

Support Vector Machines for Identification of HCCI Combustion Dynamics

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Abstract: Homogeneous charge compression ignition (HCCI) is a promising technology for Internal Combustion Engines to improve efficiency and reduce nitrogen oxides emissions. Control of HCCI combustion is often model-based, and it is vital to have a good model of the engine to make control decisions. The HCCI engine is characterized by complex chemical kinetics whose physical modeling is difficult and laborious. Identification is an effective alternative to quickly develop control oriented models for such systems. This paper formulates a Support Vector Regression (SVR) methodology for developing identification models capturing HCCI combustion behavior. Measurable quantities from the engine such as net mean effective pressure (NMEP) and crank angle at 50% mass fraction burned (CA50) can be used to characterize and control the HCCI engine and are considered for identification in this study. The selected input variables include injected fuel mass (FM) and valve events {intake valve opening (IVO), exhaust valve closing (EVC)}. Transient data from a gasoline HCCI engine recorded at stable HCCI conditions is used for training, validating and testing the SVR models. Comparisons with the experimental results show that SVR with Gaussian kernels can be a powerful approach for identification of a complex combustion system like the HCCI engine.

1 INTRODUCTION

In recent years, the requirements on automotive performance, emissions and safety have become increasingly stringent. In spite of advanced concepts entering the industry, achieving fuel economy, emission and cost targets simultaneously still remains an arduous task. HCCI engines gained the spotlight from traditional spark ignited and compression ignited engines owing to its ability to reduce emissions and fuel consumption significantly (Thring, 1989; Christensen and Johansson, 1997; Aoyama and Sato, 1996). In spite of its known advantages, HCCI combustion poses several challenges for implementation. A major challenge is achieving stable combustion over a wide operating range. HCCI control is a hard problem and a predictive model is typically used to make decisions (Chiang and Chen, 2010; Bengtsson, 2010; Ravi and Gerdes, 2009). Hence it becomes extremely important to develop accurate HCCI models that can operate with less computational demand so that it can be implemented on-board for controls and diagnostics purposes. HCCI combustion is characterized by

complex nonlinear chemical and thermal dynamics, which are extremely laborious and tedious to model using physics. Also, the model may be required to predict the nonlinear dynamic behavior of the engine for several steps ahead of time for analysis and optimization. Hence a key requirement is to develop a model quickly that can capture the required dynamics for control purposes and has the potential to be implemented on-board.

For the HCCI identification problem, Support Vector Machine based regression was selected for its fast operation and good approximation capabilities to fit nonlinear systems (Hammer and Gersmann, 2003; Clarke and Simpson, 2005). Also, when SVR is trained on real-world data, it represents the real system and makes no simplifying assumptions of the underlying process. The dynamics of sensors, actuators and other complex processes, which are usually overlooked/hard to model using physics, can be captured using the identification method. In addition, for a system like the combustion engine, prototype hardware is typically available, and sufficient experimental data can be collected. The application of

SVR to system identification (Gretton and Scholkop, 2001; Drezet and Harrison, 1998; Trejo, 2006; Ramon, 2006; Wang and Pan, 2009; Chitralkha, 2010), time series modeling (Mller and Vapnik, 1997; Kim, 2003) and predicting chaotic behavior (Sun and Luo, 2006) has been reported in the literature though major practical implementations were less abundant (Wang and Pan, 2009; Chitralkha, 2010). Identification of HCCI combustion is not common owing to its complex and unstable behavior. A subspace based identification was the only reported approach (Bengtsson and Johansson, 2006) where linear models were developed for HCCI model predictive control. A non-linear system identification for HCCI has not been reported in the literature to the best of the authors' knowledge. This paper aims to be the first application of support vector machines for nonlinear identification of the HCCI combustion which is the main contribution of this paper. A gasoline homogeneous charge compression ignition engine is considered in this paper. This paper is organized as follows. The basic idea and formulation of the SVR model is presented, followed by experiment design for collecting stable HCCI data from the engine. Tuning of hyperparameters of the SVR model using cross-validation is demonstrated, followed by validation of the model using predictions based on unseen data.

