Kernel based Partially Linear Models and Nonlinear Identification

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Abstract

In this paper we propose Partially Linear models with Least Squares Support Vector Machines (LS-SVMs) for nonlinear ARX models. We illustrate how full black-box models can be improved when prior information about model structure is available. A real-life example, based on the Silverbox benchmark data, shows significant improvements in the generalization ability of the structured model with respect to the full black-box model.

Keywords: Partially Linear Models, Nonlinear System Identification, Kernels, LS-SVM.

1 Introduction

The objective of nonlinear system identification is to estimate a relation between inputs $u(t)$ and outputs $y(t)$ generated by an unknown dynamical system. Let $\boldsymbol{z}(t)$ be the regression

vector corresponding to the output $y(t)$ in a NARX model, $\boldsymbol{z}(t) = [y(t-1); \cdots; y(t-p); u(t); u(t-1); \cdots; u(t-q)]$. The nonlinear system identification task is to estimate a function g such that $y(t) = g(\boldsymbol{z}(t)) + e(t)$, where $e(t)$ is a disturbance term. Under the nonlinear black box setting, the function g can be estimated by using different techniques (artificial neural networks [6], (least-squares) support vector machines ((LS)-SVM) [13, 14], wavelets [17], basis expansions [11], splines [15], etc.), involving a training and validation stage [13]. The one-step-ahead prediction is simply $\hat{y}(t) = \hat{g}(\boldsymbol{z}(t))$ using the estimated $\hat{g}$; simulation $n-$steps ahead can be obtained by iteratively applying the prediction equation replacing future outputs by its predictions [7, 11]. In this paper we focus on the case where the nonlinearity in the model does not apply over all the inputs, rather a subset of it, leading to the identification of a partially linear model [12, 9, 5]. We propose the Partially Linear LS-SVM (PL-LSSVM) [2] to improve the performance of an existing black-box model when there is evidence that some of the regressors in the model are linear. Consider e.g. a system for which the true model can be described as $y(t) = 0.5y(t-1)^3$ $-0.5y(t-2) + 0.3u(t) - 0.2u(t-1) + e(t)$. For this model, the regression vector is defined by $\boldsymbol{z}(t) = [y(t-1); y(t-2); u(t); u(t-1)]$. If a linear parametric model is estimated, it may have a misspecification error because the nonlinear term may not be known a priori to the user. However, by moving to a full nonlinear black-box technique, the linear parts are not identified as such, yet as a part of the general nonlinear model. In this case, a nonlinear black-box model will show a better performance than a full linear model, but it has a complexity which may be larger than required. The identification of a partially linear model may not only improve the model complexity and generalization ability for this case, but it also may enhance the interpretability of the nonlinear component [4]. We illustrate considerable improvements by following this methodology on the Silverbox benchmark problem. This paper is organized as follows. Section 2 contains some preliminaries. Section 3 presents the derivation of the PL-LSSVM for use with NARX models. Section 4 applies the PL-LSSVM as a tool for empirical model structure identification to different examples.

2 Preliminaries

Let $\boldsymbol{z}(t)$ be the regression vector corresponding to the output $y(t)$ in a NARX model. Let $\mathcal{Z} = \{\boldsymbol{x} : \boldsymbol{x} \text{ is a component of the vector } \boldsymbol{z}(t)\}$. Define an arbitrary partition $\mathcal{Z} = \mathcal{Z}^a \cup \mathcal{Z}^b$ with $\mathcal{Z}^a \cap \mathcal{Z}^b = \emptyset$. Define a vector $\boldsymbol{z}^a(t)$ with regressors $\boldsymbol{x} \in \mathcal{Z}^a$, and a vector $\boldsymbol{z}^b(t)$ with regressors $\boldsymbol{x} \in \mathcal{Z}^b$. The superscript a (resp. b) represents the subset of regressors that enters linearly (resp. nonlinearly) into the model. The original regression is partitioned as $\boldsymbol{z}(t) = [\boldsymbol{z}^a(t); \boldsymbol{z}^b(t)]$. Let $\mathcal{M}_0$ denote the model class containing all models estimated by a nonlinear black-box model over the full set of regressors with orders (p, q) of the form

$$y(t) = g(\boldsymbol{z}(t)) + e(t). \tag{1}$$

We denote by $\mathcal{M}_a$ the model class containing all models of the form

$$y(t) = \boldsymbol{\beta}^T \boldsymbol{z}^a(t) + g(\boldsymbol{z}^b(t)) + e(t). \tag{2}$$

