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Virtual Sensing: A Neural Network-based Intelligent Performance and Emissions Prediction System for On-Board Diagnostics and Engine Control

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ABSTRACT

A neural network-based engine performance, fuel efficiency and emissions prediction system has been developed for both spark-ignited and compression ignition engines. Through limited training on an engine dynamometer, the neural network system is able to predict accurately real-time engine power output, fuel consumption and regulated exhaust emissions using readily measured engine parameters, across highly transient engine operating cycles. Applications for the models developed using this process include engine diagnostics, virtual sensing of unmeasured or unmeasurable engine emissions, engine control, and engine and vehicle modeling. Results from the prediction of the performance and emissions from a 300 hp CIDI engine and a 120 hp SI engine are presented, showing the potential of this newly developed approach.

INTRODUCTION

A neural network-based engine performance, fuel efficiency and emissions prediction system has been developed for both spark-ignited (SI) and compression ignition (CI) engines. The neural network (NN) system is able to predict real-time engine power output, fuel consumption and emissions using readily measured engine parameters. The system consists of a predictive engine model that is designed to run on a microprocessor in parallel with the engine in real time, taking input signals from the same sensors as the engine itself. The NN model of the engine is able to make highly complex, time-variant, nonlinear and multi-dimensional associations between preselected engine input parameters and outputs in realtime. This allows the accurate prediction of engine performance (real-time torque output), engine emissions (HC, CO, NOx, CO2 and PM in diesel engines) and fuel consumption across the full range of engine operation. During limited dynamometer testing, the NN model learns in real-time and on the fly the precise relationship between all designated inputs and outputs. Once in the field or when operating in a vehicle, the model is able over time to update those relationships and to adapt to allow for engine or component wear, subtle changes in fuel composition or extreme combinations of operating or environmental variables.

This system, which allows for virtual emissions sensing, is equally well applicable to SI or CI engines, and has been demonstrated in both engine applications. Uses of this system include emissions prediction for engine control, on-board diagnostics and virtual emissions measurement for light and heavy-duty vehicles, stationary engines and marine, off-highway and locomotive diesels. Further applications include engine modeling, both for reducing the time required to develop engine control algorithms, and for light and heavy-duty vehicle emissions inventory prediction.

MOTIVATION

Ever increasingly stringent emissions requirements and rising fuel costs place an important premium on close control of combustion in internal combustion engines for all applications. Future technological advances such as infinitely variable valve timing (through camless operation) and direct injection of both gaseous and liquid fuels will probably allow the spark-ignited (SI) piston engine to be used successfully into the next century in automotive applications, possibly as hybrid vehicle power plants. These engines will have the potential to satisfy ever increasing fuel efficiency and environmental requirements, while meeting consumer expectations of power density, reliability, NVH and total life-cycle cost. The SI engines of the future will incorporate significant advances for improved performance, economy and emissions. These engines will certainly require the use of more sophisticated and adaptive control systems than those used today. For example, the engine of the future will certainly be camless, use drive-by-wire throttle actuation, and will implement load control through exhaust gas recirculation, and both intake and exhaust valve actuation with infinitely variable valve timing control. Fuel injection (gaseous or liquid) may occur in the intake ports or directly in-cylinder but it is certain that primary engine control will be effected through fuel delivery control, valve actuation (for load control, reducing throttling losses and increasing rates of exhaust gas recirculation), supercharger or turbocharger boost (for varying the effective compression ratio and load control) and ignition timing control.

For the foreseeable future, CI engines will continue to be used in fuel cost-sensitive applications such as in heavy-duty buses and trucks, power generation, locomotives and off-highway applications, as well as having application in light trucks and hybrid electric vehicles. Close control of combustion in these engines will be essential to achieve ever-increasing efficiency improvements while meeting increasingly stringent NOx and PM standards. Future direct injection CI engines will utilize increasingly higher combustion and injection pressures with exhaust gas recirculation (to offset the higher NOx levels produced by the elevated combustion pressures), variable geometry turbocharging and possibly infinitely variable valve timing, while being truly low emissions and fuel-flexible.

Close control of combustion in future SI and CI engines will be of overriding concern for both efficiency and emissions. As an example, in an ultra low emissions vehicle or ULEV, operation through one day with a failed engine sensor or control system may well produce a higher contribution to the emissions inventory than operation for a year with a fully functional system. Advanced on board diagnostic capability (OBD) and the ability to reconfigure control "on the fly" following fault detection will be an indisputable requisite in the future. These engines of the future will require significantly more complex control, having very many more degrees of freedom than those of today.

Standard classical "one-dimensional" or map-based control, in which fueling, ignition and EGR (in today's SI engines) are controlled somewhat independently, will prove woefully inadequate in dealing with the multiple independent degrees of freedom presented by wide range fuel, EGR, ignition, boost and valve control in future SI engines. Likewise the multiple degrees of freedom offered by injection rate shaping, EGR, boost and valve control in future CIDI engines will require truly simultaneously optimized, multidimensional control. Moreover, the costs, time required and complexity associated with engine development, performance mapping, and control system development and calibration, are increasing significantly.

What is required is a truly multidimensional, adaptive, learning control system that does not require the laborious development of an engine model, while having excellent performance and emissions prediction capabilities across the full life of the engine, for all engine operating conditions. Neural network-based engine modeling offers all of these capabilities. The excellent generalization capabilities achieved through on-line learning means that the engine control system designer need make no assumptions about the governing equations dictating the engine performance and combustion characteristics. The virtual sensing system automatically develops the engine control laws by learning the engine behavior over time. This allows a truly optimized and adaptive engine prediction and control system to be developed with the minimum of effort.

OPERATION OF THE VIRTUAL SENSING SYSTEM

The virtual sensing system developed here consists of a predictive engine model that is designed to run on a microprocessor in parallel with the engine in real time, taking input signals from the same sensors as the engine itself. The neural network (NN) model of the engine is able to learn the highly complex, non-linear and multi-dimensional associations between the pre-selected input parameters and outputs in real-time. Once the system has been trained to mimic the performance and emissions of the engine, it permits the accurate prediction of engine performance (real-time torque output), engine emissions (unburned hydrocarbons, carbon monoxide and oxides of nitrogen) and fuel consumption across the full range of engine operation.

