The Prediction of Torque in a Diesel Engine
Using Ion Currents and Artificial Neural Networks

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Abstract

Ion currents in engines contain important information on combustion that sensors that are currently used are unable to detect. This study focuses on the analysis of ion current signals in a CI engine operating on commercial ultra-low sulphur diesel fuel conforming to Australian Fuel Quality Standards Act 2000. First, the various features of the ion current signal are described in context of the heat release rate and in-cylinder pressure signal to better understand the components of the ion current. Then, a variety of back-propagation artificial neural networks are used to predict engine torque from the ion current signal. The factors affecting the performance of the artificial neural network that were investigated were the number of hidden layers, number of hidden nodes and the desired training error. A 4-hidden layer network with 20 neurons in each hidden layer was found to be the best performing network with an RMS prediction error in torque of 5.6%. The effect of averaging on the signal was also tested. Averaging signals at the input to the network was found to reduce the accuracy of predictions of the network, as a result of the reduction in size of the training set.

Nomenclature

ANN Artificial neural network
ATDC After top-dead-centre
BTDC Before top-dead-centre
CI Compression ignition
RMS Root mean square
SI Spark ignition
P In-cylinder pressure (bar)
ROHR  Apparent rate of heat release (J/s)  

Y  Experimental engine torque (Nm)  

$C_i$  Engine cycle  

$y_i$  Engine out torque as predicted by the ANN for engine cycle $C_i$ (Nm)  

$\overline{E}$  Mean percentage error in $y_i$ at a given torque setting (%)  

$\sigma_{y_i}$  Standard deviation of $y_i$ at a given torque setting (Nm)  

$I$  Instantaneous ion current value (V)  

$I'$  Average value of ion current signal at a certain torque setting (V)  

$I''$  RMS value of ion current signal at a certain torque setting (V)  

$E_{TR}$  Maximum acceptable training error (%)  

$E_P$  Root mean square error in prediction at a certain torque (%)  

$\tau$  Time taken to train (s)  

1 Introduction

Ion currents in internal combustion engines are produced by the ionisation of the fuel-air mixture in the cylinder of an engine during combustion [1]. These ions are able to carry an electric charge between two oppositely charged electrodes in the cylinder, creating what is known as the ion current. Since the current is a direct result of the concentration and mobility of ions in the cylinder and the production of these ions is a direct result of combustion, the ion current can be used as a measure of combustion.

Kubach et al. [1] described some of the most important ionisation mechanisms. These mechanisms are divided into primary and secondary ionisation mechanisms. Primary ionisation mechanisms produce ions from neutral particles. Some examples of primary ionisation mechanisms are shown below:

- Chemical ionisation: $CH + O \rightarrow CHO^+ + e^-$
- Electron deposit: $C_nH_x + e^- \rightarrow C_nH_x^-$

In secondary ionisation mechanisms, new ions are generated from a combination of primary ions and neutral species. Some secondary ionisation mechanisms are shown below:

- Proton-transfer: $CHO^+ + CH_2 \rightarrow CH_3^+ + CO$
- Electron-transfer: $O_2^- + C_nH_x \rightarrow O_2 + C_nH_x^-$

One or more of the products of these reactions are ions. It is these ions that are responsible for the carrying of charge when they are neutralised at one or the other of the electrodes.
Ion current sensors have been used in SI engines to measure quantities like the air-fuel ratio and peak pressure point as well as input to control spark-advance timing and to predict knock [2, 3, 4, 5, 6]. Gazis et al. [7] used a simple artificial neural network to predict the in-cylinder pressure in an SI engine. More recently, Mehresh et al. [8] used ion sensors in homogeneous charge compression ignition (HCCI) engines to estimate CA50, the crank angle at which 50% of the cumulative heat release is achieved. The same authors [9] showed that the ion current was sensitive to the fuel used and so could be used to differentiate between different fuels.

Ion current sensors have also been used in CI engines. Glavmo et al. [10] used the time derivative of the ion current signal to detect the start of combustion. The authors [10] proposed a closed-loop start of combustion control system in order to correct for changes in ignition delay caused by changes in factors such as temperature and fuel properties. Henein et al. [11] qualitatively described the various components of the ion current signals in SI, CI and HCCI engines. The different mechanisms of ionisation were identified and the role each played in the ion current curve was described. The location of different peaks were attributed to swirl in the intake air flow. Thus, they depend on the geometry of the combustion chamber and the location of the sensor in it.

