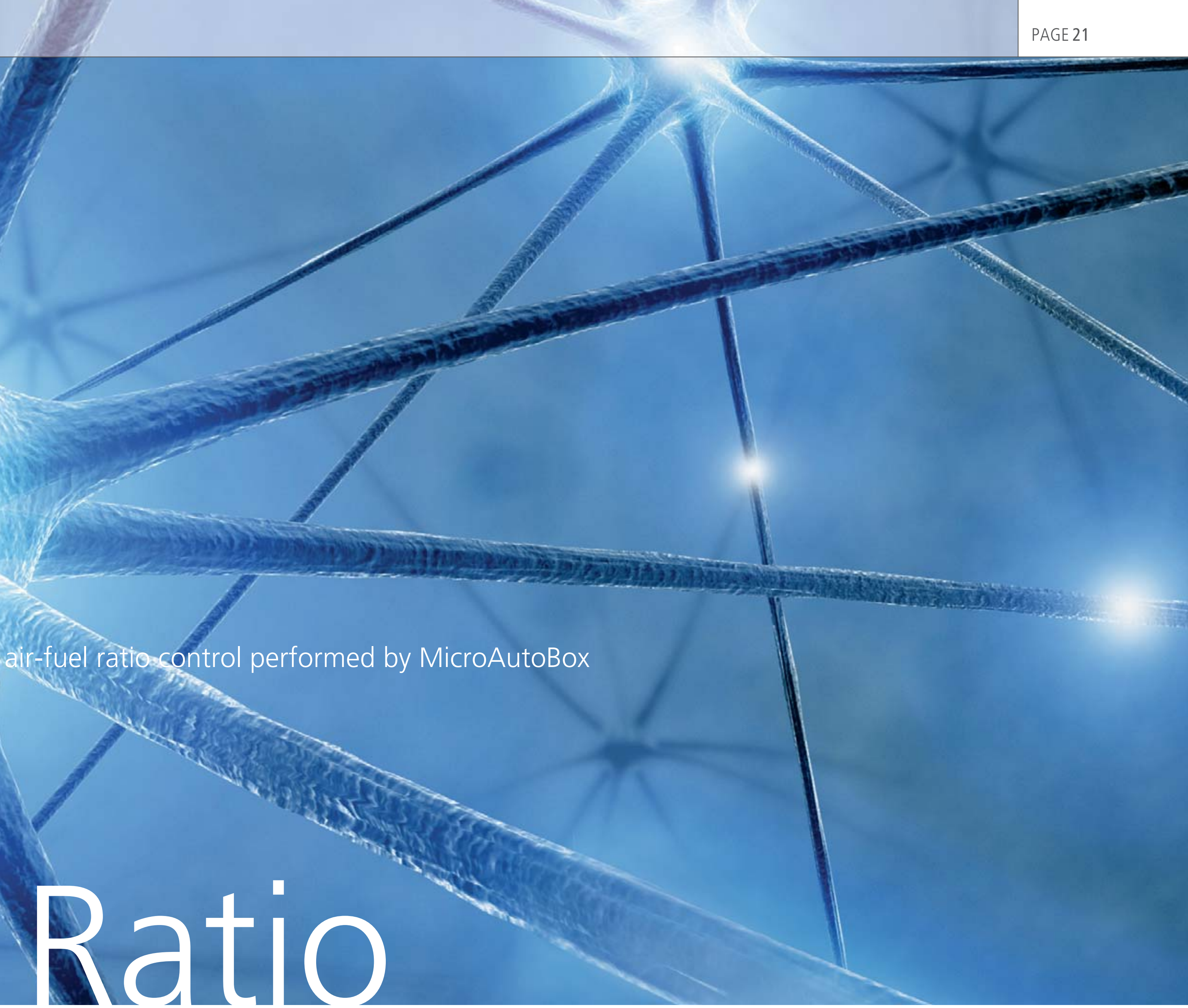
Neural networks for

Optimal Air-fuel

Engine test bench equipped with lambda sensors in the exhaust pipe.

