High-Precision, Robust Cascade Model for Closed-Loop Control of Ceramic Glow Plug Surface Temperature in a Diesel Engine

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KEYWORD

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ABSTRACT

A closed-loop control of a glow plug in a diesel engine is a solution to replace a table-based regulation algorithm to minimise application effort and increase robustness. This paper proposes a method to develop a robust, real-time and accurate temperature model to be used with a model-based temperature controller. Analytical models provide *a priori* knowledge to the design and optimisation of steady-state temperature estimation for the nonlinear part of a Hammerstein-type dynamic model. Accuracy and robustness are improved compared to those of a classical multivariate nonlinear regression model and an artificial neural network model. Experimental results of a preliminary controller based on the developed model on a test bench and in a test vehicle show excellent dynamic accuracy.

INTRODUCTION

A modern glow plug system is equipped with a glow control unit (GCU), whose function is to regulate the glow voltage of the installed glow plugs, in order to satisfy the glow temperature demanded by the engine control unit (ECU). The importance of the glow temperature is not only in the cold start behaviour but also in the exhaust gas quality, (Last et al., 2008).

A current temperature control strategy is a lookup table-based voltage regulation (Houben et al., 2000), with the input variables of the current engine operating points and a desired glow temperature, and the output of a glow voltage to supply to the installed glow plugs. The lookup tables are predetermined during the development phase of the GCU, which involves comprehensive measurements on engine test benches and in test vehicles, to experimentally evaluate the required glow voltage for each desired temperature nouveau under almost all possible engine operating points. With every application variation, in the engine design or in the glow plug type, this tremendous effort, both time-consuming and expensive, must be undertaken again.

Another disadvantage of the current strategy is that it does not take into account the glow plug behaviour variation due to manufacturing tolerances between individual glow plugs. The production yield is consequently severely limited due to the imposed tolerance bandwidth on the product specification to ensure reliability.

PROPOSED SOLUTION

A closed-loop control of glow plug temperature is a solution to eliminate the rigidity of the table-based regulation strategy and the necessity of high development effort. The main requirement of the control loop in Figure 1 is the glow plug surface temperature estimation, due to the unavailability of a temperature signal in serial-production glow plugs.

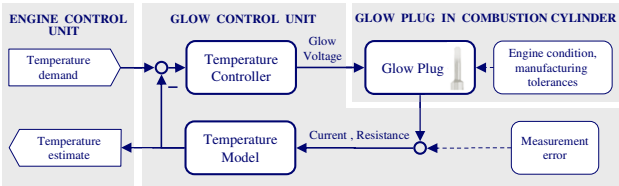

Figure 1: Closed-Looped Temperature Controller

By considering a glow plug as a system whose internal uncertainty is the manufacturing tolerances, affecting electrical and heat conduction, and energy conversion within the heating element; and whose external disturbances are the engine conditions, influencing the heat transfer between the glow plug surface and the surrounding, three crucial aspects in the development are as follows:

Aspect 1: Using the response of the installed glow plug as an indicator to evaluate the external influences, replacing the measurement signals of the engine operating condition and eliminating the dependency of the table-based algorithm thereof.

Aspect 2: Identifying individual glow plug characteristics to improve robustness against the manufacturing tolerances by adapting the controller accordingly.

Aspect 3: Designing for real-time application.

The third aspect imposes restriction on the computational complexity of the model. Existing glow plug simulation models, such as a finite-difference model (FDM) in (Formaggia et al., 2007) and FEM during the glow plug design phase, coupled with heat transfer analysis in a diesel combustion chamber, such

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as those reviewed in (Finol and Robinson, 2006), can offer detailed insights, but are invariably too computational intensive and not suitable for a system with unknown tolerances. On the other hand, artificial neural networks (ANN) can achieve high accuracy with adjustable complexity without requiring detailed knowledge of the system, but still require careful selection of the training regime, and can still result in complex computations of multiple nonlinear functions.

The most efficient model is thus a single-output temperature model based purely on the electrical behaviour with sufficiently high dynamic accuracy to simplify the control algorithm to a classical temperature controller. The structure of this paper follows the model development: Section 1 gives an overview of an analytical model of a BorgWarner ceramic glow plug, which presents an insight into the thermal-electrical behaviour; Section 2 lays a foundation of the temperature model by identifying the most influential electrical properties and their correlation to internal and external disturbances in sensitivity analyses based on the model in Section 1; and Section 3 bridges the gap between the analytical model and experimental data, gives a detailed procedure of temperature model optimisation with the consideration of application-related criteria, and presents the optimum temperature model structure to be used in closed-loop control.