Research into ion currents has not been as popular as many other areas of engine research. This is due to the inherent difficulty in analysing a signal as complex as the ion current [12]. Curran et al. [13] found that the main chemical kinetic mechanism was driven by 179 species and 1125 reactions. This is a very large number of chemical reactions to solve, particularly if the intent is to use this technology in automobile engines in transient operation. Since the ion current is affected by so many factors, it contains information on all these variables. However, the complexity of the ion current signal makes it difficult to separate the effects of different variables and obtain meaningful information [14].

Added to this complexity is the effect the in-cylinder flow has on the ion current [11]. Depending on the cylinder head design and piston crown design, the turbulent properties of in-cylinder flow resulting from swirl and tumble are difficult to predict without a computational fluid dynamics model of both the fuel spray and the combustion chamber geometry. Such models are complicated and slow to process. A less computationally expensive method of ion signal analysis is through the use of an artificial neural network (ANN) [7]. An ANN has the advantage that it requires no complex physical model of the ion sensor and current generated; rather, it relies on linking known outputs to known inputs to construct a predictive statistical model of the system. In this paper this approach is taken to predict the torque developed by a diesel engine. The paper begins with a discussion of the sensor used and the signal developed over a range of engine conditions. This is followed by a development of the ANN used and a detailed discussion on the predictive capacity of the ANN to changes in input, output and ANN topology.
2 Experiment

The diesel engine used in this study is a 4 litre, 4 cylinder naturally aspirated direct-injection Hino W04D running on commercial ultra-low sulphur diesel fuel conforming to Australian Fuel Quality Standards Act 2000. The specifications of the engine are shown in Table 1. Engine out torque is measured by a Heenan Froude eddy current dynamometer controlled by a Froude-Hofmann V4 controller operating at 1Hz. The engine is fully instrumented to measure engine and in-cylinder parameters via an AVL Indicom measuring system. The crank angle is measured using an AVL crank angle sensor at a resolution of 0.2 CAD. The in-cylinder pressure is measured using an AVL GU21C high pressure transducer. The rate of heat release is calculated using a single-zone thermodynamic model [15]. These target variables are obtained at the same resolution as the crank angle. A more detailed description of the experimental setup has been made in a previous paper [16].

A cross-sectional view of the ion sensor is shown in Figure 1. A ceramic adhesive (2) is used between the sensor casing (1) and the electrode (4) for electrical insulation of the electrode. A plastic washer (3) at the top of the casing allows for the attachment of electrical terminals without shorting the electrode. The electrode is positively charged and maintained at $+120V$ relative to the casing. The casing is grounded to the engine block. Ion sensors such as these necessarily measure the concentration of ions only in the proximity of the sensor [17]. Head gasket ion sensors have been shown to produce more global results [3] but are more difficult to manufacture and install.

Four locations for the ion sensor were tested by Kubach et al. [1] and the best signal was found to come from the sensor installed in the glow-plug port of the cylinder head. This location is easy to use since no holes have to be drilled into the cylinder head. Hence, the sensor shown in Figure 1 was inserted into the glow-plug port in cylinder #3 of the Hino engine.

The instantaneous ion current signal $I$ was recorded by an A/D converter at
a constant engine speed setting of 1600 RPM and at 6 torque settings varying from 80 Nm to 180 Nm in steps of 20 Nm. The signal was recorded at each torque setting in 4 different groups, each group consisting of 180 contiguous engine cycles. The resolution of the ion current signal was matched to that of the crank angle sensor.

The ion current signal at 100Nm and 1600RPM is shown in Figure 2. Also shown on the graph are the in-cylinder pressure $P$ and the apparent rate of heat release $R_{OHR}$. The in-cylinder pressure and apparent rate of heat release were measured and calculated at a different time to the ion current signal; the mounting positions of the ion sensor and the pressure transducer were identical so both could not be measured in the same cylinder simultaneously.