Optimal air-fuel ratio is a key challenge and keeps coming up as an open issue for the engine control community. Since the 1980s, the transition from carburetors to electronically controlled injection systems has been motivating researchers to concentrate on this topic. Proper control of the air-fuel ratio is greatly beneficial to the performance of three-way catalysts in both steady and transient operations. This control task therefore plays a fundamental role in limiting exhaust emissions in SI, GDI and lean-burn engines.



air-fuel ratio control performed by MicroAutoBox

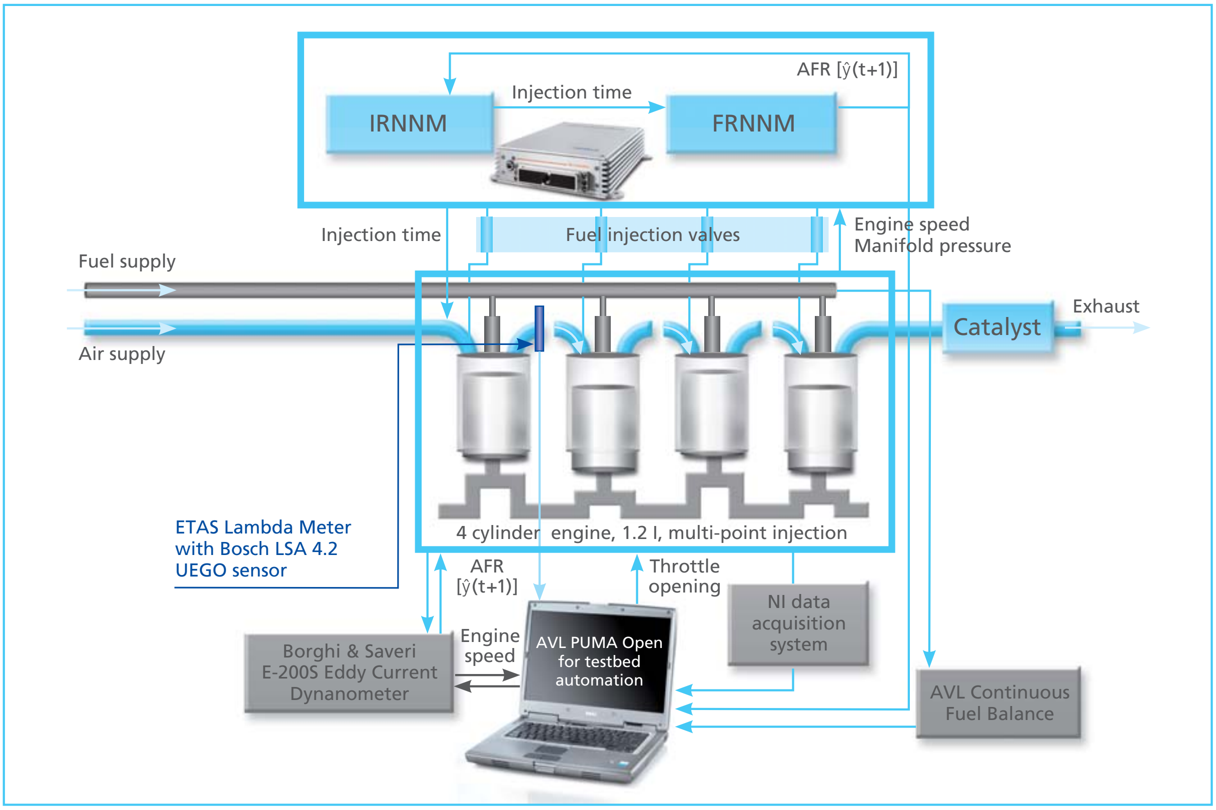
Ratio

Requirements For Air-fuel Ratio Control

Despite the considerable efforts made in limiting exhaust emissions, the increasingly stringent environmental regulations imposed throughout the world still make achieving a satisfactory air-fuel ratio an ambitious goal. Furthermore, engine control system designers have to deal with the onboard diagnostics requirements, introduced in 1996 in the US and later in Europe. This represents a more critical goal in the field of automotive control, since it requires the continuous monitoring of all powertrain components to prevent critical faults in exhaust systems. Air-fuel ratio (AFR) control presently relies on a mean value engine model representation. But these mean value models have some significant limitations, such as the high level of experiments needed for parameter identification and the intrinsic non-adaptive features. On the other hand, the AFR signal delay is a very critical issue to be mastered to improve the performance of closed-loop control strategies. Neural networks are a promising solution for these challenges. They have high mapping capabilities and guarantee a good generalization even with a reduced set of identification data. Moreover, by implementing adaptive training procedures we can consider the influence of exogenous effects on the control performance.

Developed Control Strategy

The AFR control strategy is based on a recurrent neural network (RNN). The neural network is used as a controller and its output directly determines the control actions.
A forward RNN model (FRNNM) of AFR dynamics was developed. This took into account the fact that the dynamic processes affecting the AFR response depend on both air and fuel dynamics. Therefore the output,



Experimental setup with the controller:
The control strategy is made up of two RNNs, describing inverse (IRNNM) and forward (FRNNM) dynamics.

