, i.e. neuro-fuzzy computing, fuzzy controller, swarm intelligent computing, and ensemble network design, beneficial for capturing both uncertainty and nonlinearity of the problem at hand. Furthermore, concepts of negative correlation topology design and hierarchical pair competition based parallel training are extracted from literature to form a diverse and robust ensemble identifier. Training of each neuro-fuzzy sub-component in ensemble network is carried out using a hybrid learning scheme. One feature of the antecedent part of neuro-fuzzy system, i.e. number of linguistic terms for each variable, as well as characteristics of rules in rule base are adjusted using hierarchical fair competition-based parallel adaptive particle swarm optimization (HFC-APSO) and the rest of features, i.e. the shape of (membership functions) MFs and the consequent variables of each rule, are tuned using back-propagation (BP) and steepest descent techniques. As it was mentioned, the authors try to design an ensemble identifier with acceptable rate of generalization, robustness and accuracy. These features help them to tame the intuitive uncertainties associated with the rate of T_{exh} and HC_{raw} emission over the coldstart period. To do so, the potential characteristics of sub-components (solution domain of network design) are divided into a set of partitions and then HFC-APSO is utilized to explore/exploit each of those partitions. The exploration/exploitation rate of PSO (the core of HFC-APSO) is dynamically controlled by a fuzzy logic based controller. Hence, it is expected that HFC-APSO yields a set of accurate sub-identifiers with different operating characteristics. To further foster the diversity of the ensemble, negative correlation criterion is considered which obstructs the integration of identical sub-identifiers. The identification results demonstrate that the method is highly capable of providing an authentic model for estimation of T_{exh} and HC_{raw} emission during the coldstart period.

1. Introduction

The main goal of engineers and authorities of automobile industry is to reach a practical compromise among different operating aspects of automotive engines, i.e. fuel economy, drivability, cost of product, and emissions. However, today's stringent emission standards oblige the authorities of automotive industry to exert a remarkable effort on achieving low level tailpipe emissions in SI engines. Unburned hydrocarbons (*HCs*), carbon monoxide and nitrogen oxides are among the most important pollutant materials [1,2]. Considering the most recent engineering efforts for mitigating the emissions, it can be inferred that the regulations concerned with the amount of *HCs* is of highest importance. Significant reduction/control of emitted *HCs* is the most challenging problem with emissions from today's SI engines [3]. Therefore, it is really necessary to researchers to correctly analyze performance of SI engines to cope with undesired *HC* emissions. For a typical driving cycle, during the first couple minutes after coldstarting of an SI engine,

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known as the "coldstart period", a considerable amount of *HCs* is emitted (about 80–90%). Therefore, improvements during the coldstart period have very critical impacts on reducing the total *HC* emissions to meet the requirements during the standard emission testing procedures, such as Federal Test Procedure (FTP) or Economic Commission for Europe (ECE) driving cycles. This fact motivated different researchers of automotive engineering (AE) society to analyze/model, control and optimize different aspects of coldstart phenomenon [4].

The total amount of tailpipe-emitted *HCs* or HC_{cum} is primarily a function of the engine-out hydrocarbon emission HC_{raw} and the exhaust gas temperature T_{exh} in the coldstart period. Henein et al. [5] developed a model for analyzing cycle-by-cycle *HC* emissions during the coldstart operation of a gasoline engine. Based on the results, they concluded that the main reason to undesirable *HC* emissions is that the catalytic convertor is not warmed up over the coldstart period. Initially, the engine-out hydrocarbon emissions HC_{raw} and the tailpipe emissions HC_{cum} are approximately the same, but once the catalytic convertor reaches the light-off temperature, it begins converting the combustion by-products, specifically unburned engine-out hydrocarbon emissions or HC_{raw}, at a better rate with a conversion efficiency of about 50%. Therefore, engineers have been trying to find effective and practical strategies to reduce the time required for catalytic convertors to reach the light-off temperature. It was observed that T_{exh} has a remarkable contribution to providing required heat for catalyst light-off [1,5]. Hence, along with modeling HC_{raw}, researchers of AE society have conducted a wide range of researches to analyze/model T_{exh}, as the other significant factor affecting HC_{cum}.