The base value of the ion current is not zero due to an electrically conductive layer of soot that forms on the electrode [1]. From 130 CAD to about 176 CAD, there is a gradual increase in the ion current value; increasing pressure changes the density of the soot layer on the sensor, changing its conductivity [1]. At 178.6 CAD, there is a sharp increase in the ion current value. This occurs later in the cycle than both the increase in the heat release (175 CAD) and the increase in the in-cylinder pressure (177.2 CAD). This corresponds to the start of combustion of the pre-mixed part of the fuel, when a very large number of ions are produced [1]. The rapid increase in concentration of ions is the reason for the increase in the ion current. A local maximum is reached at 180.6 CAD, whereas the local maximum of the heat release rate is located at 178.2 CAD. This delay in the increase of the ion current has been attributed to two factors [11]: (i) while the rate of heat release is a global phenomenon and it begins to increase when combustion begins, the ion current is a phenomenon local to the ion sensor and therefore the current only begins to increase after the flame front reaches the sensor; and (ii) the delay in response in the electronic circuitry used in the ion sensor leads to lag in the ion current signal. The electronic delay is of the order of $10^{-6}$ s and so does not cause the delay shown (~0.2 ms). It must be concluded that the first factor is the dominant one.

From this peak, the recombination of ions leads to a lower concentration of ions in the cylinder [11]. The ion current drops to a local minimum at 189.4 CAD. The ion current then climbs again till 193.4 CAD, as a result of mixing-controlled combustion. From 193.4 CAD onwards, the ion current begins to drop at a decreasing rate. This decreasing rate leads to the ion current being higher.
Figure 2: In-cylinder pressure $P$, apparent rate of heat release $ROHR$ and ion current $I$ at 100Nm, 1600RPM
after combustion than before, even at the same pressure. For example, at crank angles of 155 CAD and 215.4 CAD, the in-cylinder pressures are the same (20.6 bar), whereas the ion voltages are 0.15V and 0.22V respectively. This difference is due to ionic species that are still present after the end of combustion. Lahde et al. [18] reported that the ion concentration in diesel engines drops by a factor of 10 in about 0.02s (approximately 180 CAD at 1600RPM) after the completion of combustion. The presence of these longer lived species would explain the difference in the ion voltage values.

It must be noted that there is significant cycle-to-cycle variation in the ion current signal. This was attributed to the non-homogeneity of the fuel-air mixture in the combustion chamber due to turbulence that is not identical for every engine cycle [14]. The cycle-to-cycle variability was not identical at different torque settings. To quantify this variability, two variables \( I' \) and \( \bar{I} \) were defined. \( \bar{I} \) was defined as the cycle-averaged ion current value at a particular torque setting. The RMS ion current value, \( I' \), calculated over all engine cycles at a particular torque setting, was then defined by Equation 1.

\[
I' = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (I - \bar{I})^2} \quad (V)
\]

Figure 3 shows a plot of \( I' / \bar{I} \) and \( \bar{I} \) at 80 Nm, 140 Nm and 180 Nm. While the RMS component \( I' \) is very similar at all torque settings, the larger value of the mean component \( \bar{I} \) at higher torque settings means that the RMS component \( I' \) accounts for a smaller proportion of the instantaneous ion current \( I \).

### 3 Artificial Neural Networks

As mentioned before, the ion current is a very complex signal since it is affected by many engine variables and the mechanism of ion generation consists of a large number of chemical reactions. A traditional analytical thermodynamic model for the ion current would require the solving of all of these chemical equations [19], which would be too slow to incorporate into transient applications.

Another method that can be used to model the ion current signal is artificial neural networks (ANNs), which are a non-linear statistical data analysis technique. ANNs are modelled on biological neural networks in that they use a connectionist approach to computing [20]. This approach makes use of many simple units (nodes) linked to each other to form more complex networks. Nodes are organised into layers which separate stages of data processing. The topology of an ANN is determined by the number of layers and the number of nodes in each layer. In the example three layer ANN shown in Figure 4, \( A_1 \) and \( A_2 \) are the only two input nodes, \( x_1 \), \( x_2 \) and \( x_3 \) are the only three hidden nodes in the single hidden layer and \( O_1 \) is the single output node of the network. More inputs \( A_3, A_4...A_n \) and more outputs \( O_2, O_3...O_m \) can be added as the requirements of the application change. More hidden nodes and/or more hidden layers can be
Figure 3: $\bar{I}$ and $I'/\bar{I}$ at 80 Nm, 140 Nm and 180 Nm. The thinner lines refer to $\bar{I}$ while the heavier lines refer to $I'/\bar{I}$.
Figure 4: A three layer ANN

added to increase the complexity of the ANN to better fit the input and output data.