1 Analytical Model of a Nominal Glow Plug

A ceramic glow plug can be modelled as a thermal-electrical system, whereby the specially designed, electrically conductive ceramic materials convert electrical power into heat production via the Joule effect. The electrical and thermal domains are further coupled by the temperature-dependant material properties.

The thermal-electrical behavioural model of an outer-heating ceramic glow plug by BorgWarner has been developed by BorgWarner. It is a two-dimensional FDM representing an axial-symmetric three-layer ceramic heating rod, protected by a steel outer sleeve and a steel body, as shown in Figure 2.

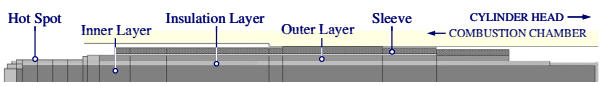

Figure 2: FDM Element Definition of an Outer-Heating Ceramic Glow Plug for Sensitivity Analysis

The thermal-electrical behaviour is described by a system of heat equations at each finite volume i:

$$\nabla q_i = I_{GP}^{\,2}\left(\rho_{el,i}\frac{L_{el,i}}{A_{el,i}}\right) - \rho_i c_i \frac{dT_i}{dt}, \qquad (1)$$

where ∇q is the net heat flux output of the element; L_{el} and A_{el} the effective length and cross-sectional area with respect to electrical conductance; $\rho_{el}(T)$, $\rho(T)$, and $c(T)$ the temperature-dependent specific electrical resistance, density and heat capacity, respectively; and T the local temperature. Material properties were implemented as polynomial functions of temperature; for instance, heat capacity of a material m:

$$c_m = c_{o,m} + k_{c1,m}(T - T_o) + k_{c2,m}(T - T_o)^2, \qquad (2)$$

with the polynomial coefficients $\boldsymbol{c}_o \in \mathbf{R}^{1\times m}$ and $\boldsymbol{k}_c \in \mathbf{R}^{2\times m}$ determined using least-square method to fit literature tabular data, and T_o the reference temperature at 20°C. The net heat flux term is expanded by heat conduction to neighbouring elements and the cylinder head, and by convective and radiation heat transfer from surface elements to the surrounding. Surrounding condition under no external influence is modelled with free-convection. The electrical current I_{GP} is calculated from the glow voltage U_{GP} divided by the total resistance of the electrically-conductive elements, R_{GP}. The analytical model of a nominal glow plug under no external influence, that is, free convection, is referred to hereafter as the nominal model.

To simulate the dynamic behaviour, a discrete-time explicit calculation of the changes in temperature profile, material properties, and heat balance equations were carried out to yield time-variant temperature profile $\boldsymbol{T}(t)$ and resistance distribution $\boldsymbol{R}(t)$. Alternatively, by setting Dirichlet boundary conditions $\boldsymbol{T}(t{=}0){=}T_{RT}$ and $\nabla \boldsymbol{q}_i - \boldsymbol{q}_{i,Joule}$ $(t{=}t_{ss}){=}0$, the system of equations could be solved for the steady-state temperature profile $\boldsymbol{Tss}=[T_1 \ldots T_i]$ and electrical resistance distribution $\boldsymbol{Rss}=[R_1 \ldots R_i]$.

It is clear from Equations 1, 2, and higher-order temperature terms from radiation, that the glow plug is a highly nonlinear, dynamic system. However, most relevant to this work are the desired maximum surface temperature $T_{max} \in \boldsymbol{T}$, and the measurable total resistance R_{GP} and current I_{GP}.

2 Sensitivity Analyses

The aim of this phase is to analyse the glow plug behaviour to ascertain the correlation between the measurands I, R and the controlled variable T_{max}, the inputs and output of the temperature model, respectively. A theoretical approach was based on the nominal glow plug model with glow plug's ideal geometry and material properties, as detailed in the previous section. The system disturbances were introduced into the model as (a) raw material tolerances via temperature-dependent modification functions augmented to the polynomials in Equations 2; (b) geometrical tolerances in the critical areas via modification factors $\boldsymbol{k}_s$ multiplied to ideal geometric measures $\boldsymbol{s}$; and (c) external disturbances via a matrix of combined convective-and-radiation heat transfer coefficients $\boldsymbol{\alpha}_{equiv}$ at the glow plug surface layer. A parallel experimental approach was based on test-bench measurement data, with (a,b) tolerance uncertainties among 79 glow plugs from 14 different manufacturing batches, and (c) disturbances by means of pressurised air stream with adjustable flow rate directed head-on at the glow plug.

The experimental setup on a test bench allows the surface temperature to be measured by a pyrometer, and the total electrical resistance and current by a shunt.