Class $\mathcal{M}_a$ is a more restrictive class of models than $\mathcal{M}_0$. The condition $\mathcal{Z}^a \cap \mathcal{Z}^b = \emptyset$ is required, as pointed out in [12], because when using the same regressor in both components the linear coefficient $\boldsymbol{\beta}$ is not uniquely represented without any further constraints on g. For example, the system $y(t) = u(t-1)^3 + u(t-1)$ can be identified as $y(t) = g(u(k-1)) + \rho u(k-1)$ with $g(x) = x^3 + (1-\rho)x$ for any ρ because g is, in principle, allowed to contain a linear term itself.

3 Partially Linear LS-SVM for System Identification

Consider the model $y(t) = \boldsymbol{\beta}^T \boldsymbol{z}^a(t) + \boldsymbol{w}^T \boldsymbol{\varphi}(\boldsymbol{z}^b(t)) + c + e(t)$ for $t = 1, \ldots, N$, where $\boldsymbol{z}^a(t) \in \mathbb{R}^{N_a}, \boldsymbol{\beta} \in \mathbb{R}^{N_a}, \boldsymbol{z}^b(t) \in \mathbb{R}^{N_b}$, and c is a constant (bias) term. The $e(t)$ values are assumed to be i.i.d. random errors with zero mean and constant (finite) variance. The nonlinear mapping $\boldsymbol{\varphi} : \mathbb{R}^{N_b} \to \mathbb{R}^{N_h}$ is called the feature map from the input space to the

so-called feature space (of dimension N_h which can be possibly infinite). In the area of support vector machines and kernel-based learning this feature map is used in relation to a Mercer kernel [13, 14]. As with standard LS-SVM, a constrained optimization problem is formulated (primal problem),

$$\min_{\boldsymbol{w},c,e(t),\boldsymbol{\beta}} \quad \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + \gamma\frac{1}{2}\sum_{t=1}^{N} e(t)^2 \tag{3}$$

$$\text{s.t.} \quad y(t) = \boldsymbol{\beta}^T\boldsymbol{z}^a(t) + \boldsymbol{w}^T\boldsymbol{\varphi}(\boldsymbol{z}^b(t)) + c + e(t), \quad t = 1, \ldots, N,$$

where γ is a regularization constant.

Lemma 1 *Given the problem (3) and a positive definite kernel function $K : \mathbb{R}^{N_b} \times \mathbb{R}^{N_b} \to \mathbb{R}$, the solution to (3) is given by the dual problem*

$$\left[\begin{array}{c|c|c} \boldsymbol{\Omega} + \gamma^{-1}\mathbf{I} & \mathbf{1} & \boldsymbol{Z} \\ \hline \mathbf{1}^T & 0 & \mathbf{0}_{1\times N_a} \\ \hline \boldsymbol{Z}^T & \mathbf{0}_{N_a\times 1} & \mathbf{0}_{N_a\times N_a} \end{array}\right] \left[\begin{array}{c} \boldsymbol{\alpha} \\ \hline c \\ \hline \boldsymbol{\beta} \end{array}\right] = \left[\begin{array}{c} \boldsymbol{y} \\ \hline 0 \\ \hline \mathbf{0}_{N_a\times 1} \end{array}\right], \tag{4}$$

where $\boldsymbol{Z} = [\boldsymbol{z}^a(1)^T; \boldsymbol{z}^a(2)^T; \cdots; \boldsymbol{z}^a(N)^T] \in \mathbb{R}^{N\times N_a}$ is the matrix of linear regressors; $\boldsymbol{y} = [y(1); y(2); \ldots; y(N)]$, and $\boldsymbol{\Omega}$ is the kernel matrix with $\boldsymbol{\Omega}_{i,j} = K(\boldsymbol{z}^b(i), \boldsymbol{z}^b(j)) = \boldsymbol{\varphi}(\boldsymbol{z}^b(i))^T\boldsymbol{\varphi}(\boldsymbol{z}^b(j))$ for $i, j = 1, \ldots, N$.