In addition to the topology, the training algorithm and stopping criterion must be defined as well. The training algorithm can be chosen from a standard set included in the ANN library being used. These algorithms calculate the error in prediction at each input-output pair and update the weights of different nodes iteratively to minimise this error. Backpropagation training schemes are the most commonly used algorithms [20]. A common stopping criterion used for analogue data is desired error to which to train, denoted as $E_{TR}$. When this criterion is used, the training is complete when the RMS error of the training data set drops below $E_{TR}$. This is shown in Equation 2.

$$\sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \bar{y})^2} \times \frac{100}{Y} (%) < E_{TR}$$

$E_{TR}$ must be chosen so as not to overfit the data by setting $E_{TR}$ very low or underfit the data by setting $E_{TR}$ very high. The choice of $E_{TR}$ is made by trial and error and the best value depends on both the data and the topology of the ANN it is being applied to. Together, the topology and the training of the ANN determine its performance over a given range of inputs and outputs.

The advantages of an ANN model over an analytical thermodynamic model are its versatility and ease of use. With the use of standard ANN libraries, an ANN is very easy to set up and run. An ANN model is particularly useful in the case of the ion current because it does not require a detailed understanding of the underlying chemical mechanisms. It is for this reason that ANNs have been widely used in empirical engine-related applications. ANNs have been used to estimate and control the air-fuel ratio in SI engines during transient
The prediction of fuel properties, prediction of engine emissions with different fuels and engine control have all been performed using ANNs \[24, 25, 26, 27\]. ANNs have also seen application in the prediction of engine variables from the ion current. An ANN was able to predict the air-fuel ratio to an accuracy of 2.1%, given the ion current signal from an SI engine as input \[12\]. Traver et al. \[28\] successfully used ANNs to predict NOx and CO2 emissions in a diesel engine to a correlation coefficient of 0.998. ANNs have also been able to predict soot emissions, in-cylinder pressure, temperature and heat transfer using some very simple variables such as engine speed, load, injection timing and injection pressure as inputs \[29\].

For the reasons outlined above and their history of being used in the interpretation of complex signals, it was decided to use an ANN to predict engine performance from the ion current for this study. The Fast Artificial Neural Network Library \[30\] is a free, open-source ANN library written in C. This library was used in the development of the networks presented in this paper.

The two requirements from the ANN were accuracy and speed of prediction. The accuracy required was chosen to be similar to the accuracy of most sensors currently used on vehicles. Air-flow meters are one such type of sensor and a typical air-flow meter has an accuracy of about 4% \[31\] so an accuracy of between 4% and 6% was decided to be the minimum required. The requirement of speed limited the complexity of network topologies tested since when such a system is used in industry, a large training set will be used to improve accuracy. When large training sets are used, the time taken to train is greatly affected by small changes to the ANN, since these changes must be effected over a larger set of data. Thus, only very simple ANNs, with 3- and 4-hidden layers were considered in this study. The target variable chosen was the engine out torque. Torque is a useful quantity to measure as it can be easily converted to other quantities like the air-fuel ratio and the brake specific fuel consumption when combined with information from other sensors through the use of simple analytical models.

The input to the ANN was the ion current for one full engine cycle (720 CAD) at the previously stated resolution of 0.2 CAD. Thus, the inputs (described as $A_1, A_2, \ldots A_n$ above) consisted of 3600 values of the instantaneous ion current $I$. The output (described as $O_1$ above) was the engine torque. As described above, the ion current signal for 4 groups of 180 engine cycles were recorded at each torque setting at 1600 RPM. 3 of the 4 groups of 180 engine cycles at each torque value were used to train the ANN. The output given to the ANN for these groups during training was the dynamometer-measured torque $Y$. For training, the RPROP algorithm \[32\] was chosen as it is one of the best performing learning methods available for neural networks \[33\]. A limit of 5000 iterations was imposed on the training algorithm in order to eliminate slow performing networks. Once trained, the remaining group of 180 engine cycles at each torque value was used to evaluate the performance of the ANN in predicting engine torque. The output for any input engine cycle $C_i$ was the ANN-predicted torque $y_i$. 

4 Results and Discussion

4.1 Effect of engine torque on prediction error

The accuracy of predictions was found to be different at low and at high engine torques. The prediction error tended to increase with a decrease in engine torque, leading to high error at the lower torque values of 80Nm and 100Nm and low errors at 160Nm and 180Nm. This is a trend observed over the entire data set with all ANNs used. This was a result of the higher variability in the ion current signal at the lower torque values, as discussed earlier.