LEARNING

During limited dynamometer testing, the NN model learns in real-time and on the fly the precise relationship between all designated inputs and outputs. The NN model assigns global or general weights between all designated inputs (engine operating parameters) and corresponding outputs (torque, fuel consumption and regulated emissions) on the basis of results learned during engine dynamometer testing. A further (local) set of weights is allowed to vary in time across the life of the engine in the field, thereby providing a true learning, adaptive prediction system. (The addition of the local weights allows for the long-term analysis of integral engine component degradation). As a result the NN model is able to provide to the driver, to a smart diagnostic system or to an engine controller, the apparent results from a virtual suite of sensors. These virtual sensor results may either be unmeasured or unmeasurable engine parameters, or duplicate estimation of already measured variables. One immediate application is in the virtual measurement of engine-out NOx emissions for on-board diagnostics (OBD) in both spark-ignited and compression ignition engines. Virtual sensing can also offer an added level of protection against existing engine sensor failure, as in the case of exhaust oxygen sensing in stoichiometric or lean-burn SI engines, for example.

VIRTUAL SENSOR ARCHITECTURE

The neural network architecture used is that of a partially recurrent net, which is found to have more accurate mapping than a multi-hidden layer net [1]. Figure 1 shows the schematic of the neural network architecture, and the online learning or training configuration. The input vector includes instantaneous engine parameter values as well as a receding history window of 5-10 seconds of the same data (depending on engine type). Including this sliding window has been found to be necessary to capture the full dynamics of transient engine operation, including turbocharger spool-up in diesel engines and the emissions arising from transient fueling variations in both SI and CI engines. All raw engine measurements, either obtained from a fully instrumented engine on a dynamometer during training or obtained from an engine in the field during normal operation, are captured at a regular 20 Hz data-sampling rate. This rate can be increased or decreased depending on the balance between desired accuracy and computational effort required. The data are filtered on-line through an infinite impulse response filter to provide smoothing while retaining their integrity. The transport delays and finite response times inherent in the existing engine sensors are taken into account in the virtual sensor modeling.

APPLICATION TO DIESEL ENGINES

Virtual sensing has been applied to the prediction of engine-out emissions, fuel efficiency and power output of three engines, including a 300 hp heavy-duty diesel engine, certified to 1994 US EPA heavy-duty emissions standards. In predicting the real-time performance of this compression ignition heavy-duty diesel engine (described in Table 1), the NN-based prediction model uses the real-time values of:

- intake manifold air temperature,
- intake manifold boost pressure,
- fuel rack position,
- engine coolant temperature,
- exhaust gas temperature,
- engine speed, and
- fuel rail temperature and pressure.

Using instantaneous values of these input parameters as well as a sliding, weighted window of their most recent values (extending 10 seconds back in time to capture turbocharger dynamics), the NN model is able to predict:

- instantaneous engine torque or power output,
- fuel consumption (and carbon dioxide emissions),
- exhaust gas temperature, and
- engine exhaust emissions (carbon monoxide, unburned hydrocarbons, oxides of nitrogen and smoke, as measured by whole exhaust opacity).

PROOF OF CONCEPT VIRTUAL SENSOR DEMONSTRATION - I –

Table 1. CI Demonstration Engine Parameters

Engine Type	10 liter, in-line 6cylinder DI
Fuel	diesel (D2)
Compression Ratio	15:1
Turbocharger	150 kPa gauge maximum boost
Fuel Injection System	mechanical cam-driven jerk-type
Maximum Power	300 hpk (224 kW) (at 2200 rpm)

A limited set of emissions data was obtained from the engine described in Table 1, to conduct a proof of concept study (the data had previously been de-skewed to remove the effect of variable response and delay times in the measurement of each of the emissions). The first 250 seconds of the data set were included in the engine training data, due to the limited total amount of data available, while the last 50 seconds of each data set shows the NN predictions on data on which the net was not trained online. In either case, the predictions are "open-loop", implying no on-line learning or reinforcement. Figure 2 to 7 show the predicted versus measured engine torque, HC, CO, NOx, CO_2 and smoke emissions. All emissions have been non-dimensionalized with respect to the maximum value of that constituent found in the complete data set. These figures show the results of a blind prediction, although in this CI engine study alone, the difference between the measured and predicted exhaust gas temperature gives the local NN weights limited authority in modifying the prediction in an on-line adaptive fashion.

VIRTUAL SENSING PREDICTION ACCURACY

In the case of CI engine prediction, the virtual sensor prediction model is able to predict these engine performance and emissions parameters to within 5-10% of their instantaneous values, given approximately 30 minutes of highly transient hot engine dynamometer training, and to well within 5% on an integrated basis. It should be borne in mind that this is achieved within 30 minutes of training, and that more training will reduce the instantaneous and integrated error significantly. Moreover, it should also be remembered that the virtual sensing system is calibrated (through training) to predict emissions in real, measurable units, as opposed to merely providing emissions trends. Finally, it should also be noted that a significant further benefit of the system is the fact that it provides relatively high accuracy predictions of all regulated emissions and CO_2, simultaneously. In the case of engine emissions, further testing of the system on a SI engine has shown that the accuracy of the prediction can be improved to the point that it is of the same order as the accuracy of the measurements provided by the emissions analyzers used to provide the training data, integrated across a transient engine cycle.

VIRTUAL SENSING SYSTEM TRAINING

For the diesel engine described above, it was not necessary to vary all input parameters individually in a multi-dimensional test matrix, but rather to exercise the engine (as a system) through a wide cross-section of its expected performance envelope. By this is meant that it is not required to vary manifold air temperature, manifold boost pressure, commanded fuel rack position, engine coolant temperature, exhaust gas temperature, engine speed and load, and fuel rail pressure individually and independently, but rather to provide the NN with as wide a range of engine performance data as is feasible. The NN-based system has excellent generalization capabilities, provided that a wide range of representative engine performance has been used in generating the training data. Modeling of cold-start engine performance and emissions is quite feasible and could be accomplished through obtaining data from several cold starts at various initial engine and ambient air temperatures.

APPLICATION TO SPARK-IGNITED ENGINES

Virtual sensing has been also been applied to the prediction of emissions, fuel efficiency and power output of a 120 hp, DOHC 16 valve gasoline engine. In predicting the real-time performance of this SI engine (described in Table 2), the NN-based prediction model uses the real-time values of:

- engine speed
- manifold air pressure
- manifold air temperature
- throttle position
- ignition timing
- fuel injection pulsewidth
- engine coolant temperature
- exhaust gas oxygen concentration, and
- EGR valve position.