Proof. Consider the Lagrangian of problem (3) $\mathcal{L}(\boldsymbol{w}, c, e(t), \boldsymbol{\beta}; \alpha_t) = \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + \gamma\frac{1}{2}\sum_{t=1}^{N} e(t)^2 - \sum_{t=1}^{N}\alpha_t[\boldsymbol{\beta}^T\boldsymbol{z}^a(t) + \boldsymbol{w}^T\boldsymbol{\varphi}(\boldsymbol{z}^b(t)) + c + e(t) - y(t)]$ where the $\alpha_t \in \mathbb{R}$ are the Lagrange multipliers. The conditions for optimality ($\frac{\partial\mathcal{L}}{\partial\boldsymbol{w}} = 0$, $\frac{\partial\mathcal{L}}{\partial c} = 0$, $\frac{\partial\mathcal{L}}{\partial e(t)} = 0$, $\frac{\partial\mathcal{L}}{\partial\boldsymbol{\beta}} = 0$, $\frac{\partial\mathcal{L}}{\partial\alpha_t} = 0$) are given by $\boldsymbol{w} = \sum_{t=1}^{N}\alpha_t\boldsymbol{\varphi}(\boldsymbol{z}^b(t))$, $\sum_{t=1}^{N}\alpha_t = 0$, $\alpha_t = \gamma e(t)$ $(t = 1, \ldots, N)$, $\sum_{t=1}^{N}\boldsymbol{z}^a(t)\alpha_t = 0$ and $y(t) = \boldsymbol{\beta}^T\boldsymbol{z}^a(t) + \boldsymbol{w}^T\boldsymbol{\varphi}(\boldsymbol{z}^b(t)) + c + e(t)$ $(t = 1, \ldots, N)$. By elimination of $\boldsymbol{w}$ and $e(t)$, we obtain $y(t) = \boldsymbol{\beta}^T\boldsymbol{z}^a(t) + \sum_{k=1}^{N}\alpha_k K(\boldsymbol{z}^b(k), \boldsymbol{z}^b(t)) + c + \frac{\alpha_t}{\gamma}$ with the application of Mercer's theorem [14], $\boldsymbol{\varphi}(\boldsymbol{z}^b(k))^T\boldsymbol{\varphi}(\boldsymbol{z}^b(t)) = K(\boldsymbol{z}^b(k), \boldsymbol{z}^b(t))$ with a positive definite kernel K. Building the kernel matrix $\boldsymbol{\Omega}_{i,j} = K(\boldsymbol{z}^b(i), \boldsymbol{z}^b(j))$ and writing the equations in matrix notation gives the final system (4). □

Remark 1 *[Kernel functions and their corresponding feature map $\boldsymbol{\varphi}(\cdot)$]. Any positive definite kernel can be chosen. Some typical choices are: $K_{lin}(\boldsymbol{x}_i, \boldsymbol{x}_j) = \boldsymbol{x}_i^T \boldsymbol{x}_j$ (linear kernel); $K_{pol}(\boldsymbol{x}_i, \boldsymbol{x}_j) = (\boldsymbol{x}_i^T \boldsymbol{x}_j + r)^d$ (polynomial of degree d, with $r > 0$ a tuning parameter); $K_{RBF}(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp(-\|\boldsymbol{x}_i - \boldsymbol{x}_j\|_2^2/\sigma^2)$ (RBF kernel), where σ is a tuning parameter. On the other hand, the mapping $\boldsymbol{\varphi}(\boldsymbol{x}) = \boldsymbol{x}$ for $\boldsymbol{x} \in \mathbb{R}^n$ gives the linear kernel; the mapping $\boldsymbol{\varphi}(x) = [1; \sqrt{2}x; x^2]$ for $x \in \mathbb{R}$ gives the polynomial kernel of degree 2. The mapping for the RBF kernel has been shown to be infinite dimensional [14]. The feature map should not be explicitly known in general. Taking a positive definite kernel guarantees the existence of the feature map.*