The effect of this phenomenon can be seen in the spread of predictions at different torque settings for one particular ANN. In this case, an ANN with 4 hidden layers and 20 neurons in each hidden layer, trained to an \( E_{TR} \) of 4.4% was used. The mean percentage error \( \bar{E} \) and the standard deviation \( \sigma_y \) were used as measures of the bias error and the precision error respectively. They were calculated using Equations 3 and 4 respectively.

\[
\bar{E} = \frac{1}{n} \sum_{i=1}^{n} (y_i - Y) \times \frac{100}{Y} \quad (\%) \tag{3}
\]

\[
\sigma_y = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (y_i - \bar{y})^2} \quad (Nm) \tag{4}
\]

Figure 5 shows the mean percentage error \( \bar{E} \) and the standard deviation \( \sigma_y \) over the torque range tested. Not only was \( \bar{E} \) much greater at lower torque than at higher, but \( \sigma_y \) also reduced from 4.0 Nm at 80Nm to 0.9 Nm at 180Nm.

4.2 Effect of ANN topology and training on prediction error

In the study of the topology of ANNs and their effect on the accuracy of predictions, the two main factors were the number of layers and the number of nodes in each layer. For simplicity and to reduce processing time, the number of nodes was the same in all layers for a given ANN. The criterion for accuracy was \( E_P \), defined in Equation 5.

\[
E_P = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - Y)^2} \times \frac{100}{Y} \quad (\%) \tag{5}
\]

Figure 6 shows the effect of changing the number of layers and number of nodes on the prediction error \( E_P \). The ANNs shown were all trained to the same value of \( E_{TR} \) to negate the effect of differing amounts of training. The error is significantly higher at lower torque values, as described before.

It was observed that the behaviour of all networks investigated was very similar at the higher torque settings, while the networks with 30 nodes were better at low torque settings. In general, increasing the number of nodes decreased the error, but the effect of changing the number of layers was mixed.
Figure 5: $E(\%)$ and $\sigma_y$(Nm) at different torque settings when an ANN with 4 hidden layers and 20 neurons, $E_{TR} = 4.4\%$ in each hidden layer was used.
Figure 6: Comparison of accuracy of predictions with different numbers of hidden layers and nodes but the same training error.
Figure 7: Comparison of time taken to converge at different $E_{TR}$ for different network topologies. The 30-node networks were unable to converge for $E_{TR} < 6.1\%$
With an increase in complexity of the network, the time taken to train, $\tau$, increases as well. Figure 7 shows $\tau_n$, the time taken to train normalised by the time taken to train for the slowest performing network tested. It shows that the number of nodes has a greater effect on training speed than the number of layers. Increasing the number of nodes increases the number of weights that need to be updated by a much larger factor than increasing the number of layers. Hence, while a greater number of nodes produces a lower error as seen in Figure 6, the time taken to train is vastly increased. At an $E_{TR}$ of 6.1%, a network with 30 nodes in each layer takes up to 7 times as long to train as one with 20 nodes.

Figure 7 also shows the difference between networks with the same number of nodes in each layer but a different number of layers. Generally, at higher $E_{TR}$, the 3-hidden layer networks are marginally quicker to converge to a solution than the 4-hidden layer networks, as shown by the networks with 30 nodes in each layer. At a lower $E_{TR}$, the opposite is true. This is shown more clearly in the case of networks with 20 nodes in each layer. These networks are of similar speed for $E_{TR} \geq 5.2\%$ but at $E_{TR} = 4.4\%$ the 4-layer network converges in $\tau_n = 0.71$ whereas the 3-layer network converges in $\tau_n = 1.0$. This is because at high $E_{TR}$, greater time is needed to update weights; 3-hidden layer networks have fewer weights to update than the 4-hidden layer networks. At lower $E_{TR}$, the larger number of degrees of freedom of a 4-layer ANN means it is able to converge in fewer iterations and hence has to update weights fewer times before training is complete. This more than compensates for the slower updating time and hence at lower $E_{TR}$, a greater number of layers is beneficial for training speed.