As in the case of the CI engine, using instantaneous values of these input parameters as well as a sliding, weighted window of their most recent values (extending approximately 5 seconds back in time for this normally-aspirated engine), the NN model is able to predict:

- instantaneous engine torque,
- fuel consumption (and carbon dioxide emissions), and
- engine exhaust emissions (carbon monoxide, unburned hydrocarbons, and oxides of nitrogen).

PROOF OF CONCEPT VIRTUAL SENSOR DEMONSTRATION - II

Table 2. SI Engine Parameters

Engine Type	1.9 liter, 4 cylinder DOHC
Fuel	gasoline
Compression Ratio	9.7:1
Induction	naturally aspirated
Fuel Injection System	pulse-width modulated, O2 feedback
Maximum Power	120 hp (89.5 kW) at 5000 rpm

Figure 8 shows the measured speed and power characteristics of an arbitrary transient engine test cycle used to validate the NN model accuracy. The resultant engine cycle is one on which the NN model was not trained, but merely represents a somewhat arbitrarily chosen highly dynamic dynamometer cycle. Figures 9 to 12 show the predicted versus actual measured engine exhaust emissions for HC, CO, NOx and CO_2 for the SI engine demonstration (in units of grams per second), showing the blind prediction capability of the NN method. These particular results show the predictive capability of the NN method after approximately 180 minutes of hot, stabilized engine training. Due to the fact that exhaust emissions from SI engines vary significantly around their nominally stoichiometric fueling set-point, these engines require somewhat more training time than CI engines, which tend to emit far more consistently.

REAL-TIME COMPUTATIONAL REQUIREMENTS

Typical virtual sensing computational power requirements for running the NN model described above in real-time with data rates of 20 Hz are easily met by an Intel Pentium 100 MHz microprocessor-based personal computer. Running the NN on a dedicated RISC processor would reduce its computational requirements significantly, allowing for the use of a far cheaper dedicated computational processor, for on-board vehicle use. Efforts in reducing computational overhead and effort are continuing.

APPLICATIONS OF VIRTUAL SENSING

The virtual sensing system described here has immediate application in

- engine diagnostics,
- engine control, and
- engine or vehicle modeling.

ENGINE DIAGNOSTICS

In terms of engine diagnostics, a virtual sensing system may be integrated into a smart OBD system to give immediate warning of emissions exceedances. Moreover, the NN system can provide real-time values of unmeasured or difficult to measure parameters (such as NOx emissions or PM emissions for diesel engines), from which the engine can be controlled. Virtual sensing can form the basis of a diagnostic information system, and can provide significantly more information on engine or vehicle performance and emissions than is presently available, while still using an existing sensor suite. Virtual sensing also allows the development of virtual O2, NOx, HC, CO and PM sensors, from which the engine can be controlled in real time [2,3]. Real time fuel consumption and torque measurement for on and off-highway CI engines is also made feasible through this approach, as is the real-time prediction of emissions from stationary or marine engines for continuous emissions measurement (CEM) purposes.

By developing multiple NN performance prediction systems, each employing a sub-set of the full suite of available engine sensors, failure in a single sensor can be detected by comparing the results generated by each NN. Redundant prediction of the same engine output variable in this fashion could aid in the identification and isolation of both sensor and integral engine component failure. Virtual sensor prediction also provides a high level of redundancy albeit without additional sensor cost or hardware complexity. As an example, the instantaneous fuel consumption of the diesel engine is calculated by the NN based on the engine speed, rack position, manifold boost pressure and temperature, engine temperature and (perhaps) measured air flowrate into the engine. The fact that several of these input parameters are interrelated and dependent on each other, provides a significant level of in-built redundancy in the event of the failure of one of the engine sensors in that set.

The additional input to the NN system of output from further exhaust emissions sensing devices (such as a viable NOx sensor, when developed) would serve to strengthen the prediction capabilities of the virtual sensing method. The virtual sensor suite provides a true learning capability, and could allow for reconfigurable control to be used in the event of the failure of such a sensor or an integral engine component.

ENGINE CONTROL

SI engines enjoy the benefit of a remarkably powerful fueling feedback control parameter in exhaust gas oxygen sensing. CI engines on the other hand, suffer from the lack of readily available feedback parameters. This research seeks to redress that. The real-time NN prediction of engine performance and emissions allows for effectively "closed loop" control on the basis of virtual sensing of NOx, CO, HC, or PM emissions, without requiring any additional engine sensors [2,3]. It can be used to control specific actuators or devices, such as EGR valves, fuel injection, ignition, boost control, or can be used for the full multidimensional control of fueling, ignition, EGR and variable valve timing (VVT) in SI engines, or fueling, boost, EGR and variable geometry turbocharger (VGT) devices in DI engines. Moreover, using the NN system in a predictive fashion will allow an engine to be operated at any pre-selected optimum, such as the lowest emissions level or the best power or best efficiency limit.

The addition of measured in-cylinder pressure as an extra input into a CI engine emissions prediction model, will, it is believed, allow the prediction of NOx emissions (specifically) on a cycle-to-cycle basis. In addition, exhaust gas temperature (chosen for its robustness and ease of measurement) has been explored as a surrogate feedback parameter for CI engines, with some success.

ENGINE MODELING

Once developed on an existing or prototype engine, NN engine predictive models can be used to provide engine mapping data to reduce the time required for controller development. Instead of requiring extensive dynamometer time to establish full transient engine performance and emissions, the fully trained NN model of an engine can be used as a computational surrogate of the engine itself. In this way, engine control laws can be developed and optimized computationally, rather than requiring large amounts of dynamometer time.

While the work presented here describes the development of NN-based engine models, this technique can be used to develop combined SI engine-catalyst models, in which catalyst-out (as opposed to engine-out) emissions are predicted. Additional sensor input, probably from wide-range oxygen sensors upstream and downstream of the catalyst, and the temperature of the catalyst (as a measure of catalyst activity or efficiency), could be used to train the model to mimic the engine-catalyst combination. Likewise, a vehicle model can be developed, either for light or heavy duty vehicles, that includes transmission and drive-line efficiency effects, using both chassis dynamometer measurements of vehicle performance and emissions, and engine dynamometer measurements of engine-only performance.