2 SUPPORT VECTOR REGRESSION

The Support Vector Regression (Vapnik and Smola, 1996; Drucker, 1996; Scholkopf and Williamson, 1998) was developed as an extension to the Support Vector Machines (SVM) originally developed for classification. The SVR model approximates the given input-output data by forming an error boundary (error tube) (Drucker, 1996) around the data by solving a convex constrained optimization problem. The kernel trick is typically used for nonlinear systems where a kernel function transforms the input variables to a high dimensional feature space so that the input-output relationship can be approximated as a linear function in this transformed space. An important property of the SVR method is that the obtained model could be a sparse representation of the nonlinear system which can have benefits in terms of storage.

In general, the non-linear time-invariant dynamic model of the HCCI combustion system can be represented as

$$\dot{z}(t) = g(z(t), u(t)) + v_1 \quad (1)$$

$$y(t) = h(z(t), u(t)) + v_2 \quad (2)$$

where t represents time, $z(t) \in \mathbb{R}^{z_d}$, $y(t) \in \mathbb{R}^{y_d}$ and $u(t) \in \mathbb{R}^{u_d}$ represent the system states, outputs and input respectively while v_1 and v_2 represent the disturbance on state and measurements respectively. The terms z_d, y_d and u_d represent the dimensions of the state, output and input respectively. In an identification approach, the functions $g(\cdot)$ and $h(\cdot)$ are unknown nonlinear mappings and it may not be always possible to have state measurements. Hence a generic nonlinear identification model using the nonlinear auto regressive model with exogenous input (NARX) is considered as follows

$$y(k) = f[u(k), u(k-1), \dots, u(k-n_u), y(k-1), \dots, y(k-n_y)] \quad (3)$$

where $u = [FM \ NVO]^T$, $y = [NMEP \ CA50]^T$, k represents the discrete time index, $f(\cdot)$ represents the nonlinear function mapping by the model and n_u, n_y represent the number of past input and output samples required (order of the system). Let x represent the augmented input vector

$$x = [u(k), u(k-1), \dots, u(k-n_u), y(k-1), \dots, y(k-n_y)]^T \quad (4)$$

Consider the independent and identically distributed training data $\{(x_1, y_1), \dots, (x_n, y_n)\} \in \mathcal{X} \times \mathcal{Y}$, where \mathcal{X} denotes the space of the input features (Here $\mathcal{X} = \mathbb{R}^{u_d(n_u+1)+y_d n_y}$ and $\mathcal{Y} = \mathbb{R}$). The goal of SVR is to approximate the underlying input-output function mapping $f(\cdot)$ by minimizing a risk functional with respect to the model parameters

$$R(w) = \frac{1}{n} \sum_{i=1}^n L(y_i - \hat{y}_i(x, w)) + \frac{1}{2} w^T w \quad (5)$$

where $\hat{y}(x, w)$ represents the model prediction given by

$$\hat{y}(x, w) = \langle w, \phi(x) \rangle + b \quad (6)$$

Here, $w \in \mathbb{R}^{u_d(n_u+1)+y_d n_y}$ and $b \in \mathbb{R}$ represents the model parameters, ϕ is a function that transforms the input variables to a higher dimension feature space \mathcal{H} and $\langle \cdot, \cdot \rangle$ represents inner product. The first term of equation (5) represents the error minimizing term while the second term accounts for regularization. The SVR model deals only with the inner products of ϕ and a kernel function can be defined that takes into account the inner products implicitly as

$$K(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle \quad (7)$$

The function ϕ is not required to be known but any kernel function that satisfies the Mercer's condition

(Vapnik, 1995) such as radial basis functions, polynomial and sigmoidal functions can be used. In this study, a gaussian kernel function is used. The kernel transforms the input variables to a high dimension space \mathcal{H} and aids in converting a nonlinear map in the $\mathcal{X} - \mathcal{Y}$ space to a linear map in \mathcal{H} space. This is known as *kernel trick* in the literature.

