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بدینوسیله گواهی می شود مقاله با عنوان: **Condition monitoring of engine load using a new model based on adaptive neuro fuzzy inference system (ANFIS)**

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Condition monitoring of engine load using a new model based on adaptive neuro fuzzy inference system (ANFIS)

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Abstract

Condition monitoring (CM) of engine load is becoming increasingly important in modern maintenance and control systems. As a problem, torque estimation needs intensive efforts and costly sensors or devices such as dynamometer. In this research, a model was proposed based on soft computing technique to estimate ITM285 tractor engine torque using some low cost sensors. Adaptive neuro fuzzy inference system (ANFIS) was used for engine torque estimation, based on the data obtained from some inexpensive sensors including engine speed, fuel mass flow and exhaust gas temperature. Three methods namely grid partitioning (GP), sub-clustering (SC) and fuzzy c-means (FCM) were used to construct the fuzzy inference system (FIS). The results showed that the FCM was the most suitable method. It is concluded that models based on soft computing especially ANFIS are able to estimate the engine torque using data obtained from inexpensive and accessible sensors.

Keywords: ANFIS, Condition monitoring, Engine torque, Low cost sensor.

1. INTRODUCTION

Diesel engines are the power source and core component of most of machinery and equipment especially tractors. They offer a better fuel to power conversion efficiency than spark ignition (SI) types [1] and the lower volatility of their fuel makes them safer to handle [2]. Many agricultural implements are powered by diesel engines through power-take-off (PTO) shaft of tractor. Monitoring the load of tractor engine is necessary for engineers to design and for farm experts to manage and to make proper decision. Moreover, accurate measurement of the engine load is time consuming and costly. Accordingly, condition monitoring (CM) of the torque of tractor engine can be useful for control system applications especially in precision farming.

CM is the process of monitoring a parameter(s) of condition in machinery (vibration, temperature, sound, etc.), in order to identify a significant change which might be indicative of a developing fault. It is a major element of predictive maintenance. Many publications on CM to diagnose faults of mechanical systems and components, such as metal lathe machine [3], rolling element [4], cutting tools [5, 6], grinding process [7], mining equipment [8], pump-turbines [9], wind turbines [10], flexible rotor [11], centrifugal pump [12], reciprocating compressor [13], bearings [14-16], planetary gearboxes [17-21], gear transmission systems (a review) [22], helical gears [23], cylinder misfire [24], engine power disturbance [25] and engine valve leakage [26] have appeared in the literature, showing an attractive subject for academia. In addition, CM is used in control systems to assess the situation and make proper decision. Monitoring tractor engine load in agricultural operations with harsh working condition is one of such applications of CM that can assist the operator to regulate the engine load in accordance with the working conditions.

In automation control system applications, CM of the transmitted engine torque is unavoidable for control strategies [27]. Furthermore, manufacturers require to know engine torque range in order to design the power train components (e.g. gearbox and crankshaft) and to regulate the engine and the gearbox for optimized performance and reduced emissions [28]. Several solutions are presented for driveline automation to manage the engine performance; all of them need accurate torque estimation [27]. For example, the engine torque is used in hybrid vehicle applications to assess the proportion of electric motor and thermal engine torque [29, 30]. Furthermore, the engine torque is necessary for engine management [31, 32]. As another example, an estimator for the transmitted clutch torque was used in the driveline to improve the clutch control performance during vehicle launch and gearshifts [33]. Zhao et al. [34] also analyzed a dual clutch transmission (DCT) shifting process, wherein the torque transmitted by a twin clutch during the upshifting process was estimated by employing the unscented Kalman filter (UKF) algorithm. The experimental results demonstrated that the applied UKF torque estimation algorithm could adequately estimate the transmission torques of the two clutches in a real time manner.