A fully predictive engine model can also be used in a strategy-based vehicle control algorithm, such as in determining how to merge and combine energy from two sources in a hybrid electric vehicle. The model can also be used in a forward-looking strategy, limited only by the computational capability resident on the vehicle.

FUTURE APPLICATIONS

Further applications, such as engine and vehicle modeling for emissions inventory gathering are also feasible [4]. For example, once a NN model of the emissions characteristics of a vehicle has been established through limited testing on a chassis dynamometer, a computational model of the vehicle can be derived. This computational emissions model of the vehicle can then be "driven" across any driving cycle, or given topographic data, across any road. Integrating the fully predictive emissions model with a traffic simulation model or with real-time data from a GPS-equipped vehicle, could allow the prediction of emissions from the vehicle under a wide range of vehicle operating conditions, driver behavior and traffic conditions.

Many such applications of virtual sensing and this method of neural network-based engine performance and emissions modeling remain to be explored.

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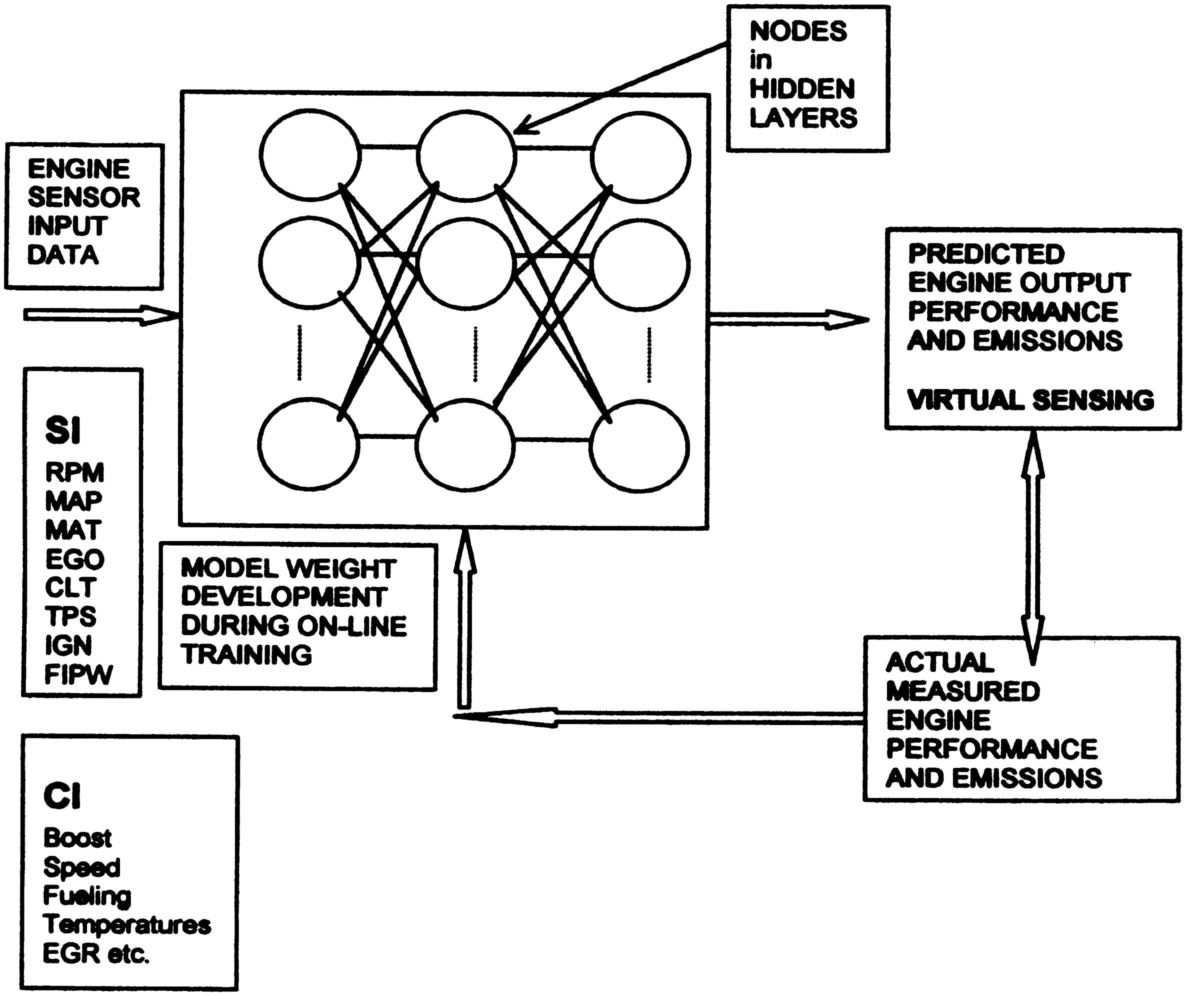

Figure 1. Partially Recurrent Neural Network Architecture, Showing Dynamometer-based Training Used to Develop Full Input-Output Parameter Associations and Weights.