There are two different formulations for SVR based on accuracy control such as ϵ -SVR (Vapnik and Smola, 1996; Smola and Scholkopf, 2003) and ν -SVR (Scholkopf and Williamson, 1998). In ϵ -SVR, the objective is to find a function $f(x)$ that has at most ϵ deviation from the actual targets y for the training data while in ν -SVR the ϵ is automatically tuned in the algorithm. The ν -SVR is considered in this study, as the tradeoff between model complexity and accuracy (controlled by ν) can be tuned to the required accuracy and sparseness. Also, the ϵ -insensitive loss function (8) can be used. Other loss functions can be used if specific information about the noise model is known (Scholkopf and Smola, 2001). For instance, it is known that a quadratic loss function performs well for gaussian distributed noise (Hastie and Friedman, 1995) while a huber loss function can be used if the density describing the noise is smooth is the only information that is available. For the ν -SVR considered in this paper, the following ϵ -insensitive loss function is used for achieving model sparseness. The loss function (8) is defined to be zero when the predicted output falls within the error tube and the magnitude of the distance away from the error tube when the prediction falls outside the tube.

$$L(y - \hat{y})_\epsilon = \begin{cases} 0 & \text{if } |y - \hat{y}| \leq \epsilon \\ \epsilon - |y - \hat{y}| & \text{otherwise} \end{cases} \quad (8)$$

The goal of SVR training is to determine the optimal model parameters (w^*, b^*) that minimizes the risk function (5). However, solving (5) involves minimization of the loss function L in (8) for every data point. Since L is minimum for the points lying inside the error tube, this translates to minimizing L for points that lie outside the error tube. If a slack variable is assigned to every data point such that the slack variable is the measure of discrepancy between the predicted output and the error tube, the problem reduces to minimizing the slack variables ζ and ζ^* which leads into the following optimization problem

$$\min_{w, b, \epsilon, \zeta_i, \zeta_i^*} \frac{1}{2} w^T w + C(\nu \epsilon + \frac{1}{n} \sum_{i=1}^n (\zeta_i + \zeta_i^*)) \quad (9)$$

$$\text{subjected to } \begin{cases} y_i - (\langle w, \phi(x_i) \rangle + b) \leq \epsilon + \zeta_i \\ (\langle w, \phi(x_i) \rangle + b) - y_i \leq \epsilon + \zeta_i^* \\ \zeta_i, \zeta_i^*, \epsilon \geq 0 \end{cases} \quad (10)$$

for $i = 1, \dots, n$.

It should be noted that the slack variables take values of zero when the points lie inside the error tube. Also, separate slack variables ζ and ζ^* are assigned for points lying outside the error tube on either side of the function. The above optimization problem is usually referred as the primal problem and the variables w, b, ζ, ζ^* and ϵ are the primal variables. In the above formulation (9), ϵ is considered as a variable to be optimized along with the model parameters. This allows ν to set a lower bound on the fraction of data points used in parameterizing the model (Scholkopf and Bartlett, 2000) and hence by tuning ν one can achieve a tradeoff between model complexity (sparseness) and accuracy. A value of ν close to one will try to shrink the ϵ tube and reduce sparseness (all data points become support vectors) while reducing ν close to zero will result in a sparse model (very few data points are used in model parametrization) with possible under-fitting. This flexibility is the prime reason for selecting the ν -SVR algorithm for this study.

The lagrangian can be formulated as follows

$$\begin{aligned} L(w, b, \zeta, \zeta^*, \epsilon, \alpha, \alpha^*, \beta, \beta^*, \gamma) = & \\ & \frac{1}{2} w^T w + C(\nu \epsilon + \frac{1}{n} \sum_{i=1}^n (\zeta_i + \zeta_i^*)) \\ & + \sum_{i=1}^n \alpha_i (y_i - (\langle w, \phi(x_i) \rangle + b) - \epsilon - \zeta_i) \\ & + \sum_{i=1}^n \alpha_i^* ((\langle w, \phi(x_i) \rangle + b) - y_i - \epsilon - \zeta_i^*) \\ & - \sum_{i=1}^n (\beta_i \zeta_i + \beta_i^* \zeta_i^*) - \sum_{i=1}^n \gamma_i \epsilon \end{aligned} \quad (11)$$

where $\alpha, \alpha^*, \beta, \beta^*, \gamma$ are the lagrange multipliers or the dual variables. The derivatives of (11) with respect to the primal variables $w, b, \zeta_i, \zeta_i^*, \epsilon$ yields