One of the other variables to be studied in the training of the ANN was the training error $E_{TR}$ and its effect on the accuracy of predictions. This is shown in Figure 8. The trend of higher error at lower torque is the same as shown before. As with increasing the complexity of the network, it was found that decreasing the training error, $E_{TR}$, led to a decrease in the prediction error $E_p$. $E_{TR}$, however, could only be reduced to the lower limit of 4.4%, below which none of the networks was able to converge to a solution. At this lower limit, the average prediction error over the entire torque range $E_{P} = 5.6\%$. In addition, it was found that decreasing $E_{TR}$ greatly increased the time taken to train the network, Figure 7.

### 4.3 Effect of averaging on prediction error

The ion current signal has, as discussed previously, significant cycle-to-cycle variation. This phenomenon leads to difficulty in using the instantaneous ion current to predict other engine variables. One of the methods to reduce this variability, and hence make it easier to use the ion current signal, is averaging.

Averaging can be performed either on the input or on the output side of the ANN. When performed on the input side, the ion current signals from a certain number of cycles are averaged and the result is the input to the ANN. The output from the ANN is then the final prediction.

When averaging is performed on the output side of the ANN, the ion current
Figure 8: Comparison of accuracy of predictions with different training errors but the same number of hidden layers and nodes.
signals from a certain number of cycles are individually treated as inputs to the ANN. The outputs from the ANN are then averaged and the result of the averaging process is the final prediction.

Shown in Figure 9 is the prediction error $E_P$ for the best performing networks with no averaging and with both 5- and 10-cycle averaging at both input and output. The figure shows that averaging at the output makes very little difference to the eventual result, with the single cycle, 5-cycle averaged at output and 10-cycle averaged at output curves all following each other very closely, with $E_P \approx 5.6\%$.

Averaging at the input is shown to increase the error in prediction. The 10-cycle average performed marginally worse than the 5-cycle average, with $E_P = 10.7\%$ and $E_P = 10.0\%$ respectively. This substantial drop in performance results from the decreasing size of the training set as more cycles are averaged. The complete training set contained 180 engine cycles per group, as mentioned above, whereas the training set for the 5-cycle averaged ANN contained only 36 engine cycles per group and the 10-cycle averaged training set contained only 18 engine cycles per group (a necessity of the averaging process). Although not shown here, a non-averaged training set of similar size to the 5-cycle averaged (36 engine cycles per group) was found to perform similarly to the 5-cycle averaged ANN.

This limitation can be overcome by the recording of a larger training set. However, this takes more time and increases the cost of training. Two further
disadvantages of averaging, whether of inputs or of outputs is that the information obtained is not instant and that cycle-specific information is lost during the averaging process. In real-world applications where the engine operating conditions are changing in real time, averaging may not be an option.

5 Conclusion

This study focused on the analysis of the ion current signal from a CI engine using artificial neural networks to predict torque. Several topologies of ANNs were tested, but this study limited the complexity of the networks to allow for quick training and prediction. Networks with 3 and 4 hidden layers were tested. The number of nodes in each hidden layer was varied as well. It was found that increasing the number of nodes had a significant effect on the performance of the ANN. An increasing number of nodes was found to improve the accuracy of predictions at low torque values but was also found to take a longer time to train.

It was also found that, in general, lowering the allowable training error $E_{TR}$ reduced the prediction error $E_P$. The lower limit of $E_{TR}$ was found to be 4.4%, below which the network could not converge to a solution. When trained to this error, a 4-hidden layer network with 20 nodes in each layer was found to be the best performing ANN, with $E_P = 5.6%$.

The effect of changing $E_P$ and ANN topology on time taken to converge $\tau$ was studied. It was found that reducing $E_{TR}$ to below 6.1% and increasing the number of nodes resulted in significantly larger values of $\tau$. In comparison, changing the number of layers had relatively little effect on $\tau$ at high values of $E_{TR}$, but increasing the number of layers reduced $\tau$ at low values of $E_{TR}$.

In order to reduce the effect of cycle-to-cycle variation in the ion current, averaging of the signal was performed. Averaging the outputs of the ANN was found to have little effect on the accuracy of prediction. Averaging the ion current signal before input to the ANN was found to reduce the accuracy of the predictions. This was due to the smaller training set used by the input-averaged schemes.

The ability of this study to predict the engine out torque to an accuracy of 5.6% has demonstrated the utility of the ion current signal. The ion current is a phenomenon that is easy to measure with the use of a replacement glow-plug and heating circuit and no other modifications required to the engine. With further study, it may be possible to predict other target variables like the air-fuel ratio, in-cylinder pressure, rate of heat release and emissions.

References