control and external input variables are: AFR, injection time, engine speed, and manifold pressure. The output feedbacks are simulated by the network itself, so the FRNNM does not require any AFR measurement to perform the online estimation. This makes the controller a suitable solution for AFR virtual sensing when the lambda sensor does not guarantee an accurate measurement, which happens during cold start phases. It also allows the delay due to engine cycle, transport phenomena and sensor response to be removed.

Neural controller

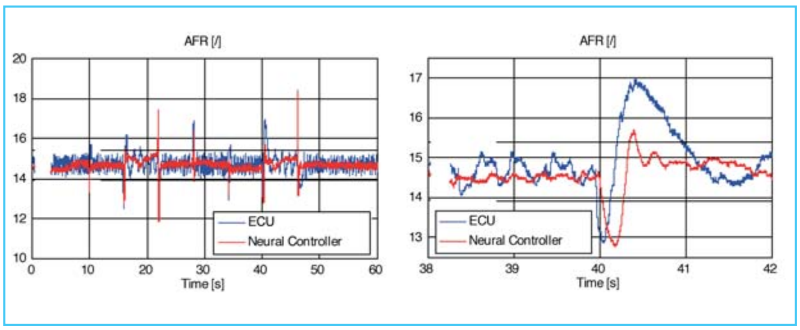
The control actions are computed by an inverse RNN model (IRNNM) as a function of sensor measurements of engine states and external inputs. The output values predicted by the FRNNM are fed as feedbacks to the IRNNM which evaluates the control actions as a function of the desired output at the next time step. The more accurate the FRNNM prediction, the less the difference between the FRNNM and plant outputs.

Experimental Setup

The developed control strategy was trained and tested vs. transient data sets measured on an engine test bench. The lambda sensor was placed right after the exhaust valve of the first cylinder to investigate the air-fuel mixing process in one cylinder only. This choice allows the dynamic effects induced by gas transport and mixing phenomena occurring in the exhaust pipes to be removed. Non-predictable effects generated by cylinder-to-cylinder unbalance due to uneven processes such as air breathing, thermal state and fuel injection can also be neglected. Therefore, the time shift between the injection timing and the lambda sensor measurement mostly accounts for the intake and exhaust valve phasing. As mentioned before, the time delay could be a significant problem for control applications.
For the real-time application the controller was modeled with MATLAB®/Simulink® and then uploaded to a dSPACE MicroAutoBox. This compact prototyping system lets all engine tasks be controlled directly and customized variants of the controller be performed immediately. The direct controller is intended to provide the actual injection time by processing actual and earlier measurements of the engine speed and manifold pressure, and the earlier prediction of AFR performed by the FRNMM. Furthermore, the target AFR was imposed and was set to the stoichiometric value (i.e. 14,67) for the current application. Due to the lambda

> “We replaced the ECU with a dSPACE MicroAutoBox. It allowed us to control all engine tasks and easily customize the control laws.”