$$\sum_{i=1}^n (\alpha_i^* - \alpha_i) \phi(x_i) = w \quad (12)$$

$$\sum_{i=1}^n (\alpha_i^* - \alpha_i) = 0 \quad (13)$$

$$\frac{C}{n} - \alpha_i - \beta_i = 0, i = 1, \dots, n \quad (14)$$

$$\frac{C}{n} - \alpha_i^* - \beta_i^* = 0, i = 1, \dots, n \quad (15)$$

$$C\nu - \sum_{i=1}^n (\alpha_i^* + \alpha_i) - \beta = 0 \quad (16)$$

The other KKT conditions are given by

$$\alpha_i (y_i - (\langle w, \phi(x_i) \rangle + b) - \epsilon - \zeta_i) = 0 \quad (17)$$

$$\alpha_1^* (\langle w, \phi(x_i) \rangle + b) - y_i - \varepsilon - \zeta_i^* = 0 \quad (18)$$

$$\beta_i \zeta_i = 0 \quad (19)$$

$$\beta_i^* \zeta_i^* = 0 \quad (20)$$

$$\gamma \varepsilon = 0 \quad (21)$$

for every $i = 1, 2, \dots, n$. Also, since every data observation cannot lie on both sides of the function simultaneously,

$$\alpha \alpha^* = 0 \quad (22)$$

$$\beta \beta^* = 0 \quad (23)$$

Substituting the above equations in (11), we get the following dual optimization problem

$$\max_{\alpha_i, \alpha_i^*} \sum_{i=1}^n (\alpha_i^* - \alpha_i) y_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (\alpha_i^* - \alpha_i) (\alpha_j^* - \alpha_j) K(x_i, x_j) \quad (24)$$

$$\text{subjected to } \begin{cases} \sum_{i=1}^n (\alpha_i^* - \alpha_i) = 0 \\ \sum_{i=1}^n (\alpha_i^* + \alpha_i) \leq \nu C \\ 0 \leq \alpha_i \leq \frac{C}{n} \\ 0 \leq \alpha_i^* \leq \frac{C}{n} \end{cases} \quad (25)$$

for $i = 1, \dots, n$. The SVR model is given by

$$f(x) = \sum_{i=1}^n (\alpha_i^* - \alpha_i) K(x_i, x) + b \quad (26)$$

where ε and b can be determined using (10). This is the well known SVR model and the following are some known properties. The parameter w can be completely described as a linear combination of functions of the training data (x_i) . The model is independent of the dimensionality of \mathcal{X} and the sample size n and the model can be described by dot products between the data.

3 EXPERIMENT DESIGN

The data for system identification is collected from a variable valve timing gasoline HCCI engine whose specifications are listed in Table 1. For identification of the HCCI combustion, an amplitude modulated pseudo-random binary sequence (A-PRBS) has been used to design input signals. The A-PRBS signal excites the system at several different amplitudes and frequencies so that rich data about the system dynamics can be obtained (Agashe and Agashe, 2007). The steps of a PRBS data set can be tuned to remain constant for a specified time. This determines if the excitation is dominantly transient or steady state. For the

HCCI system, the step signal was held constant for at least 25 cycles so that the data captures both transient and steady state behavior fairly equally. The data is sampled using the AVL Indiset acquisition system where in-cylinder pressure is sensed every crank angle while NMEP and CA50 are determined on a combustion cycle basis. The input signals are designed off-line and loaded into the rapid prototyping hardware that provides commands to the engine controller.

Table 1: Specifications of the experimental HCCI engine.

Engine Type	4-stroke In-line
Fuel	Gasoline
Displacement	2.0 L
Bore/Stroke	86/86
Compression Ratio	11.25:1
Injection Type	Direct Injection
Valvetrain	Variable Valve Timing with hydraulic cam phaser (0.25mm constant lift, 119 degree constant duration and 50 degree crank angle phasing authority)
HCCI strategy	Exhaust recompression using negative valve overlap

HCCI is unstable beyond certain operating conditions and hence large input steps close to unstable regimes tend to misfire the engine or operate on limit cycles. For this purpose, the input excitations are required to be filtered using prior knowledge about the system. As a first check, a design of experiments model (DOE) (Kruse and Lang, 2010) using a set of steady state experiments is used to eliminate the unstable input combinations. The feasible limits of inputs at a speed of 2500 RPM as given by the DOE model are shown in Table 2. The feasible HCCI load range is shown in Figure 1, and the stable HCCI boundary for different fueling inputs is shown in Figure 2.