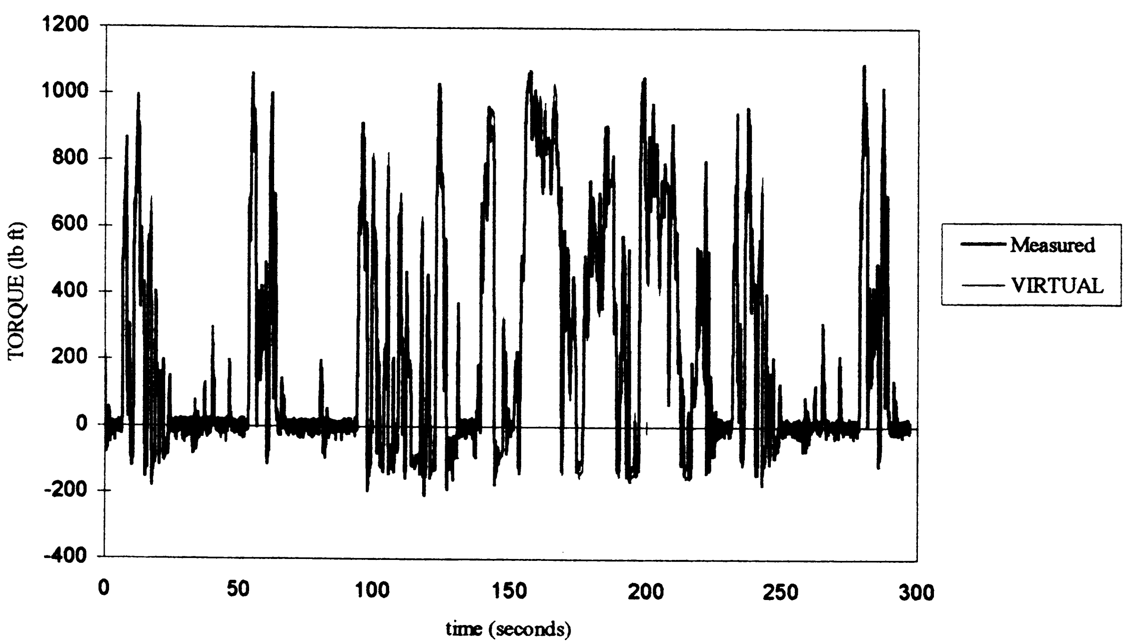

Figure 2. Measured versus Predicted Engine Torque for CI Engine NN Model Validation

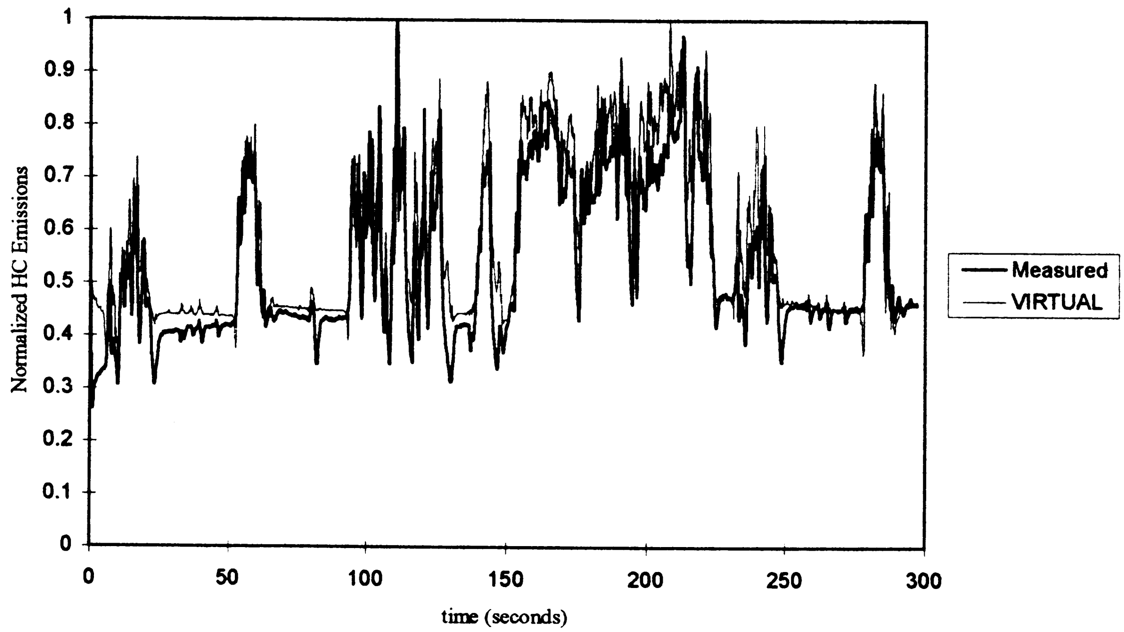

Figure 3. Measured versus Predicted Hydrocarbon Emissions for CI Engine NN Model Validaton

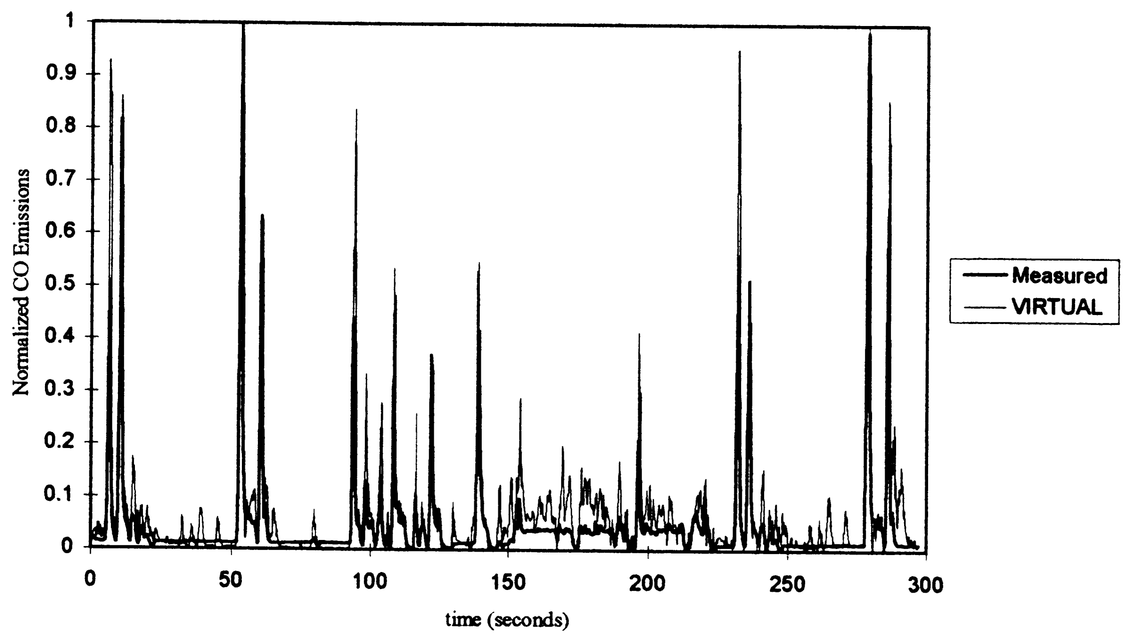

Figure 4. Measured versus Predicted Carbon Monoxide Emissions for CI Engine NN Model Validation

