Adaptive Model Predictive Control for SI Engines Fuel Injection System

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Abstract This paper presents a model predictive control (MPC) based on a neural network (NN) model for air/fuel ration (AFR) control of automotive engines. The novelty of the paper is that the severe nonlinearity of the engine dynamics are modelled by a NN to a high precision, and adaptation of the NN model can cope with system uncertainty and time varying effects. A single dimensional optimization algorithm is used in the paper to speed up the optimization so that it can be implemented to the engine fast dynamics. Simulations on a widely used mean value engine model (MVEM) demonstrate effectiveness of the developed method.

• Key Words : Air-fuel ratio control, SI engine, Adaptive neural networks, Nonlinear programming, Model predictive control

I. Introduction

Many of the current production fuel injection controllers utilize feed-forward control based on a mass airflow sensor located upstream of the throttle plus a proportional integral (PI) type feedback control. The feed-forward control with look-up tables requires a laborious process of calibration and tuning. Furthermore, it is difficult to apply this method since it needs the output magnitude information that is not available in the A/F ratio control [1]. A variety of researches have been conducted during past decade on advanced control strategies on AFR. Onder and Geering [2] made an LQR regulator to improve the air-fuel ratio control. It obtained fairly good AFR when throttle angle ranging from 4° to 8°, but is impractical due to heavy computations resulting from the high order of linearized model.

A nonlinear MPC control scheme for air-fuel ratio based on a RBF model is developed in this paper. The RBF network is on-line adapted to model engine parameter uncertainties and severe nonlinear dynamics in different operating regions. Based on the multiple-step-ahead prediction of the air fuel ratio, an optimal control is obtained to maintain the stoichiometric value when throttle angle changes. A single dimensional optimization algorithm, Secant method, is used to reduce the optimization time, so that the developed method can be implemented to the fast dynamics of automotive engines. Satisfactory AFR control results are obtained by using the developed MPC scheme, as demonstrated on the MVEM [3].

II. Engine Dynamics

The engine dynamics concerned with air/fuel ratio control include air intake manifold, fuel injection, crankshaft speed, and exhaust oxygen measurement. A schematic diagram of the engine dynamics is shown in

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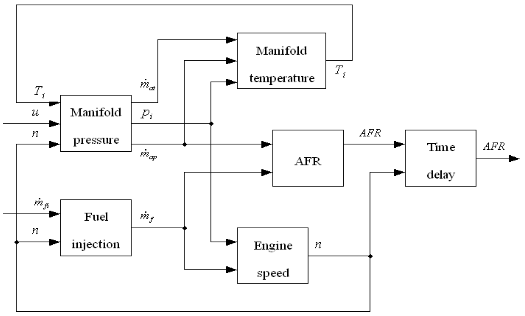
Fig.1.



[Fig. 1] Schematic diagram of engine dynamics

The system has one input, the injected fuel mass flow rate $\dot{m}_{fi}$ one output, air/fuel ratio AFR. Besides, the system is subjected to a significant disturbance, the throttle angle u. Due to the space limitation, the dynamics of each of the four sub-systems, anumber of differential and algebraic equations, are not included. The interested reader can refer to [4].

The manifold filling dynamics can be described by manifold pressure and temperature dynamics,

$$\dot{p}_i = \frac{\kappa R}{V_i}\left(-\dot{m}_{ap}T_i + \dot{m}_{at}T_a + \dot{m}_{EGR}T_{EGR}\right) \quad (1)$$

$$\dot{T}_i = \frac{RT_i}{p_i V_i}\left[-\dot{m}_{ap}(\kappa-1)T_i + \dot{m}_{at}(\kappa T_a - T_i) + \dot{m}_{EGR}(\kappa T_{EGR} - T_i)\right] \quad (2)$$

The crankshaft speed dynamics can be described as

$$\dot{n} = -\frac{1}{In}\left(P_f(p_i,n) + P_p(p_i,n) + P_b(n)\right) + \frac{1}{In}H_u \eta_i(p_i,n,\lambda)\dot{m}_f(t-\Delta\tau_d) \quad (3)$$