Generally, the most concentration of AE researchers was on utilizing physics-based engine dynamic models to investigate the characteristics of various subsystems, including catalytic convertors, for coldstart analysis and control. Dobner [6] utilized both linear and nonlinear modeling formulations to provide a dynamic model for controlling the main characteristics of a given engine. In that work, the author mainly focused on modeling the throttle and the intake manifold dynamics of the engine. The results of that investigation were then extended by Moskwa and Hedrick [7] and Cho and Hedrick [8] to facilitate the real-time control of the key characteristics of the engine. Tunestal and Hedrick [9] used the net heat released data to estimate the air/fuel ratio of cylinders. Zavala et al. [10] developed a physics-based model to identify the fuel dynamics over the coldstart period. Sanketi et al. [11] used a hybrid modeling/controlling framework to reduce the amount of coldstart *HC* emissions in automotive engines. Sanketi et al. [12] developed an optimal controller via convex relaxation for reducing the amount of emitted *HCs* during coldstart. Shen et al. [13] developed a precise physical model of a catalyst with 13-step kinetics and 9-step oxygen storage mechanisms to investigate the performance of catalytic convertors during coldstart period. Chan and Hong [14] analyzed the chemical conversions of carbon monoxide and unburned hydrocarbons in the oxidation process of coldstart period by a precise heat transfer modeling. Fiengo et al. [15] proposed a new real-time optimal control technique for the warm-up phase of three-way catalyst of an SI engine. Zavala et al. [16] developed simple control-oriented models to predict both HC_{raw} and T_{exh} during coldstart period.

Together with implementations of physics-based models, numerical and semi-empirical techniques have been used for modeling and controlling of HC_{raw} and T_{exh} during coldstart period. Jones et al. [17,18] investigated the applicability of semi-empirical techniques for real-time control of transient characteristics of a three-way catalyst. Koltsakis and Tsinoglou [19] used genetic algorithm (GA) to tune the parameters of a control-oriented model that aimed at identifying the thermal response of close-coupled catalysts during light-off. Soumelidis et al. [20] developed four different nonlinear dynamic models for three-way catalyst control and diagnosis. Gonatas and Stobart [21] used a black-box model to predict the emissions and oxygen storage over coldstart period. McNicol et al. [22] used an expert knowledge based Bayesian calibration algorithm for optimizing coldstart emissions. Recently, Azad et al. [1] proposed a systematic numerical procedure, including validation test, optimal control and sensitivity analysis, to determine the required accuracy of a model used for real-time optimal control of *HC* emissions during coldstart period. In another work, Azad et al. [23] proposed a sliding mode control with bounded inputs for T_{exh} to reduce *HC* emissions during coldstart period.

As it can be seen, in spite of fruitful and comprehensive researches, there are rare reports in literature addressing the applications of soft computational approaches to control, modeling and minimization of coldstart *HC* emissions. This is while soft computing and computational intelligence (CI) concepts proved their authenticity for handling design, optimization, power management and control problems of different types of automotive propulsions, such as electric vehicle (EV), hybrid electric vehicle (HEV) and plug-in hybrid electric vehicle (PHEV) powertrains. Yildiz et al. [24] used particle swarm optimization algorithm (PSO) for nonlinear constraint component sizing of PHEV powertrains. They observed that PSO can yield precise and efficient results as compared to conventional techniques. Jain et al. [25] proposed a multiobjective genetic algorithm (MOGA) for optimal powertrain component sizing of a fuel cell PHEV. Mozaffari et al. [26,27] used both single objective and multiobjective mutable smart bee algorithm (MSBA) to optimize the most crucial parameters of an irreversible Atkinson engine. Feldkamp et al. [28] used a recurrent neural network for energy management of a mild hybrid electric vehicle with an ultra-capacitor. Piccolo et al. [29] used genetic algorithm (GA) to efficiently manage the energy flow in HEVs. Shi et al. [30] developed a fuzzy controller for parallel HEVs. Mohebbi and Farrokhi [31] developed a neural controller for parallel HEVs. As it can be seen, soft computing has been vigorously applied to different problems in AE.

Actually, the applications of soft computing techniques are not limited to automotive systems. That would not be an exaggeration if we contend that soft methods have been utilized for handling a wide spectrum of engineering problems in the fields of manufacturing [32,33], smart materials [34], aerospace [35], robotics [36], energy systems [37] and etc. The promising feed-back of above researches has instigated the authors to investigate the potentials of soft techniques for modeling the crucial variables of the coldstart phenomenon. Indeed, the aim of the current research is to elaborate the applicability of soft computing for identifying T_{exh} and HC_{raw} during coldstart operation, which is a highly nonlinear, transient and uncertain situation.

To this end, the authors take the advantages of a self-organized ensemble identifier. Ensemble identifiers proved their generalization, robustness and accuracy over various researches. It has been demonstrated that such tools are quite useful for modeling highly nonlinear engineering phenomena. In this study, a novel ensemble approach which integrates the concepts of negative selection [38], bi-level learning [39], and fuzzy controlled swarm based optimization [40,41] is presented. The main motivations behind the use of such an identification tool are:

(1) Ensemble intelligent tools benefit from several characteristics such as robustness, accuracy, and generalization [42] which suit them to be used for identifying the transient and nonlinear rate of HC_{raw} over coldstart period [1].

(2) As it will be shown in the next section, the database of coldstart problem consists of different informatics streams. In other words, the database is quite large, and thus it is very hard for a sole identifier to capture the entire knowledge required