Remark 2 *[Primal and Dual expressions]. The estimated model becomes $\hat{y}(t) = \hat{\boldsymbol{\beta}}^T \boldsymbol{z}^a(t) + \sum_{k=1}^N \alpha_i K(\boldsymbol{z}^b(k), \boldsymbol{z}^b(t)) + c$, expressed in terms of the dual variables α_t, which corresponds to a nonparametric regression on the nonlinear component [5] that contains N coefficients and kernel evaluations. Even for the case of a linear kernel with linear regression in primal space in (3), the expression $\sum_{k=1}^N \alpha_k K_{lin}(\boldsymbol{z}^b(k), \boldsymbol{z}^b(t)) = \sum_{k=1}^N \boldsymbol{z}^b(k)^T \boldsymbol{z}^b(t)$ is a nonparametric regression. Working in dual space, therefore, leads to a nonparametric representation of the model. On the other hand, working explicitly with the $\boldsymbol{\varphi}(\cdot)$ mapping in primal space, provides parametric framework where the solution is expressed directly in terms of the coefficient vectors $\boldsymbol{\beta}, \boldsymbol{w}$.*

Remark 3 *[Estimation in Primal Space and Large Scale problems]. It is possible to obtain a finite dimensional approximation $\hat{\boldsymbol{\varphi}}(\cdot)$ of the nonlinear mapping from any kernel matrix $\boldsymbol{\Omega}$ by means of the Nyström technique [16]. The $i-th$ component of $\hat{\boldsymbol{\varphi}}(\cdot)$ evaluated at $\boldsymbol{x}$ is obtained as $\hat{\boldsymbol{\varphi}}_i(\boldsymbol{x}) = \frac{N}{\sqrt{\lambda_i}} \sum_{k=1}^N u_{ki} K(\boldsymbol{x}_k, \boldsymbol{x})$ where u_{ki} is the $k-th$ element of the $i-th$ eigenvector of $\boldsymbol{\Omega}$, and λ_i is the $i-th$ eigenvalue. Working in primal space is practical when the number of datapoints N is large and the system in (4) becomes too large for computational storage because it leads to a sparse representation. In this case a smaller*

matrix $\boldsymbol{\Omega}_M$ *of dimensions* $M \times M$ *with* $M \ll N$ *computed from a fixed subset of* M *datapoint provides the starting point to build the approximation* $\hat{\boldsymbol{\varphi}}(\cdot)$*. This leads to the fixed-size LS-SVM formulation [13]. When working in primal space it is possible to apply all classical parametric techniques for system identification [7].*