Both the friction power P_f and the pumping power P_p are related with the manifold pressure p_i and the crankshaft speed n. The fuel injection dynamics are

$$\dot{m}_{ff} = \frac{1}{\tau_f}\left(-\dot{m}_{ff} + X_f \dot{m}_{fi}\right) \quad (4)$$

$$\dot{m}_{fv} = \left(1 - X_f\right)\dot{m}_{fi} \quad (5)$$

$$\dot{m}_f = \dot{m}_{fv} + \dot{m}_{ff} \quad (6)$$

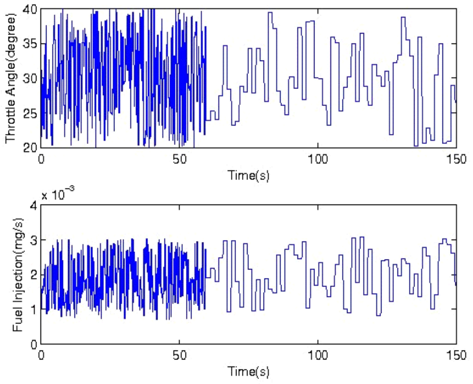
where the model is based on keeping track of the fuel mass flow. The parameters in the model are the time constant for fuel evaporation, τ_f, and the proportion X_f of the fuel which is deposited on the intake manifold, $\dot{m}_{ff}$, or close to the intake valves, $\dot{m}_{fv}$.

III. Adaptive neural network model

The advantage of using adaptive neural network is that it can track the time-varying properties of the process to provide efficient information to the controller, under circumstances where the process parameters change. Radial basis function networks (RBFN) with Gaussian transfer function are chosen in this application as it has been shown to map a nonlinear function arbitrarily well, and possess the best approximation property [5].

A. *Data Collection*

A set of random amplitude signal (RAS) combining short pulse width (transient state) and long pulse width (steady state) was designed for throttle angle and fuel injection, therefore the RBFN model after trained would produce adequate transient and steady state performance. Throttle angle was bounded between 20 and 40 *degree* and the range of fuel injection is from 0.0014 to 0.0079*(kg/s)*, the sample time is set to be 0.1*s*. The excitation signal is shown in Fig.2 partially, consisting of two parts. The length of square waves is set 0.3*s* in the first part and 1.5sin the second part. A set of 3000 data samples of AFR obtained was divided into two groups. The first 1500 data samples were used for training RBFN model and the rest would be remained for model validation.

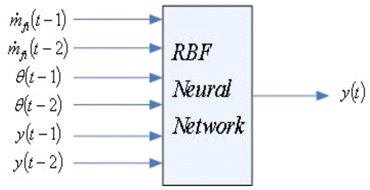


[Fig. 2] Training data with mixed pulse width

B. *Engine Modelling*

Given the expanded engine model as shown Fig.1, the RBFN engine model has 6 inputs and one output as shown in Fig.3, where orders and delays are determined through experiments. The centres c and the width σ in hidden layer nodes of the RBFN were determined using K-means algorithm and ρ -nearest neighbourhood heuristic respectively. RLS algorithm was used for training the neural network and the corresponding parameters were set as follows, $\mu = 0.99$, $w(0) = 2.22 \times 10^{-16} \times U_{n_h \times 2}$ and $P(0) = 1 \times 10^4 \times I_{n_h \times n_h}$, where I is the identity matrix and U stands for a matrix whose components are ones.

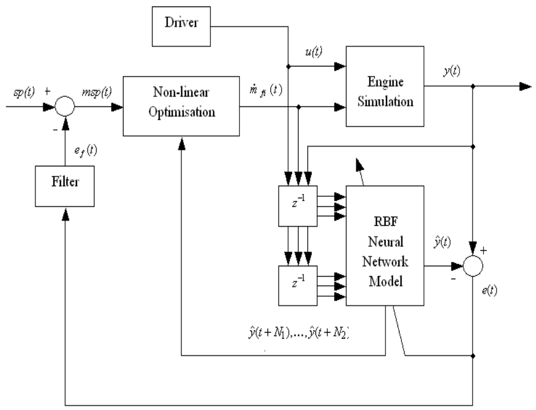
After training with the training data set and test with the test data, the modelling error of the AFR in the normalized value with the mean absolute error, MAE = 0.0265.