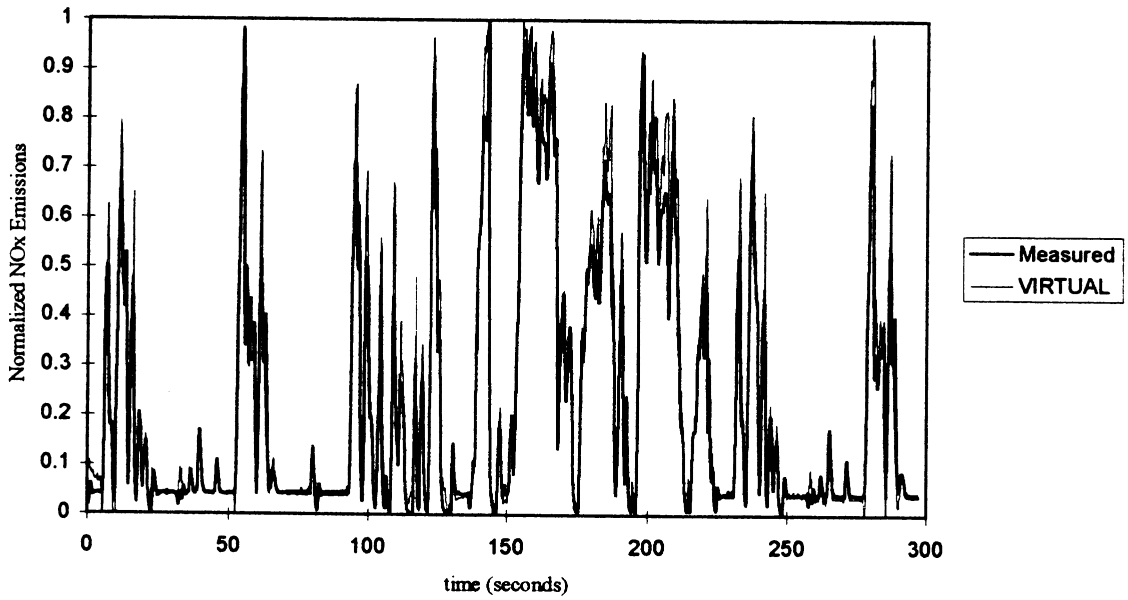

Figure 5. Measured versus Predicted Oxides of Nitrogen Emissions for CI Engine NN Model Validation

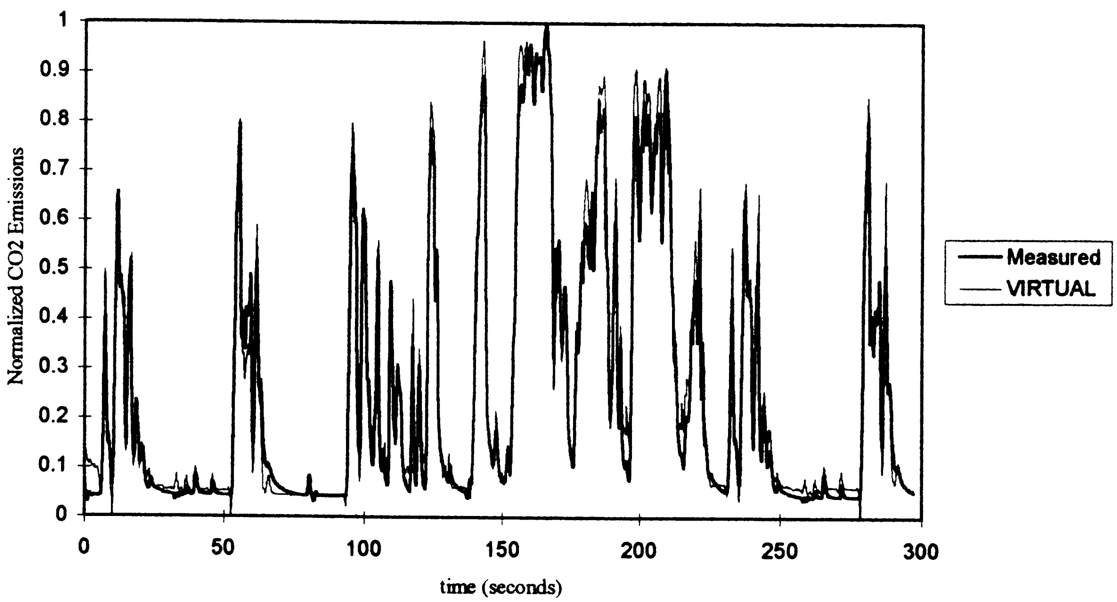

Figure 6. Measured versus Predicted Carbon Dioxide Emissions for CI Engine NN Model Validation

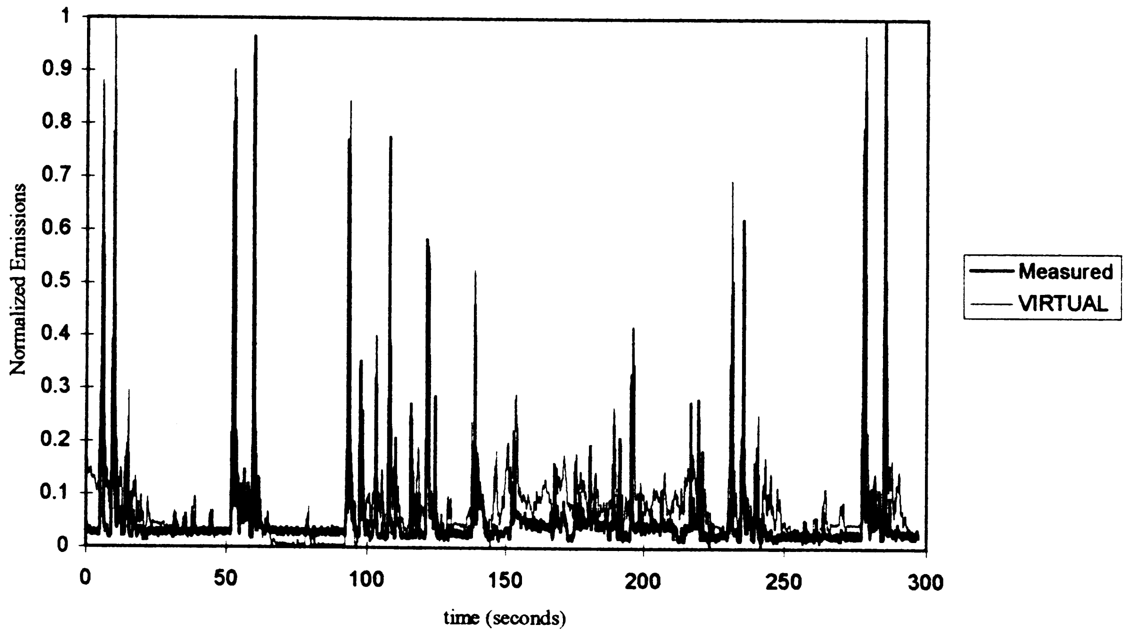

Figure 7. Measured versus Predicted Smoke Emissions for CI Engine Model Validation