Table 2: Actuator Extremes for stable HCCI (from the steady state DOE model). The valve events are measured in degrees after top dead center (deg aTDC).

Input	Min Limit	Max Limit
Fuel Mass (mg/cyc)	7.0437	12.9161
I VO (deg aTDC)	78	128
EVC (deg aTDC)	-119	-69

The A-PRBS sequence is designed to excite the engine within this stable HCCI region defined by the DOE model. It should be noted that the DOE filtered input limits are valid only for steady state conditions and a large step near the boundary of stable HCCI can

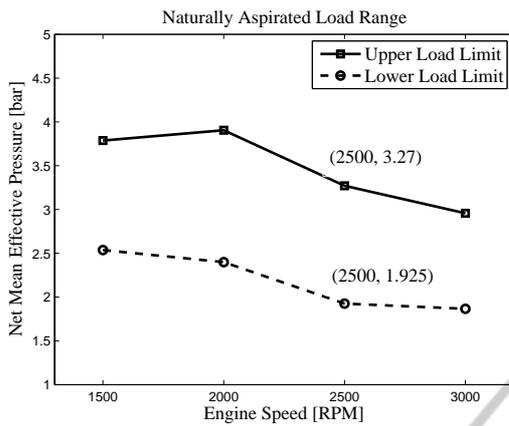


Figure 1: Load range (in NMEP) of naturally aspirated HCCI engine.

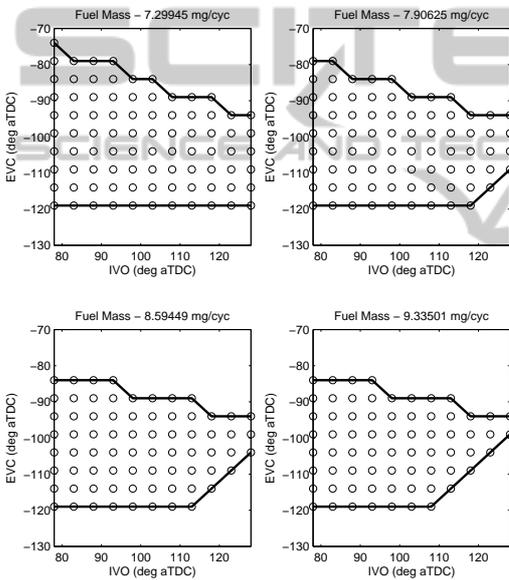


Figure 2: Stable HCCI operating region at given actuator settings of IVO, EVC and Fueling.

lead to instabilities. Hence as a means of precaution against running the engine in an unstable manner and to save time during experiments, a simple feedback was created, which attempts a particular input combination and if found to be unstable, quickly skips to the next combination in the A-PRBS sequence. As a first attempt, the CA50 was considered the feedback signal. During a small time window, any input combination that resulted in a CA50 above 21 (found by observing the CA50 during several misfires) is immediately skipped, and the engine is run on the next combination in the sequence. Finally, post-processing was performed on the data to remove misfire and post-misfire data.

A subset of the bounded input signals and the

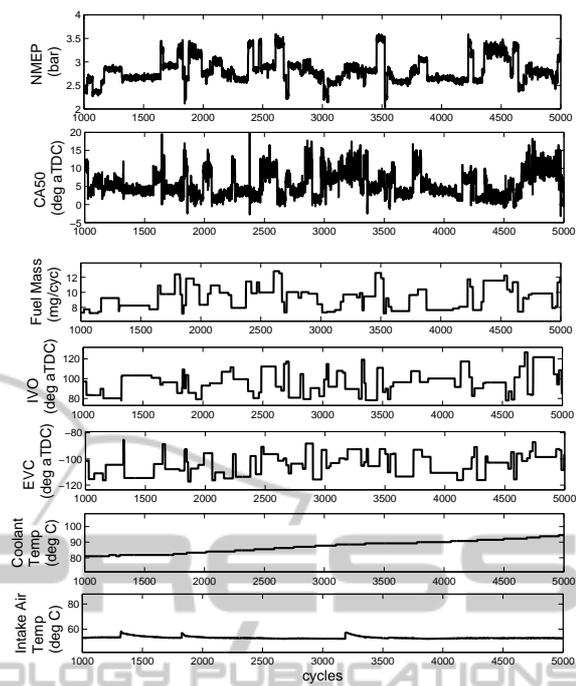


Figure 3: A-PRBS input-output sequence.

recorded outputs from the engine are shown in Figure 3. It has to be noted that the engine coolant temperature and the intake air temperature varies slightly during the experiment and their variations are recorded and considered inputs to the model. Nearly 30000 cycles of data were collected, which corresponds to about 25 minutes of engine testing. About 30% of the data were found to be arising from unstable operation and were removed.