[Fig. 3] RBFN structure

IV. mpc of air fuel ratio

A. *Control System Structure*



[Fig. 4] Configuration of model predictive control on AFR

The idea of model predictive control with neural network has been introduced in details by Draeger [6]. The strategy is shown in Fig.4. The obtained adaptive RBF neural network is used to predict the engine output for N_2 steps ahead. The nonlinear optimizer minimizes the errors between the set point and the engine output by using the cost function,

$$J(k)=\sum_{i=k+N_1}^{k+N_2}\left[msp(i)-\hat{y}(i)\right]^2+\xi\sum_{i=k}^{k+N_u}\left[\dot{m}_{fi}(i)-\dot{m}_{fi}(i-1)\right]^2 \tag{7}$$

Here, N_1 and N_2 define the prediction horizon. ξ is a control weighting factor which penalizes excessive movement of the control input, the fuel injection $\dot{m}_{fi}$. N_u is the control horizon. Then the remaining main problem of MPC is to solve the nonlinear optimization problem, i.e. in each sample period, calculate a series of optimal $\dot{m}_{fi}(k), \dot{m}_{fi}(k+2), \cdots, \dot{m}_{fi}(k+N_2-1)$, from which the neural network model generates outputs to minimize $J(k)$ in (30). Finally the first control variable $\dot{m}_{fi}(k)$ is used to control the process and this procedure is repeated in the next sample period.

B. *Single-Dimensional Optimization Approach*

As second-orderRBFN structure was chosen to achieve the minimum prediction error in engine modelling, the optimization problem involved in the paper is multi-dimensional and constrained. That is, we are going to find the future input $\dot{m}_{fi}(k), \dot{m}_{fi}(k+1), \cdots, \dot{m}_{fi}(k+N_2-1)$ that can minimize $J(k)$ such that the predicted outputs $\hat{y}(k), \hat{y}(k+1), \cdots, \hat{y}(k+N_2)$ coincides with the modified set-point input $mspi(k)$, $mspi(k+1)$, $,\cdots, mspi(k+N_2)$, here the fuel injection rate is bounded within the region from 0.0014 to 0.0079*(kg/s)*. Sequential Quadratic Programming (SQP) can be used to acquire the accurate solution, which is perhaps one of the best methods of optimization, would be shown in next section. However, the multi-dimensional optimization always requires heavy computation, especially when constraints exist.

Practical applications often place emphasis on computation speed on the premise that all the performance requirements are met. Therefore, we chose the simplest structure in this paper and assumed that the input $\dot{m}_{fi}$ will remain constant over the prediction horizon: $\dot{m}_{fi}(k) = \dot{m}_{fi}(k+1) = \cdots, \dot{m}_{fi}(k+N_2-1)$, in this case, there is only one parameter $\dot{m}_{fi}(k)$ that we are going to find. The optimization problem to be solved is reduced as one-dimensional. Secant method is chosen to find the solution of this nonlinear programming (NLP) problem and our experiments show that it is more efficient and reliable in this application if compared with the other interpolation methods.

1) *Secant Method:*

The general nonlinear programming problem could be defined as,

$$\min_{x \in R^n} J(x) \tag{8}$$

subject to

$$\begin{aligned} c_{eq}(x) &= 0 \\ c_{in}(x) &\le 0 \end{aligned} \tag{9}$$

where $J: R^n \to R$ is the objective function, $c_{eq}: R^n \to R^m$ and $c_{in}: R^n \to R^p$ are constraint functions. All of these functions are smooth. Only inequality constraint applied in our case, as fuel injection rate is bounded within a region.

The Secant Method is to find the improved design vector X_{i+1} from the current design vector X_i using the formula

$$X_{i+1} = X_i + \zeta_i^* S_i \tag{10}$$

where S_i is the known search direction and ζ_i^* is the optimal step length found by solving the one-dimensional minimization problem as

$$\zeta_i^* = \min_{\zeta_i}[J(X_i + \zeta_i S_i)] \tag{11}$$

Here the objective function J is to be evaluated at any trial step length t_0 as

$$J(t_0) = J(X_i + t_0 S_i) \tag{12}$$

Similarly, the derivative of the function J with respect to ζ corresponding to the trial step length t_0 is to be found as

$$\left.\frac{dJ}{d\zeta}\right|_{\zeta=t_0} = S_i^T \Delta J\Big|_{\zeta=t_0} \qquad (13)$$