In analysing the internal influences, Spearman rank- and Pearson product-moment correlation coefficients (ρ_S, ρ_P) were averaged from individual {$\boldsymbol{\alpha}_{equiv}$ | Flow rate} scenarios; whereas in analysing the external influences, the coefficients were averaged from individual {model's (a, b) configuration | glow plug} cases. In most cases, the coefficients (ρ_S, ρ_P) resulted in an identical ranking of influences. Table 1 and 2 show the top three main effects' ranking from the model-based and the experiment-based sensitivity analyses against internal and external disturbances, respectively. The suffix *nom* denotes the nominal value specified as reference points for voltage at 5.6V, and temperature at 1200°C*; HS*, denotes the simulated value at the element where the maximum temperature occurs. The symbol > is used in place where the influence rankings of the left-hand side has marginally more effect; while = is for equal influence. The symbol Δ stands for the difference between the scenario's simulated result and the result of the nominal model excited by the same voltage. By exciting a nominal glow plug under no external influence, or simulating the nominal model, with two voltages [U_{nom} $U_{nom}+dU$], the additional *reference resistance* $R_f = R_{GP}(U_{nom})$ and the *reference resistance gradient* $g_R = dR/dU$ can be calculated. The values were consequently independent of measured glow voltage U, and thus offered a bias-free glow plug characteristics.

Table 1: Sensitivity Analysis of Glow Plug Temperature Against Manufacturing Tolerances

Response	Main effects	
	Simulation	Experiment
Temperature T at nominal voltage U_{nom}	1. $I_{GP} > P_{HS} > P_{GP}$ 2. R_{HS} 3. $R_f > g_R$	1. $I_{GP} > P_{GP}$ 2. $R_f > g_R$ 3. R_{GP}
Temperature gradient dT/dU	1. $R_{HS} > R_f$ 2. I_{GP} 3. g_R	1. R_f 2. I_{GP} 3. g_R

Table 2: Sensitivity Analysis of Glow Plug Temperature Against External Disturbances

Response	Main effects	
	Simulation	Experiment
Temperature T at nominal voltage U_{nom}	1. $\Delta I_{GP} = \Delta R_{HS}$ 2. ΔR_{GP} 3. P_{GP}	1. I_{GP} 2. P_{GP} 3. R_{GP}
Temperature gradient dT/dU	1. $\Delta I_{GP} = P_{GP}$ 2. I_{GP} 3. ΔR_{HS}	1. P_{GP} 2. I_{GP} 3. R_{GP}

According to Table 1, the model-based and the experiment-based results show an agreement in that the steady-state maximum surface temperature of a glow plug has the largest correlation to the glow plug current, logically due to the thermal power being proportional to the electrical power $I_{GP}^2 R_{GP}$, then to the power, and the resistance. The second row predicts that the thermal response to the change in excitation voltage, at the same surrounding conditions, should be estimable from glow plug characteristic resistance measured at the nominal voltage, under no external influences.

From Table 2, the influence rankings between the simulation and the experimental data again were in good accord. Under variation of external influences, the most promising factors in determining the temperature at a nominal voltage $T(U_{nom})$ were the measured current, followed by the resistance and electrical power. The response of the temperature with respect to glow voltage, dT/dU was most correlated to the measured electric power P_{GP}. Mechanistic analyses by extracting changes of the current I_{GP} and power P_{GP} when compared to those of a nominal glow plug under no external influence offer even a better correlation. Analogous to the reference parameters from Table 1, these ΔI_{GP}, ΔP_{GP} and ΔR_{GP} *comparators* provide nearly glow plug-neutral behavioural indicators. The fact that neither the indicative $\boldsymbol{\alpha}_{equiv}$ nor the flow rate *FL* was in the top-three main effects was a positive sign that the external influence can indeed be deduced from the glow plug's electrical behaviour alone.

An advantage of the model-based sensitivity analysis is the complete transparency of the manufacturing tolerances' effects on the glow plug behaviour. While the results from both approaches agree that the measurable electrical signals (R_{GP}, I_{GP}) can be further utilised as indicator signals for the external disturbances and internal uncertainties, the simulation results make a step farther by ensuring that these signals are indeed good indicators regardless of the source or magnitude of manufacturing tolerances. The simulation model also offers a much quicker preliminary analysis of a new glow plug type, to predict whether the proposed model development procedure can be adapted successfully.

3 Procedure for Development of Cascade Temperature Model of Glow Plug in Engine

The previous phase demonstrates that both the intrinsic behaviour of a glow plug and the external influences by way of heat exchange behaviour with the surrounding can be estimated qualitatively from merely electrical resistance and current signals. This phase aim is to predict the temperature quantitatively using the available signals and *a priori* knowledge from the simulation models.