4 SVR TRAINING

This section details the training procedure using the SVR method described in section 2. The SVR is coded in Matlab using LIBSVM package (Chang and Lin, 2011). For each output, the model has four hyper-parameters namely the system order (n_u and n_y , assumed to be the same), the cost parameter C , kernel parameter ω and SVR parameter ν . To obtain a model that generalizes well and captures the right order of dynamics, the above hyper-parameters need to be optimized based on cross-validation.

4.1 Tuning Hyper-parameters

The data set comprising of (x, y) is divided into a training set that constitutes 80% of the data while the remaining 20% is separated out for testing. Fur-

thermore, the training data is divided into validation training and validation testing data sets for tuning the model hyper-parameters. The testing data set is never seen by the model during the training and validation phases. The parameter v determines the tradeoff between the sparseness and accuracy of the models. An optimal value of v results in the minimum model parameters required for the given accuracy level. It can be seen using Figure 4 that the knee of the curve is located at v of 0.2 and increasing v beyond this value doesn't improve the the prediction accuracy even though more parameters are used to fit the data (increase in sparseness). Hence the knee of the validation error curve is chosen the optimal v . However for the case of NMEP, the desired accuracy level has been achieved with the minimum value of v of 0.1. In order to have a simple model (minimum sparseness), this value is taken as the optimal v . In this study, sparseness is defined as follows

$$sparseness = \frac{n_{sv}}{n} \quad (27)$$

where n_{sv} is the total number of support vectors.

The cost parameter C determines the relative importance given to the outliers and hence the sensitivity to measurement noise. A large value of C tries to fit the model for outliers thereby over-fitting the data. The kernel parameter ω is required to be tuned for the same reason of having good generalization. The system order determines the number of previous measurements required to predict the future output. An optimal value of the order represents the system dynamics correctly and a large value not only makes the model complex by increasing the dimension of x but also gives a bad prediction of the system's response. It can be seen from Figure 5 that the validation error increases beyond the optimal values of C , ω and system order even though training error continues to decrease. Hence it is important to tune the hyper-parameters in combination. A full grid search is performed where the validation training data set is used to train the model with all combinations of the considered hyper-parameter values and validation error found by testing the models on the validation test data set. Table 3 lists the best combination of hyper-parameters for NMEP and CA50 which had the minimum validation errors. Furthermore the optimal hyper-parameters are used for retraining with the full training data set before which it is used for testing.

4.2 SVR Prediction Results

The SVR models with the optimized hyper-parameters are then trained with the entire training

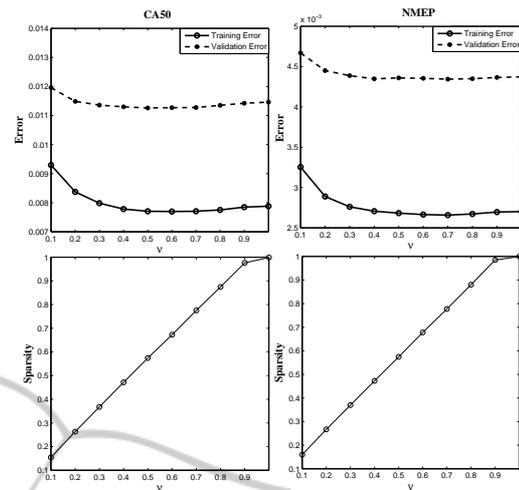


Figure 4: Tuning the accuracy vs sparsity tradeoff parameter v using cross-validation.