Most of former researches on torque estimation have focused on internal combustion (IC) engine models. The inputs of these models typically consist some engine measurements such as air [35] or fuel [36] mass flow, throttle position [37, 38], fuel properties [39], spark advance [35, 38], engine speed [35, 36, 38-40], acoustic emission features [41]. Lee et al. [32] introduced two torque estimation techniques, namely "Stochastic Estimation Technique" and "Frequency Analysis Technique", for an in-line, four-cylinder SI engine under a wide range of engine operating conditions (different engine speeds and loads). Franco et al. [42] presented a real-time engine brake torque estimation model, where the instantaneous engine speed served as the model input. Liu et al. [43] proposed a practical method to estimate the friction and torque load based on the characteristics of the instantaneous torque profile during an engine cycle. The work aimed to develop a practical solution for estimating the in-cylinder gas pressure from the crankshaft speed fluctuation. Lin et al. [44] have employed instantaneous crank angular speed (IAS) as a non-intrusive CM technique to estimate the load on a four-stroke, four-cylinder diesel engine in a laboratory condition. Aono et al. [45] developed an easier estimation method, using finite impulse response (FIR) filter to derive the crankshaft rotational speed, therefore required less calculation load. The FIR filter for differentiation was designed based on the frequency domain characteristics between crankshaft rotation speed and combustion torque. Numerous static and dynamic torque estimation methods were presented to monitor the engine torque [37, 46]. Through a research work four statistical methods were reviewed in a unified framework and compared for building the torque model: linear least squares, linear neural networks (NNs), non-linear NNs and support vector machines (SVM). It was concluded that a non-linear model structure is essential for accurate torque estimation [28].

Soft computing methods are also appropriate for modeling diesel engines with highly nonlinear dynamic systems. These intelligent methods are used for identification, modeling, control and optimization purposes [47]. A variety of soft computing methods such as fuzzy [48-50], SVM [51-53], local linear model tree (LoLiMoT) [54, 55], artificial neural network (ANN) [3, 51, 56-62], recurrent artificial neural network (RANN) [63, 64] and adaptive network fuzzy inference system (ANFIS) [65, 66] were used to model the performance parameters of internal combustion (IC) engines. Among them ANNs were intensively employed for modeling and identification of IC engine parameters, while the applications of ANFIS are scarce.

ANFIS is one of the methods that are employed for solving non-linear estimation problems [65]. It is the combination of ANNs and fuzzy systems, enjoying the upsides of the two methods. In other words, ANFIS performance, as an adaptive and educable network, corresponds to the fuzzy inference system. To achieve "if-then" fuzzy rules and to optimize the model parameters can be eliminated through the adaptive neural network [67]. In the last two decades, researchers have been interested in the use of ANFIS approach to model engineering systems. However, a gap exists between theory and experimental applications of ANFIS, this method was successfully utilized in many studies to resolve the prediction-related issues, e.g. [68].

ANFIS not only has good learning capability, but it can also be interpreted easily. Although this method has been extensively applied in dynamical nonlinear systems, more effort should be spent for nonlinear and time-invariant systems. This gap motivated the present study. ANFIS has been widely applied in fields such as intelligent control, modeling, and identification in recent years. However, the practical application of ANFIS to build a dynamic model of an IC engine torque has been rarely conducted in the literature. In a study conducted by Togun and Baysec [66], a dynamic nonlinear model was proposed to identify the dynamic nonlinear behavior of an SI engine using ANFIS. For model validation, the proposed method is compared with the more conventional identification approach called the Hammerstein method. Validation results prove that the ability of the ANFIS model can capture the highly nonlinear behavior of the engine. In the present study, the ability of ANFIS was investigated to predict the CI engine torque under various working conditions. This is done with the aim of improving the accuracy of torque estimation.

In conclusion, the engine torque is one of the most important performance parameters of IC engines, which frequently needs to be estimated during operations. However its accurate measuring is laborious, time-consuming and costly. ITM285 is the most common tractor in Iran that is widely used in agricultural operations. Accurate estimation of the output engine torque exerted by active agricultural implements through the PTO shaft of tractor can be used for instantaneous system management during field operations. This is an important and effective aspect of precision farming which is developing in the current century. Hence, the main objective of this study was to develop engine torque estimation model in a wide range of engine operating conditions (load and speed) based on soft computing methods. The specific objectives were: 1- to investigate the effectiveness of ANFIS for engine torque estimation; 2- to study the variation of model performance with different model constructions; 3- to select the most appropriate model for accurate prediction of engine torque.

2. MATERIALS AND METHODS

2.1. ENGINE CHARACTERISTICS

Currently ITM285 tractor is the most popular tractor in Iran. It was adopted with different weather conditions of country and hence most of agricultural operations are performed by this model [69]. An ITM285 tractor was employed and the experiments were performed at the Department of Biosystems Engineering, College of Agriculture, Ferdowsi University of Mashhad, Iran. The detailed characteristics of the tractor’s engine are shown in Table 1. Before commencing the experiments, all filters of the fuel and lubrication systems were renewed. Some preliminarily tests were conducted to verify the instruments and to ensure the proper status of the engine for the main tests [70].