3.1 Structure of Cascade Model

The structure of the temperature model was selected as a Hammerstein-type nonlinear dynamic system, which generally offers a good behavioural approximation in many automotive systems (Kirschbaum et al., 2009). The inputs of the nonlinear static function are measurable electrical properties (R, I) of the installed

glow plug. By selecting its output to a steady-state temperature estimate, and designating the linear dynamic transfer function to describe the dynamic response of the system to the step response, from the current temperature estimate to the next as updated by the preceding nonlinear block, the modelling task was simplified by separately tackling the steady-state accuracy and the dynamic behaviour. By setting the discrete time step Δt to that of the sampling period of GCU at 30.5ms, one further simplification is to assume that during the short interval of Δt, the dynamic behaviour can be represented by a nominal transfer function regardless of the manufacturing tolerances or the engine conditions,

$$G(s) = \frac{K(\tau_N s + 1)}{(\tau_{P1} s + 1)(\tau_{P2} s + 1)}. \tag{3}$$

The time constants were identified with least-square method from experimental data of nominal glow plugs under no external influence with temperature step variations.

The main focus of this work is the identification of the nonlinear static part, beginning by first describing the nonlinear time-invariant function as a mixed effect model,

$$\hat{T} = f_{NL}(F, N, \Theta, T_o), \tag{4}$$

where $\boldsymbol{F}$ is a vector of glow plug-specific internal influences, $\boldsymbol{N}$ a vector of indicators to external disturbances, $\boldsymbol{\Theta}$ a weighting coefficient vector of influences and disturbances, and T_o the expected temperature of a given glow plug under no external influences. Equation 4 was then broken down into a cascade of effects

$$\hat{T} = f_{NL,L1}(N, \Theta_N, T_o), \text{ and} \tag{5}$$

$$[\Theta_N, T_o] = f_{NL,L3}(F, \varphi). \tag{6}$$

That is, Equation 5 predicts the steady-state temperature of a given glow plug based on the external influence indicators, $\boldsymbol{N}$, and an expected temperature of that glow plug under no external influence, T_o. Equation 6 then in turn describes how large the impact of the external influences has on the given glow plug, $\boldsymbol{\Theta_N}$, and its expected temperature, T_o, based on the glow plug intrinsic properties $\boldsymbol{F}$ and the model parameters, $\boldsymbol{\varphi}$.

Let vector $\boldsymbol{N}$ be a regression vector composed of measured electrical properties, their higher-order terms, their relation with respect to the simulated expected values, and the interaction thereof, then Equation 5 can be converted to a linear function

$$\hat{T} = \Theta_N \times N + T_o, \tag{7}$$

with $\boldsymbol{\Theta_N} \in \mathbf{R}^{1\text{x}P}$, and $\boldsymbol{N} \in \mathbf{R}^{P\text{x}1}$ for P indicators. Let $\boldsymbol{F}$ be a regression vector of Q selected glow plug characteristic properties. Then equation 6 becomes

$$\begin{aligned} \Theta_N &= F \times \varphi_\Theta, \\ T_o &= F \times \varphi_{To} \end{aligned} \tag{8}$$

where $\boldsymbol{\varphi}_\Theta \in \mathbf{R}^{Q\text{x}P}$, $\boldsymbol{\varphi}_{To} \in \mathbf{R}^{Q\text{x}1}$, and $\boldsymbol{F} \in \mathbf{R}^{1\text{x}Q}$. From the above structure configuration, the system identification tasks were (i) the selection of external influence indicators $\boldsymbol{N}$; (ii) the selection of glow plug characteristic properties $\boldsymbol{F}$; and then (iii) the model parameter estimation.

Considering the three criteria of model development — namely, the accuracy of the temperature estimate, the robustness against the external and internal influences, and the real-time capability — the system identification tasks outlined above become intertwined with multiple objectives. An approach is to view them as multi-level optimisation, parallel to the cascade of effects. The procedure of evaluating the quality of a model structure with an arbitrary configuration $\{\boldsymbol{N_C}, \boldsymbol{F_C}\}$ based on measurement data of M glow plugs under D external influence conditions, excited by U levels of glow voltages, $(T, I, R) \in \mathbf{R}^{M\text{x}D\text{x}U}$, is then as follows:

Level 0: Define variables

$\boldsymbol{N_C}=[N_1 \ldots N_P]$ and $\boldsymbol{F_C}=[F_1 \ldots F_Q]$

Level 1: For each glow plug, at each level of external disturbance, solve for

$$\Theta_{N,L1}\big|_{m,d} = \left[\Theta_{N1,L1} \ldots \Theta_{NP,L1}\right]_{m,d} \text{ and } T_{o,L1}\big|_{m,d} \text{ at}$$

$$\min\left(rms\left(T_i - \left(\Theta_{N,L1,i} \times N_{c,i} + T_{o,L1}\right)\right)\right),$$

where i=1…U for glow voltage levels.