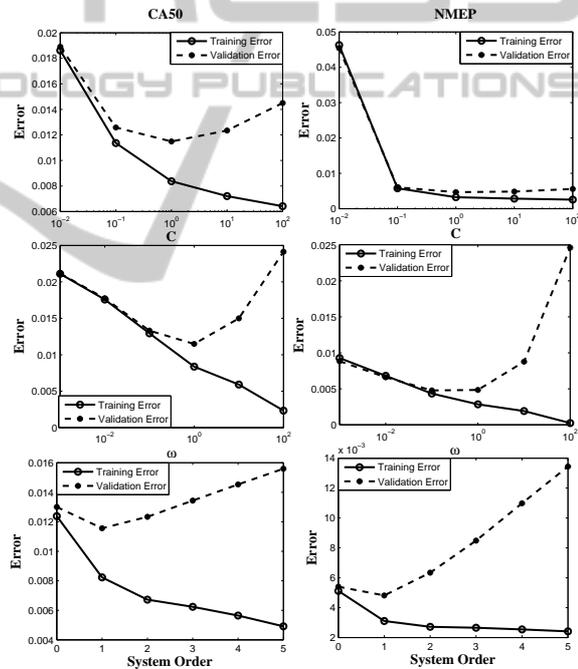


Figure 5: Tuning cost parameter C , kernel parameter ω and system order using cross-validation.

data set. The models are then simulated with the unseen test data and performance of the models are measured using mean squared error (MSE) given by

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (28)$$

Note that the MSE is different from the loss function (8) used in SVR modeling. The MSE for the NMEP and CA50 models during training and testing are given in Table 4.

Table 3: Optimal combination of model hyper-parameters.

	NMEP	CA50
C	1	1
ω	1	1
System Order	1	1
ν	0.1	0.2

Table 4: SVR performance.

	NMEP	CA50
Training MSE	0.0031	0.0085
Testing MSE	0.0042	0.0103
Model Sparseness	0.1261	0.2283

In order to observe the multi-step-ahead predictions, a completely separate data set is used from which only the inputs are given to the model along with the initial conditions of the outputs (delay initial conditions). Figure 6 and Figure 7 show the predictions of NMEP by SVR model compared against the engine's measured NMEP. Figure 8 and Figure 9 show the predictions of CA50 by SVR model compared against the engine's measured CA50. It can be observed that the model predictions match with the engine's actual response. It should be noted that the model's predictions are based on computer commanded step input sequences. The wiggly behavior in the model's predictions are due to the variations in the intake air temperature measurements which are uncontrollable parameters. HCCI combustion is very sensitive to the intake air temperature which can be considered as an independent control input. However practical realization of such a control system can be difficult in automotive applications and hence considered only as a disturbance in the identification modeling. It can also be observed that both the steady state values and the transients are sufficiently captured by the models except for some regions where there is a bias offset owing to poor approximations. Lack of excitations near such input combinations could be a reason for the bad predictions of the model.

Model sparseness in Table 4 shows that only a small fraction of the training data set (1892 parameters for NMEP model and 3425 parameters for CA50 model) is used to represent the model efficiently and these data observations constitute the support vectors in this method.

5 CONCLUSIONS AND FUTURE WORK

Support Vector Machines are one of the state of the art methods for nonlinear regression and the application

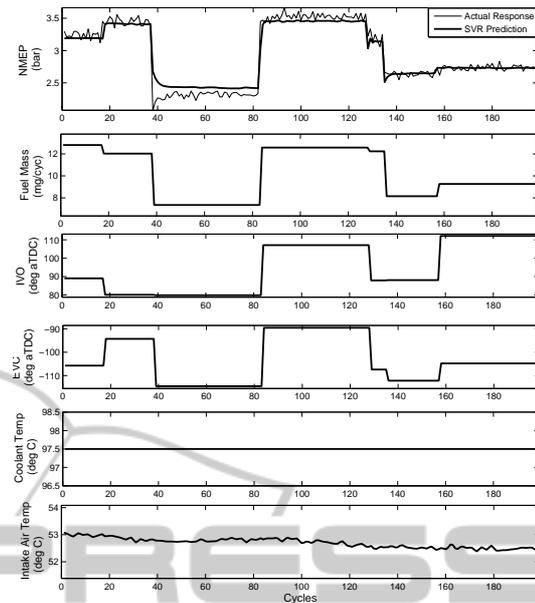


Figure 6: Comparison of NMEP (engine output and SVR prediction).