Table 1- Characteristics of the tractor’s engine.

Engine type	Perkins, four-cylinder, four-stroke, CI
Model year (MY)	2005
Cylinder bore	101 mm
Cylinder stroke	127 mm
Compression ratio	16:1
Fuel	Diesel fuel
Fuel pump	in-line injection pump
Combustion system	Direct injection
Maximum power	75 hp @ engine speed of 2000 rpm
PTO RPM	540 rpm @ engine speed of 1818 rpm

2.2. EXPERIMENTAL PROCEDURES

Experiments were conducted at 11 levels of primary engine speed (PES) including: 779, 923, 1063, 1204, 1346, 1488, 1629, 1771, 1818 (engine rated speed), 1913 and 2054 rpm (from 935 to 2465 rpm of the dynamometer speed by steps of 170 rpm). The tractor's PTO was coupled to a hydraulic dynamometer through a universal joint. At the beginning of each test, the engine speed was set and fixed at the desired level, using the hand throttle lever of tractor and the engine was sufficiently warmed up [71]. In other words, the engine hand throttle position was kept fixed while exerting the load. In each PES, the applied torque on the engine started from zero (no load) and continued to full load by increment of 10 N.m. As expected, the engine speed continuously decreased with increasing the applied torque. Hence, the engine speed at zero load and during experiment (corresponding to the applied torque) were named PES and instantaneous engine speed (IES), respectively. The overall view of the test setup is shown in Figure 1. The measured parameters include fuel consumption mass flow (FCMF), exhaust gas temperature (EGT) and IES. The experiments were carried out at ambient temperature range of 23 ± 7 °C [72].

Figure 1. The overall view of the test setup.

2.3. MEASURING PARAMETERS

A hydraulic water-flow dynamometer (PLINT, England) with maximum loading capacity of 325 N.m was used to exert rotational load on the engine, via PTO shaft (Figure 1). The instrumentations for measuring parameters and the schematic of the test bed are shown in Figure 2 and Figure 3, respectively. Data recording was performed after achieving stability in values of instrumentations at each new torque or speed points [70]. To measure the torque applied on the engine by the dynamometer, it was equipped with a load cell with capacity of 100 kg. The load cell output is sent to a personal computer (PC) and is then converted to torque unit by multiplying with torque arm (0.365 m). Prior to starting the experiments, the dynamometer was statically calibrated using the existing standard weights (two weights correspond to 50 N.m and two weights of 75 N.m). Also, the rotational measuring component of the dynamometer was calibrated using an optical tachometer. The readings of dynamometer for RPM and torque were received by an electronic interface circuit and were digitally sent to the PC and then, were displayed on a monitor. The conversion ratio of engine speed to dynamometer speed was 1:1.2. In other words, the engine speed was calculated by dividing the dynamometer speed to 1.2. For precise adjustment of a PES at an intended level, the tractor's hand throttle was disconnected from injection pump and replaced with a suitable scaled screw on control rack lever of the injection pump.
Fuel consumption (by mass) was accurately determined by means of a digital scale through weighing the weight of a temporary small fuel supply container (instead of tractor’s main fuel tank). The volumetric measurement of fuel consumption is much easier than the mess measurement but temperature corrections must be applied [70]. When consumption is measured by volume, the fuel density at 15 °C should be multiplied by the fuel temperature at which the measurement was made [72]. Hence, the fuel density variations with temperature must be considered. A digital scale (Japan, A&D Co., 6 kg capacity, ±0.01 g) was used to measure FCMF of the engine (Figure 2). The tractor’s fuel tank was disconnected from fuel system and instead a small fuel container was used and carefully put on the scale. The fuel flow from container is conveyed to primary fuel filters through a plastic pipe and another pipe was used to return the surplus fuel from injectors to the container (Figure 3). The weight of container on the scale was recorded with sampling rate of five samples per second. Afterwards, the scatter plot of the recorded values was drawn by Excel software and then the trend line of the plot is fitted. The FCMF is determined in gram per second which is corresponds to the slop of the trend line.