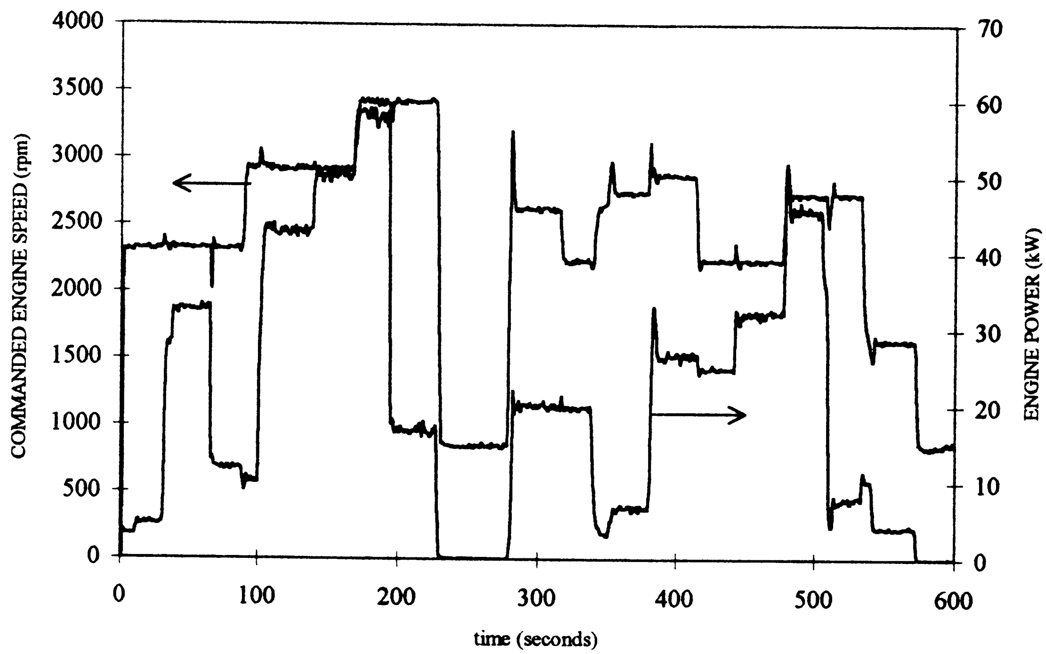

Figure 8. Commanded SI Engine Torque and Speed for NN Model Validation

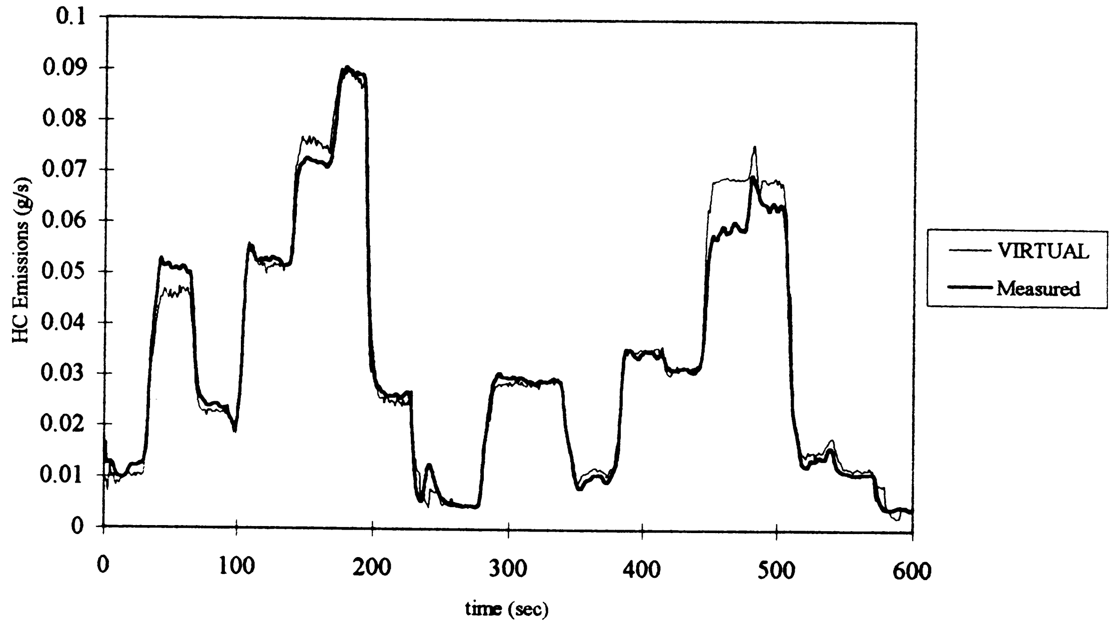

Figure 9. Measured versus Predicted Hydrocarbon Emissions for SI Engine NN Model Validation