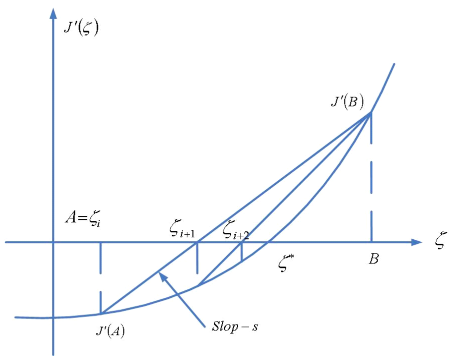
The necessary condition for $J(\zeta)$ to have a minimum of ζ^* is that $J'(\zeta^*)=0$. The Secant Method seeks to find the root of this equation [7]. The equation is given with the form as follows,

$$J'(\zeta) = J'(\zeta_i) + s(\zeta - \zeta_i) = 0 \qquad (14)$$

where s is the slope of the line connecting the two points $(A, J'(A))$ and $(B, J'(B))$, where A and Bdenote two different approximations to the correct solution, ζ^*. The slope s can be expressed as

$$s = \frac{J'(B) - J'(A)}{B - A} \qquad (15)$$

Equation (14) approximates the function $J'(\zeta^*)$ between A and B as a linear equation and the solution of equation (14) gives the new approximation to the root of $J'(\zeta^*)$ as



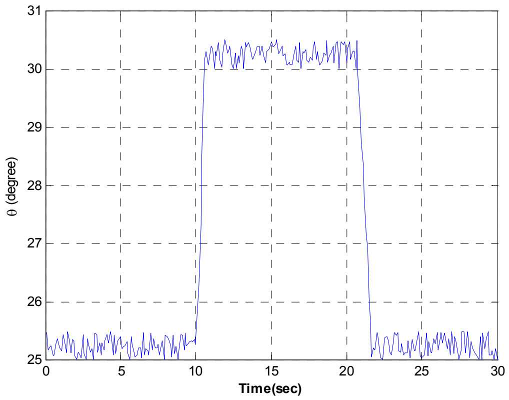
[Fig. 5] Iterative process of secant method

$$\zeta_{i+1} = \zeta_i - \frac{J'(\zeta_i)}{s} = A - \frac{J'(A)(B-A)}{J'(B) - J'(A)} \qquad (16)$$

The iteration process given in equation (16) is illustrated in Fig.5.

2) *Simulation Results using Secant Method*

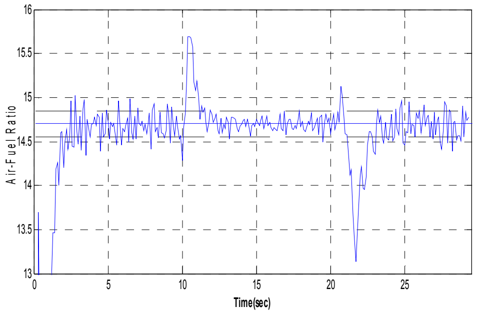
In the simulation, the set-point of the system is set to be the constant stoichiometric value 14.7. The throttle angle $\theta$is set as disturbance, a change from 25° to 30° with 0.5% uncertainty as shown in Fig.6. This is to evaluate the tracking performance and the robustness to throttle angle change of the designed system.



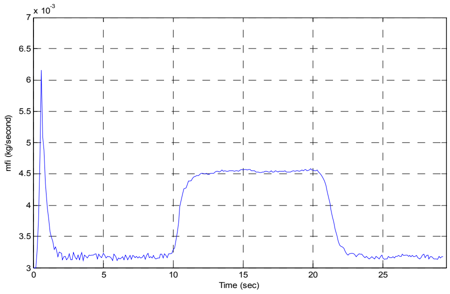
[Fig. 6] Throttle angle pattern in simulations

The AFR is to be controlled between the $\pm 1\%$ bounds of the stoichiometric value (14.7). Choosethe sampling time to be 0.1s. The parameters of nonlinear optimization were chosen as $N_1 = 1$, $N_2 = 6$, $\xi = 1$, $N_u = 0$, then the MPC of SI engines can be considered as a sub-problem of NLP problems: $\min_{x \in R^n} f(\dot{m}_{fi})$ subject to $\dot{m}_{fi}{}^l \le \dot{m}_{fi} \le \dot{m}_{fi}{}^u$, where $f: R^n \to R$, $\dot{m}_{fi}{}^l$ and $\dot{m}_{fi}{}^u$ represent the lower bound and the upper bound of the control variable $\dot{m}_{fi}$.