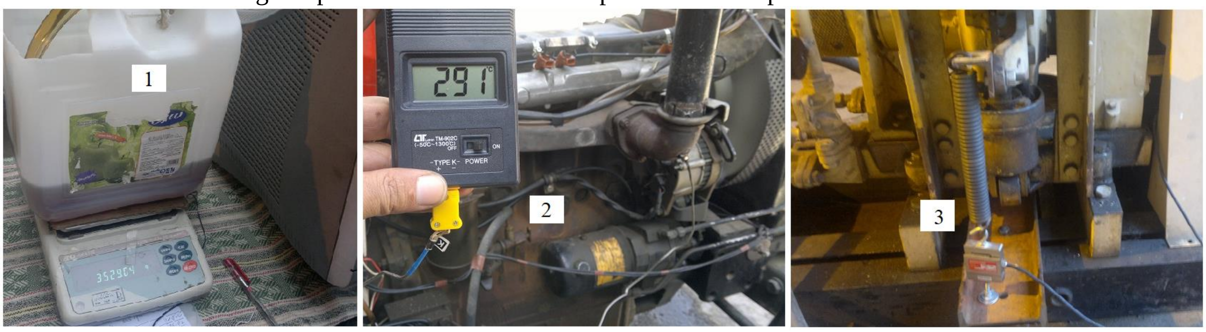

Figure 2. The instrumentations for measuring the parameters: 1- Digital scale to measure fuel consumption, 2- Temperature monitor and sensor, 3- Load cell.

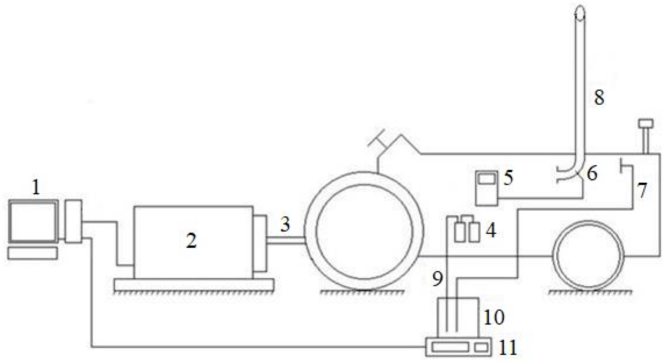

Figure 3. Schematic of the test bed: 1- Data acquisition system, 2- Dynamometer, 3- Universal joint, 4- Primary fuel filters, 5- Temperature monitor, 6- Temperature sensor, 7- Fuel return pipe, 8- Tractor exhaust, 9- Fuel inlet pipe, 10- Fuel container and 11- Digital scale.

A K-type temperature sensor (thermocouple) capable of measuring temperature up to 700 ºC [73] was installed on the exhaust elbow [74] and a temperature monitor (Lutron Co., TM-902C model, capable of monitoring temperature from -50 to 1300 ºC, resolution of 1 ºC) were used (Figure 2). The accuracy of the temperature sensor was examined by measuring the temperatures of saturated mixture of water and ice (0 ºC) and boiling water (99.62 ºC) at atmospheric pressure of 100 kPa [75]. The exhaust elbow was drilled to install the temperature sensor on the engine [74] and a hexagon nut was weld on the drilled hole. The sensor completely entered into the elbow by tightening the sensor base to the nut (Figure 2). The exhaust elbow was selected to install the temperature sensor for two reasons: 1- all exhaust gases of cylinders pass through this component, and 2- this component is the nearest place to the exhaust manifold and hence minimum reduction of exhaust gas temperature occurs. Precisely speaking, the midpoint of elbow curvature was considered as installation location of the sensor, where the exhaust gases pass tangentially to the internal wall and hence better affect the temperature sensor (Figure 3).

2.4. DATA ANALYSIS

In the present study, ANFIS model was used as an alternative method for estimating the engine torque. ANFIS model can extract relationships between inputs and output (torque) based on some fuzzy rules. In order to reduce the computations of the fuzzy model, some of the independent variables were selected and used as inputs of the ANFIS model, based on the results obtained from sensitivity analysis of the RBF model. Three methods namely comprising grid partition (GP), subtractive clustering (SC) and fuzzy c-means (FCM) clustering were used to construct the fuzzy inference system (FIS) structure.

Some important and common criteria including root mean squared error (RMSE), total sum of squared error (TSSE) and model efficiency (EF) were used to evaluate the models' performance. They are defined as follows [76]:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n}(dv - pv)^2/n} \tag{1}$$

$$\mathrm{TSSE} = \sum_{i=1}^{n}(dv - pv)^2 \tag{2}$$

$$\mathrm{EF} = 1 - \frac{\sum_{i=1}^{n}(dv - pv)^2}{\sum_{i=1}^{n}(dv - \overline{pv})^2} \tag{3}$$

where *dv* is the actual (desired) output; *pv* is the predicted (fitted) output produced by the model and $\bar{p}$ is the average of the desired output. A model with the lowest RMSE and TSSE, and the highest EF is considered to be the best.