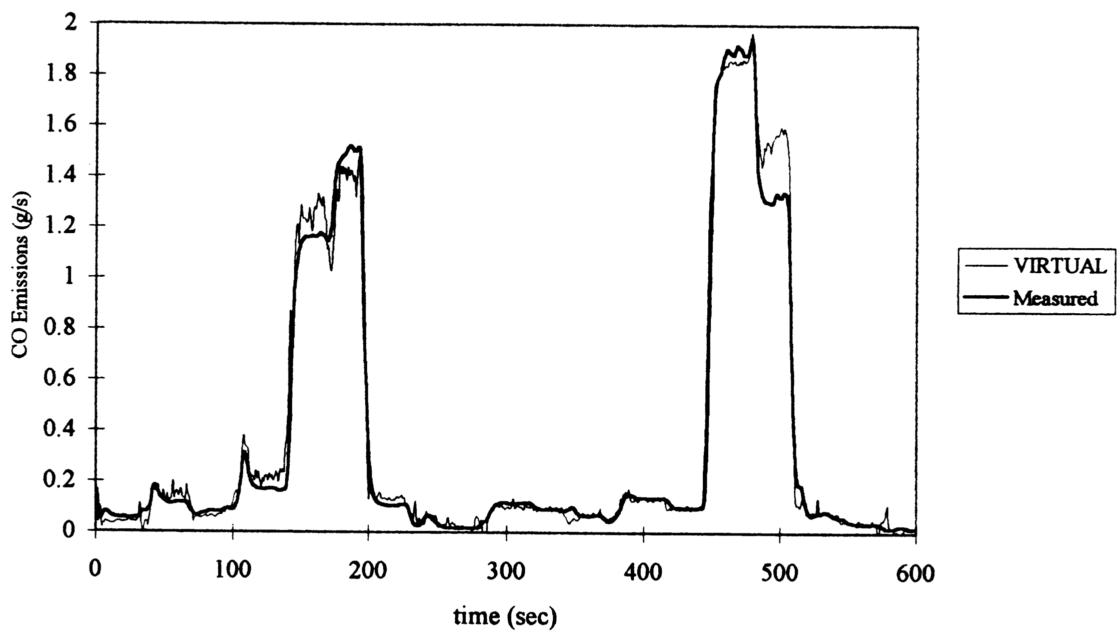

Figure 10. Measured versus Predicted CO Emissions for SI Engine NN Model Validation

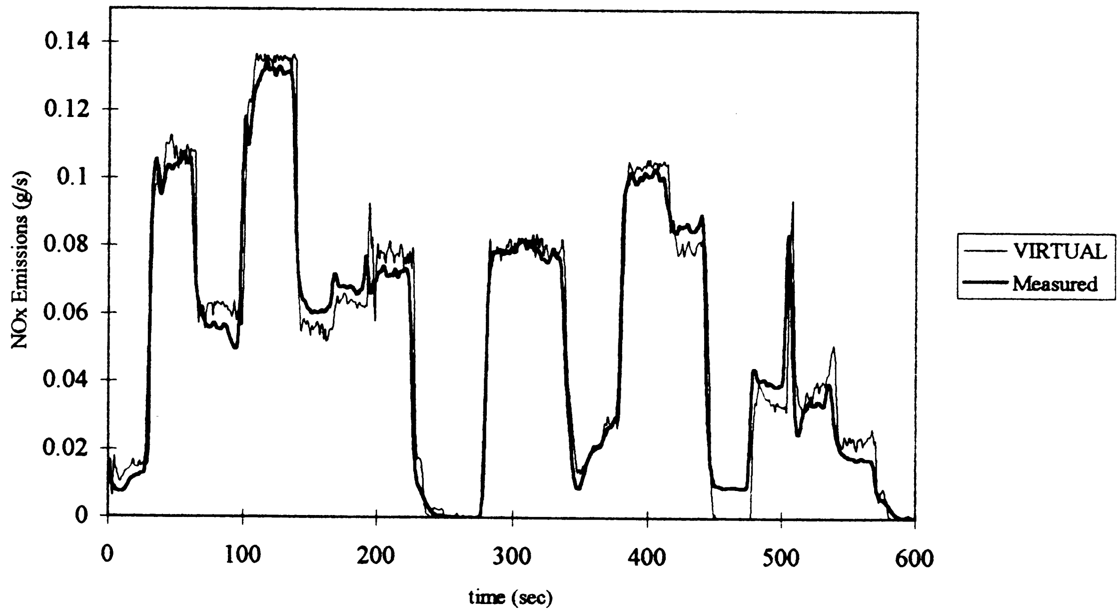

Figure 11. Measured versus Predicted NOx Emissions for SI Engine NN Model Validation

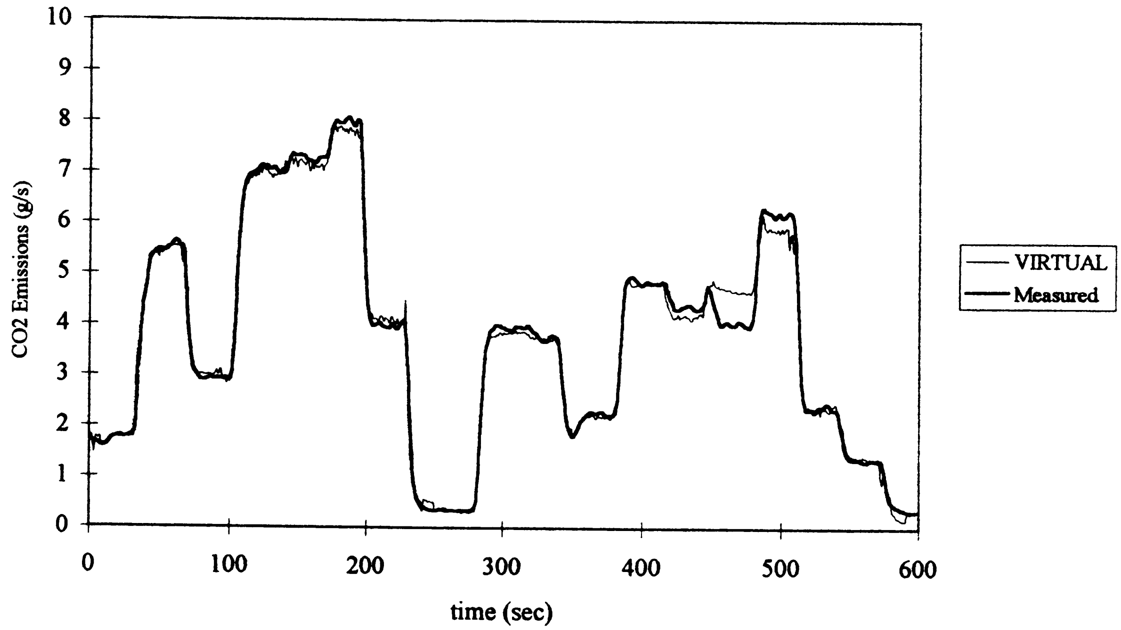

Figure 12. Measured versus Predicted CO_2 Emissions for SI Engine NN Model Validation