Level 2: For each glow plug under all conditions, find intermediate coefficients $\boldsymbol{c_\Theta}|_m=[c_{\Theta 1} \ldots c_{\Theta P}]|_m$ and $c_{To}|_m$ as functions of external influences $\boldsymbol{N_C}$ in

$$\begin{aligned} \Theta_{N,L2}\big|_m &= \left[c_{\Theta 1} \cdot N_1 \ldots c_{\Theta P} \cdot N_P\right]_{m,d=1\ldots D} \\ T_{o,L2}\big|_m &= \left(c_{To,1} \cdot N_1 + \ldots + c_{To,P} \cdot N_P\right)\big|_{m,d=1\ldots D} \end{aligned}, \text{ at}$$

$$\begin{aligned} &\min\left(rms\left(\Theta_{N,L1,j} - \Theta_{N,L2,j}\right)\right) \\ &\min\left(rms\left(T_{o,L1,j} - T_{o,L2,j}\right)\right) \end{aligned}$$

with j=1…D×U for voltage and disturbance levels.

Level 3: For all glow plugs, under all conditions, solve for the model parameters $[\boldsymbol{\varphi}_\Theta, \boldsymbol{\varphi}_{To}]$ to satisfy

$$\begin{aligned} &\min\left(rms\left(c_{\Theta,k} - F_k \times \varphi_\Theta\right)\right) \\ &\min\left(rms\left(c_{To,k} - F_k \times \varphi_{To}\right)\right) \end{aligned},$$

where k = 1… D×U×M.

Therefore, Level 3 yields the final model, with (P+1)×Q identified model parameters:

$$\hat{T} = F \times \varphi_\Theta \times N + F \times \varphi_{To}. \tag{9}$$

Notice that as the optimisation level goes higher, less specific information regarding the internal and external influences is available, and the model becomes more general. In Level 1, clear distinction of individual glow plugs must be known, as well as the level of external disturbances. The model parameters $\boldsymbol{\Theta}_{N,L1}$ and $T_{o,L1}$ only work with that specific glow plug under that known external disturbance level. In Level 2, still the identity of the glow plug must be known, but the intermediate model parameters, $\boldsymbol{c}_{\Theta}$ and $\boldsymbol{c}_{To}$, apply to that glow plug under any external disturbances. Lastly, in Level 3, the final model parameters, $\boldsymbol{\varphi}_{\Theta}$ and $\boldsymbol{\varphi}_{To}$, describe the behaviour of all glow plugs under all circumstances.

3.2 Selection of Influence Indicators

The challenge would be to optimise the accuracy and robustness of the final model in Level 3, while aiming for simplicity of the model with few but the most influential variables in $\boldsymbol{N}$ and $\boldsymbol{F}$.

Typically, the task of optimising the model structure in system identification begins with high complexity to capture the essence of the system. However, the analytical model as well as previous experimental data gave *a priori* knowledge of influential ranking to the glow plug behaviour, and thus reducing the initial complexity. From the sensitivity analyses in the preliminary phase, the temperature at a certain voltage $T(U_{nom})$, as well as the response to voltage change dT/dU, show strong correlations with electrical properties, as well as the comparators between the electrical behaviour of a glow plug under external influences and that of the same glow plug under no external influence. Hence, the logical choices for external influence indicators $\boldsymbol{N}$ are the variables I_{GP}, P_{GP}, and R_{GP}, their comparators, their nonlinear terms as well as interaction terms thereof. To reduce the computational complexity, the steady-state resistance and maximum surface temperature of the nominal model were approximated by polynomial functions, where NM signifies the results from a simplified model:

$$R_{\mathrm{NM}} = f_{NMU1}(U) = R_{NM,o}+a_{U1}U+a_{U2}U^2+a_{U3}U^3$$

$$T_{NM,U} = f_{NMU2}(U) = T_{NMR,o}+b_{U1}U+b_{U2}U^2+b_{U3}U^3, \quad (10)$$

and additional reverse models:

$$U_{\mathrm{NM}} = f_{NMR1}(R) = U_{NM,o}+a_{R1}R+a_{R2}R^2+a_{R3}R^3$$

$$T_{NM,\mathrm{R}} = f_{NMR2}(R) = T_{NMU,o}+b_{R1}R+b_{R2}R^2+b_{R3}R^3, \quad (11)$$

where the inputs U and R are the real-time measured values, and the coefficients a_U, a_R, b_U and b_R were determined from least-square fitting to the nominal model subjected to the voltage range 2…12V with ±0.5% accuracy. Therefore, the comparators $\Delta R_{GP,U}$, $\Delta I_{GP,U}$ and $\Delta P_{GP,U}$ are then calculated from:

$$\Delta R_{GP,U} = R_{GP,measured} - R_{\mathrm{NM}}(U_{GP,measured})$$

$$\Delta I_{GP,U} = I_{GP,measured} - U_{GP,measured}/R_{\mathrm{NM}}(U_{GP,measured}), \quad (12)$$

$$\Delta P_{GP,U} = P_{GP,measured} - U_{GP,measured}^2/R_{\mathrm{NM}}(U_{GP,measured})$$

Three augmented comparators, $\Delta U_{GP,R}$, $\Delta I_{GP,R}$ and $\Delta P_{GP,R}$, are also added using the reverse models.

Thus, an example of initial $\boldsymbol{N}$ vectors representing the external influence indicators is

$$\boldsymbol{N}_{initial} = [\Delta R_{GP,U} \;\; \Delta I_{GP,U} \;\; \Delta U_{GP,R} \;\; \Delta P_{GP,U}]^{\mathrm{T}} \quad (13)$$

On the other hand, based on *a priori* knowledge of the manufacturing tolerances' effect upon the change in the glow plugs' electrical properties, Table 2 illustrates that the summation of tolerances and individual glow plug characteristics under a fixed external influence can be captured by a set of bias-free reference parameters: the resistance at the nominal voltage and the resistance gradient measured at no external influence. Hence, a sample heuristic choice for the characteristic vector $\boldsymbol{F}$ is then:

$$\boldsymbol{F}_{initial} = [R_{f1} \;\; R_{f2} \;\; g_R \;\; R_{\mathrm{o}}]. \quad (14)$$

3.3 Model Structure Optimisation Procedure

The task of system identification and multi-level optimisation of the system matrix structure is summarised in Figure 3.

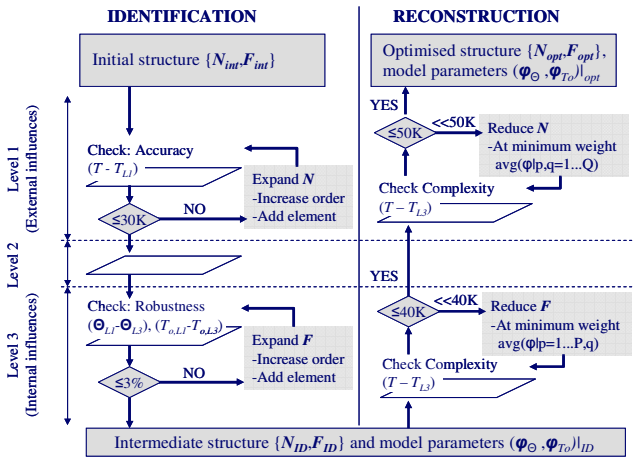

Figure 3: Optimisation Routine of Model Structure

From the guideline above, the optimal system matrices were found to be:

$$\boldsymbol{N}_{opt} = [\, I_{GP} \;\; R_{NM}^2/\Delta U_{GP,R} \;\; R_{NM}\,]^{\mathrm{T}} \quad (15)$$

$$\boldsymbol{F}_{opt} = [R_{f1} \;\; g_R \;\; 1/g_R], \quad (16)$$

with 12 model parameters ($\boldsymbol{\varphi}_{\Theta}$, $\boldsymbol{\varphi}_{To}$). The determination of each level's coefficients was with least-square method, requiring the amount of available measurement data in each case at least equal to the degree of freedom, as summarised in Table 3.

The relaxing accuracy thresholds from 30K to 50K reduce computational complexity at the cost of accuracy. The thresholds can be increased further for a loose control strategy with emphasis on hardware limitation, or conversely tightened in high-precision control. Likewise, the 3% limit imposed at Level 3 can be adjusted to change the level of robustness against internal uncertainties.

For instance, if the manufacturing tolerances can be improved to result in smaller variance between glow plugs, or if the model parameters are allowed to be identified and utilised within each manufacturing batch, the percentage as low as 1% can be achieved sufficiently by setting $\boldsymbol{F}$ to merely R_{fl} to distinguish one glow plug from another.