3. RESULTS AND DISCUSSION

As mentioned, ANFIS model was also used as alternative tool to estimate engine torque. The independent variables including PES, FCMF, EGT and IES were used as ANFIS model inputs. ANFIS model can extract the relationships between the inputs and torque (the output) based on fuzzy rules, which dominate over the problem. As previously mentioned GP, SC and FCM methods were used to construct the FIS structure. To evaluate each method, individual parameters and their different combinations were examined and results are shown in Tables 2, 3 and 4. Various membership functions (MFs) were evaluated for the GP method and the results showed that Gaussian was the best one. Using various MF numbers showed that MF number of three provided the best result

for each input. It should be mentioned that increasing the MF number did not considerably improve ANFIS performance, and on the other hand, the training time of the model also increased. Between linear and constant functions as output MF, the latter provided a better result. The best condition was obtained from ANFIS-GP4.
The optimum values of SC model parameters including influence radius, squash factor and MF number of input and output were obtained through trial and error. In all cases, the values of accepted ratio and rejected ratio parameters were considered 0.5 and 0.15, respectively. Also, the MF types of input and output in all cases were selected Gaussian and linear, respectively. The best prediction performance of ANFIS-SC model with nine MFs for each input was obtained by values of 0.15 and 1.5 for influence radius and squash factor, respectively (Table 3). The results of this model have also shown that the prediction performance of the model is improved by increasing the MF number. The optimum MF number of each input and output was nine and any more increase did not considerably improve the performance of ANFIS-SC model.
The other method for constructing the FIS, was FCM. This method determines the MFs number of inputs and output. In this method, Gaussian and linear were also used as input and output MF, respectively. As can be seen (Table 4), the number of rules and inputs and output MF were the same as the clusters number. The results showed that the prediction performance of the model is improved by increase in the clusters number. The clusters number of nine was selected as the optimum number. With increase in this number, computations of the model increased and the prediction performance was not considerably improved.

Table 2- The performance and some characteristics of the ANFIS-GP model.

Model name	Number of input MF	Type of input MF	Type of output MF	Number of output MF	Number of rule	Epochs	RMSE	TSSE	EF
GP1	[2 2 3 3]	gaussMF	Constant	[24]	24	90	0.94	179.96	0.99
GP2	[2 3 3 2]	gaussMF	Constant	[24]	24	190	1.42	408.24	0.99
GP3	[3 3 2 2]	gaussMF	Constant	[24]	24	180	1.17	277.73	0.99
GP4	[3 3 3 3]	gaussMF	Constant	[81]	81	2000	0.70	99	0.99

Table 3- The performance and some characteristics of the ANFIS-SC model.

Model name	Influence Radius	Squash Factor	Number of input MF	Number of output MF	Number of rule	Epochs	RMSE	TSSE	EF
SC1	0.13	1.5	[3 3 3 3]	[3]	3	1800	1.23	303	0.99
SC2	0.15	1.5	[5 5 5 5]	[5]	5	4500	0.97	188	0.99
SC3	0.12	1.2	[7 7 7 7]	[7]	7	1100	0.83	138	0.99
SC4	0.15	1.5	[9 9 9 9]	[9]	9	2500	0.61	76.04	0.99

Table 4- The performance and some characteristics of the ANFIS-FCM model.

Model name	Number of cluster	Number of input MF	Number of output MF	Number of rule	Epochs	RMSE	TSSE	EF
FCM1	3	[3 3 3 3]	[3]	3	500	1.17	276	0.99
FCM2	5	[5 5 5 5]	[5]	5	350	0.84	143	0.99
FCM3	7	[7 7 7 7]	[7]	7	550	0.74	108	0.99
FCM4	9	[9 9 9 9]	[9]	9	450	0.60	73	0.99

4. CONCLUSIONS

With the aim of engine torque estimation, some models were developed based on ANFIS, using some easy to measure working characteristics of ITM285 tractor including PES, IES, FCMF and EGT. Using the outcome of this research, the engine torque can be estimated using some low cost sensors instead of expensive devices and equipment (e.g. dynamometer).
The results of this research have shown that models based on soft computations are able to estimate the torque of ITM285 tractor's engine using data obtained from inexpensive and accessible sensors. Hence, the proposed models can be substituted with the conventional more expensive methods, using dynamometers.

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