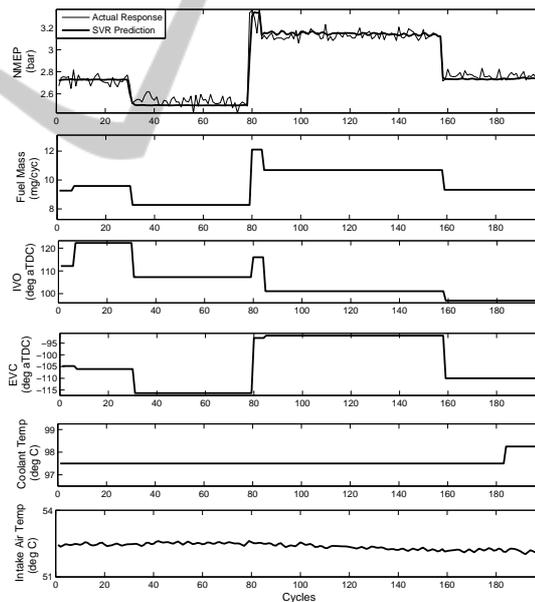


Figure 7: Comparison of NMEP (engine output and SVR prediction).

of SVR to nonlinear system identification is not abundant in spite of its attractive properties. In this paper a complex nonlinear dynamic system such as the HCCI engine is identified using v-SVR method. Data collection within the stable boundary of HCCI combustion has been accomplished by pre-screening the input sequence using the steady state DOE model of the engine and by using a closed loop control to avoid un-

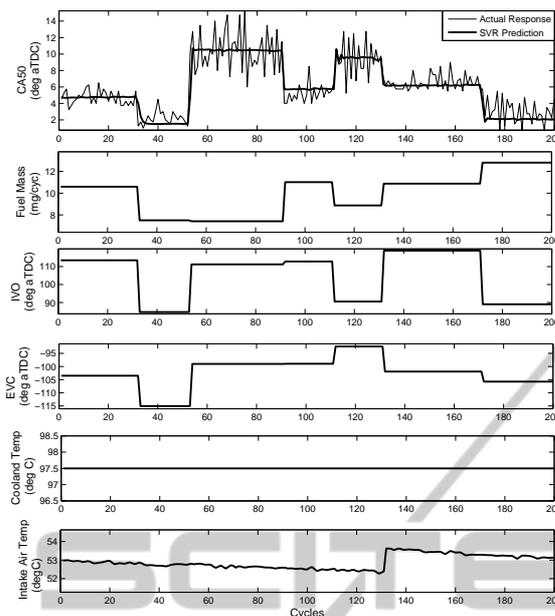


Figure 8: Comparison of CA50 (engine output and SVR prediction).

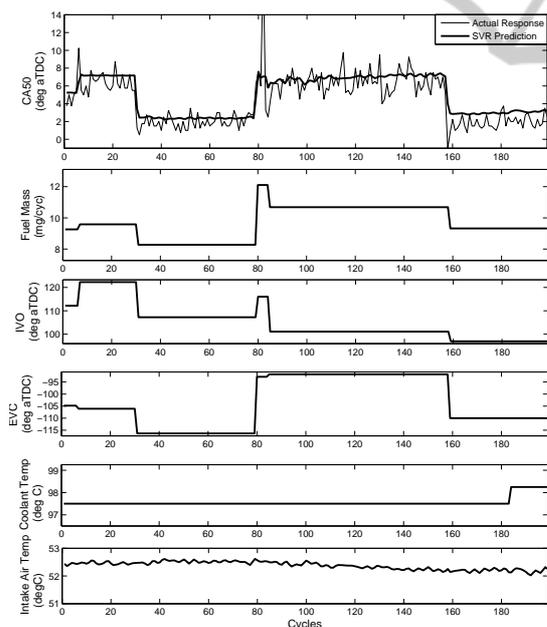


Figure 9: Comparison of CA50 (engine output and SVR prediction).

stable excitations. The dynamics of NMEP and CA50 of naturally aspirated HCCI combustion at constant speed is modeled using SVR to a good accuracy. Distinguishing features of v-SVR including global optimality and sparseness make the method very attractive compared to traditional neural networks based identification. Future research would focus on controller development using the SVR models to analyze

the suitability and effectiveness compared to existing neural network controllers.

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