Table 3: Requirement of Measurement Data Set for System Identification

Level	Specificity		Degree of Freedom	
	# Glow Plug	# Disturb. Level	Identified Parameters	Minimum # training data points
1	1	1	$\boldsymbol{\Theta}_{N,L1}$, $\boldsymbol{T}_{o,L1}$	P + 1
2	1	D	$c_{\boldsymbol{\Theta}}$, $\boldsymbol{c}_{\boldsymbol{To}}$	(P+1)·P
3	M	D	$\boldsymbol{\varphi}_{\Theta}$, $\boldsymbol{\varphi}_{To}$	(P+1)·Q

Another application-oriented approach to configure the optimisation routine is to aim for maximum number of glow plugs with acceptable maximum error. An additional residual analysis at Level 3 can also illuminate how the failed glow plugs can be identified from their reference values $\boldsymbol{F}_{fail}$, when compared to those of the passed glow plugs, $\boldsymbol{F}_{pass}$. Consequently, a glow plug that is potentially extreme in behaviour, lying outside the identified model's reliability domain, can be discarded as early as the end of production by means of reference parameter range check, or to be sorted to use with another set of model parameters $(\boldsymbol{\varphi}_{\Theta}, \boldsymbol{\varphi}_{To})|_{\#2}$ identified specifically for this glow plug subtype.

Initialisation Routine

The objectives of the initialisation routine are to identify a glow plug characteristic $\boldsymbol{F}$, and to harvest the basis of external influence indicator $\boldsymbol{N}$, at known engine condition $\mathbf{BP_o}$. The routine algorithm is to excite the installed glow plugs, measure the electrical properties, calculate and then save the resulting $\boldsymbol{F}_{BPo}$ and $\boldsymbol{N}_{BPo}$ in the glow control unit's memory. The excitation profile $U_{INIT}(t)$ is defined by the model's $\boldsymbol{N}$ and $\boldsymbol{F}$. Further details on initialisation routine can be referred in (Last et al., 2012).

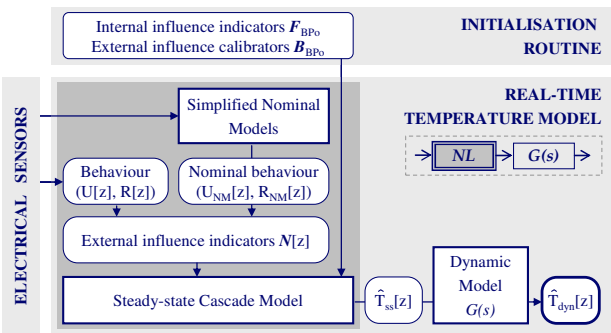

Figure 4: Dynamic Cascade Model of Glow Plug Surface Temperature

RESULTS

Simulation Results and Model Comparison

Table 4 shows a comparison of steady-state temperature accuracy, when all measurements had been used in the identification phase, among (1:CM) the cascade temperature model developed from the proposed method; (2:ANN) an artificial neural network of [U,I,R,P] inputs with one hidden-layer, 12 hidden nodes, and *tanh* activation functions, and (3:NLR) a multivariate nonlinear regression model of the electrical properties [I^n, R^n, P^n] | n=[-1, 0, 1, 2]. The measurement data for both system identification and validation were obtained from 79 glow plugs, subjected to varying test bench conditions that represent more than 80% of full engine operating range. The model complexity was quantitatively considered in three areas: (P) number of model parameters, (M) number of multiplications, and (A) number of additions

Table 4: Steady-State Accuracy Comparison with the Complexity of Steady-State Temperature Models

Model	Model Complexity		Accuracy at 100% Training	
	P M , A	Type	RMS(εT)% MAX(εT)%	% Glow Plug with MAX|εT|±3%
1	20 31 , 20	CM	2.1 14.4	89.9
2	72 - , -	ANN	4.8 19.0	40.7
3	10 13 , 9	NLR	4.8 18.5	34.2

The accuracy of the proposed Model (1) was superior to those of classical Models (2) and (3), using the criteria of overall model accuracy as well as the model applicability coverage within ±3% error threshold. However, in real application, it is not possible to measure every glow plug at the end of manufacturing and update the model parameters accordingly.