Cesare Pianese, University of Salerno



The developed control strategy is very accurate because it follows the target AFR faster and more precisely than the native ECU does.

sensor location, the controller was tested on the first cylinder only, while a classical map-based injection strategy was used for the three remaining cylinders.

Results for the Direct Controller

The trained IRNNM simulates the inverse AFR dynamics as accurately as the FRNNM does for the forward dynamics. Online tests on the developed RNNs were performed by integrating the FRNNM and IRNNM in the framework of a MicroAutoBox, resulting in the neural controller structure.

Conclusion

The virtual sensor (the FRNNM) adequately predicted the AFR dynamics with an estimation error vs. the measured trajectory lower than 2 % for most of the test transients, even when wide AFR spikes were present. This proves that the RNN dynamic behavior is satisfactorily close to the real system dynamics.
The controller, which also uses the virtual sensor prediction, was implemented on the ECU and tested over an experimental transient. The comparison with the AFR trajectory resulting from the action of the reference ECU shows that the controller performs well. In particular, the integration with the virtual sensor prediction induces a higher-order response that results in a faster AFR compensation and, particularly, in the removal of the overshoot observed by the ECU. In this context the MicroAutoBox was a great help, since its high computing power always ensured sufficient headroom for the real-time execution of the complex algorithms. The results demonstrate that neural controllers have a great potential for improving engine control strategies, especially since they significantly reduce the amount of experimentation and calibration needed by other current methods. ■

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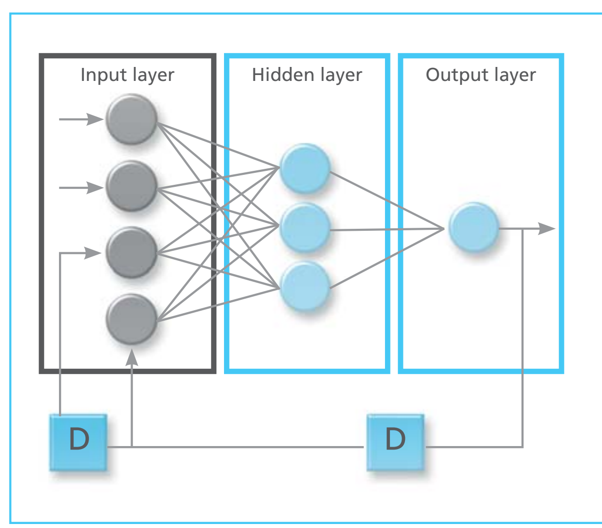
Glossary

Air-Fuel Ratio (AFR) – Mass ratio of air to fuel present during combustion. It is an important measurement for anti-pollution and performance tuning. Lambda (λ) is the alternative expression for the AFR. For pure octane the optimal ratio is λ = 1.00 (stoichiometric mixture of air to fuel 14,67:1).

Lambda Sensor – Also known as oxygen sensor. It monitors the amount of oxygen in the exhaust, so the ECU can determine how rich or lean the fuel mixture is and make adjustments if necessary.

Neural Network – Made of individual units named neurons. Each neuron has a weight associated with each input. A function is then generated as output. Typically the neurons are connected together with an input layer, an output layer and one or more hidden layers. Recurrent neural networks (RNN) are derived from the static networks by introducing feedback connections among the neurons. A dynamic effect is introduced into the computational system by a local memory process. Advantages of RNNs are that they can be sensitive and adapted to past inputs.



Recurrent neural network (RNN).