The system output under the developed MPC is displayed in Fig.7, together with the associated manipulated variable $\dot{m}_{fi}$ displayed in Fig.8. The mean absolute error (MAE) of the AFR tracking is 0.4464. One can see thatthe air-to-fuel ratio is regulated within a $\pm 1\%$ neighbourhood of stoichiometric. This performance is much better than that of PI controller [8] that is widely used in automotive industry.

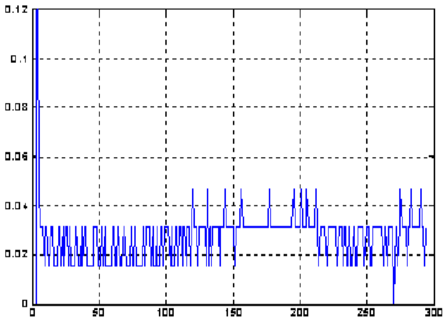


[Fig. 7] MPC on AFR using secant method



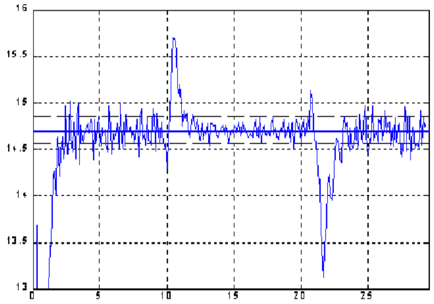
[Fig. 8] Fuel injection using secant method

The time cost in optimization in each sample period is shown in Fig 9. The mean time cost in one sample period is 0.0277 seconds.

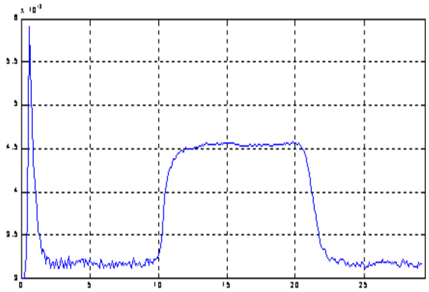


[Fig. 9] Time cost on optimization using secant method

Since the whole simulation was running in Matlab environment, we feel that the further reduction on time cost of optimization could be achieved if optimization algorithm is realized by *C*code in real application. The multi-dimensional approach for MPC was implemented using Reduced Hessian Method and is compared with Secant Method, in terms of the control performance and time consumptions on optimization (see Fig 10 and 11)

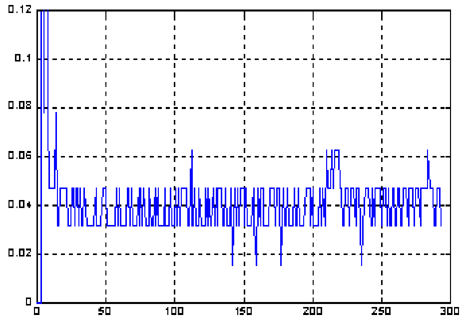


[Fig. 10] MPC on AFR using reduced hessian method



[Fig. 11] Fuel injection using reduced hessian method

The simulation results show that Reduced Hessian Method has the similar tracking performance of Secant Method;however, its time consumption in optimization is much more than that of previous method. As shown in Fig 12, the mean time cost in one sample period using this method is 0.0473 seconds in our experiment, which is nearly twice as many as that used by Secant Method.



[Fig. 12] Time cost on optimization using reduced hessian method

Ⅴ. conclusions

In thispaper, adaptive RBF model based MPC is applied to AFR control of automotive engines. The simulation results validated that the developed method can control the AFR to track the set-point value under disturbance of changing throttle angle. To meet the requirement for fast optimization in engine control, a one-dimensional optimization method, Secant Method, is implemented in the MPC and is compared with the multi-dimensional method, Reduced Hessian Method. Simulations show a much shorter optimization time using Secant Method and the achieved tracking control with similar performance to that in Reduced Hessian Method.

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