To validate the robustness against manufacturing tolerances, the identification phases of Models (1) and (2) and the training phase of Model (3) were additionally conducted with incomplete sets of measurement data. To represent the scalability of the model robustness, the percentage of a number of glow plugs used for model training versus the total number of glow plugs range from 15% to 100%. For example, at 15% training selection, the measurement data of 12 randomly selected glow plugs out of the total 79 glow plugs were used to identify Model (1) parameters, then the same data were used for the identification of Model (2) and the training of Model (3). This selecting and training procedure was carried out 100 times with different random glow plug sets, in order to compensate the dependency of artificial neural network models on randomised initial weights and also to neutralise the overall dependency on which glow plugs were selected

in a training set. Each point in Figure 5 is the average value of the model results of 100 different model parameter sets. The dashed lines represent the robustness perceived during the training phase when validated with only the selected glow plugs for training, while the solid lines represent the real robustness across all 79 glow plugs.

The limitation of the training percentage represents the real challenge in application, where only a small sample of glow plugs are available in the development phase of the simulation model to be implemented in GCUs prior to online usage. From Figure 5, the proposed cascade model's robustness is higher than those in ANN and NLR, as shown that even with reduced percentage of training data available, the temperature errors are still lower and the applicability coverage still higher.

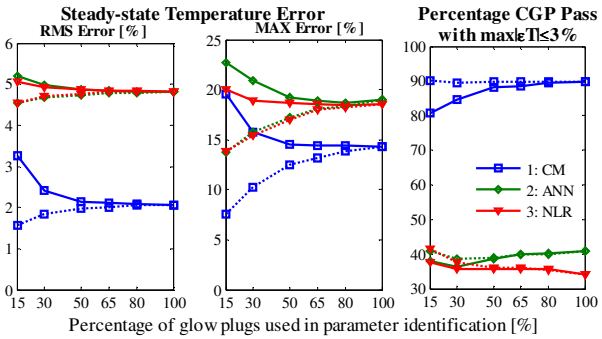

Figure 5: Robustness Comparison

Experimental Results

The developed dynamic temperature model was implemented in a rapid-prototyping system to test the closed-loop control strategy. The algorithm of the temperature model and controller was built in MATLAB/Simulink and transferred to an Autobox unit. The real maximum surface temperature was measured by a pyrometer on a test bench, and calculated as a function of internal glow plug temperature in an engine using a special-type glow plug with an internal thermocouple near the hot spot. The controller was a PI/PT_1 type. Further boundary conditions and bench specifications are discussed in more details in (Last et al., 2012).

The model robustness against external disturbances was tested with the thermocouple glow plug on a test bench with varying air flow rate directed head-on and parallel to a glow plug, and in a test vehicle driven at high dynamic range covering city driving cycle. The dynamic temperature model achieved very high precision accuracy on the test bench at ±1.7% maximum temperature error during 225-second cycle, and in the engine at ±4% calculated maximum error during a 800-second cycle. The closed-loop controller accuracy to maintain the desired glow plug temperature at T_{nom} under all conditions was excellent with 2% RMS error on test bench and 1.5% RMS error in engine. The compensation between delayed controlled voltage and over-nervous temperature estimator contributed to the disparity in model and controller accuracy in the engine.

CONCLUSION

The proposed method of model development with the aim for model-based control using *a priori* knowledge and experimental data has yielded a dynamic cascade model. The approach to model a cascade of effects, with the initial selection of physically-meaningful internal variables based on sensitivity analyses, and an integrated model structure optimisation and parameter identification procedure with configurable objectives led to a good balance between robustness, accuracy, and real-time capability. Rapid-prototype implementation on the test bench and in the test vehicle shows extremely accurate real-time dynamic temperature estimate and excellent control accuracy.

REFERENCES

B. Last, H. Houben, M. Rottner, Stotz, 2008. "Influence of modern diesel cold start systems on the cold start, warm-up and emissions of diesel engines". *8th International Stuttgarter Symposium*

H. Houben, G. Uhl, H. Schmitz, M. Endler, 2000. "Instant Start System (ISS) - The electronically controlled glow system for diesel engines". *MTZ* 61/2000

L. Formaggia, S. Micheletti, R. Sacco, A. Veneziani, 2007. "Mathematical modelling and numerical simulation of a glow-plug". *Applied Numerical Mathematics* 57/2007

C. A. Finol, K. Robinson, 2006. "Thermal modelling of modern engines: a review of empirical correlations to estimate the in-cylinder heat transfer coefficient". *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*

F. Kirschbaum, D. Boja, R. Sauermann, 2009. "Model Based Controller Calibration on Powertrains". *Design of Experiments (DoE) in Engine Development.* Expert Verlag

B. Last, M. Eberhardt, M. Sackmann, I. Demirdelen, F. Puente, R. Suteekarn, S. Schmauder, 2012. "Closed Loop Control Strategies for Glow Plug Surface Temperature". *12th International Stuttgarter Symposium*

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