Remark 4 *[Equivalent Smoother matrix and Effective Number of Parameters]. It is useful to write the vector of predictors from a model in the form* $\hat{\boldsymbol{y}} = \mathcal{S}\boldsymbol{y}$*, where* $\mathcal{S}$ *is the smoother matrix. The effective number of parameters (degrees of freedom) is given by the trace of* $\mathcal{S}$ *[8]. For the case of a fully black-box model estimated with LS-SVM, the smoother matrix takes the form* $\mathcal{S}_F = \boldsymbol{\Omega}(\boldsymbol{\Omega} + \gamma^{-1}I)^{-1}$ *with* $\boldsymbol{\Omega}_{i,j} = K(\boldsymbol{z}(i), \boldsymbol{z}(j))$*. For the PL-LSSVM model estimated in dual space (4), the smoother matrix takes the form* $\mathcal{S}_D = \mathcal{S} - \mathcal{S}\mathcal{W} + \mathcal{W}$ *with* $\mathcal{S} = \boldsymbol{\Omega}(\boldsymbol{\Omega} + \gamma^{-1}I)^{-1}$*,* $\mathcal{W} = \boldsymbol{Z}(\boldsymbol{Z}^T(I - \mathcal{S})\boldsymbol{Z})^{-1}\boldsymbol{Z}^T(I - \mathcal{S})$ *and* $\boldsymbol{\Omega}_{i,j} = K(\boldsymbol{z}^b(i), \boldsymbol{z}^b(j))$*. For the PL-LSSVM estimated using a fixed-size approximation in primal space* $\hat{\boldsymbol{\varphi}}(\boldsymbol{z}^b(t)) \in \mathbb{R}^M$ *computed from a subsample of size* M*, let* $\hat{\boldsymbol{\Phi}} = [\hat{\boldsymbol{\varphi}}(\boldsymbol{z}^b(1))^T; \ldots; \hat{\boldsymbol{\varphi}}(\boldsymbol{z}^b(N))^T] \in \mathbb{R}^{N \times M}$*, the smoother matrix is given by* $\mathcal{S}_P = \left[\begin{array}{cc} \hat{\boldsymbol{\Phi}} & \boldsymbol{Z} \end{array}\right] \left(\left[\begin{array}{cc} \hat{\boldsymbol{\Phi}}^T\hat{\boldsymbol{\Phi}} & \hat{\boldsymbol{\Phi}}^T\boldsymbol{Z} \\ \boldsymbol{Z}^T\hat{\boldsymbol{\Phi}} & \boldsymbol{Z}^T\boldsymbol{Z} \end{array}\right] + \Lambda \right)^{-1} \left[\begin{array}{c} \hat{\boldsymbol{\Phi}}^T \\ \boldsymbol{Z}^T \end{array}\right]$ *with* $\Lambda = \left[\begin{array}{c|c} \gamma^{-1}\mathbf{I} & \mathbf{0} \\ \hline \mathbf{0} & \mathbf{0} \end{array}\right]$ *with* $\mathbf{I}$ *the identity matrix of dimension* M*. This smoother matrix is used with respect to generalized cross validation [15].*

4 Examples with NARX models

4.1 Model Selection

First a full black-box model $M_0 \in \mathcal{M}_0$ is estimated with LS-SVM, using cross-validation for hyperparameter tuning and order selection. Then, a PL-LSSVM model $M_1 \in \mathcal{M}_1$ is defined using some initial partition over the regressors. If this new model M_1 has a better

		Mean Squared Error (Test data)	
System	Evaluation	Black-Box model	Partially Linear Model
System 1	One-Step-Ahead Prediction	1.44×10^{-4}	1.08×10^{-4}
	Simulation	2.01×10^{-4}	1.31×10^{-4}
System 2	One-Step-Ahead Prediction	7.66×10^{-4}	2.50×10^{-4}
	Simulation	0.0019	0.0011

Table 1: Test set performance of the models for Systems 1 and 2.

performance than M_0, measured as the cross-validation mean squared error (CV-MSE), it is assumed that M_1 is closer to the true structure of the system. The process is repeated over an arbitrary selection of linear regressors, looking for the model $M \in \mathcal{M}_1$ with the best performance. Although this may require a search over all combinations of linear and nonlinear regressors [3], practical insights from the user can reduce the search.

4.2 Example 1: The true model is known

Consider the following two systems:

$$\begin{aligned} \text{System 1: } y(t) &= (0.5y(t-1))^3 - 0.5y(t-2) + 0.3u(t) - 0.2u(t-1) + e(t) \\ \text{System 2: } y(t) &= 0.5y(t-1)^3 - 0.5y(t-2)u(t) + 0.3u(t) - 0.2u(t-1) + e(t). \end{aligned}$$

On each system, the input sequence $u(t)$ is generated from a $N(0,1)$; the error term $e(t)$ is i.i.d. $N(0, 0.001)$. Both systems were generated up to $N = 1000$ datapoints. The first 350 datapoints were discarded to avoid any transient effect; the training was done with the next 400 datapoints; the last 250 points were used for final testing. System 1 contains $[y(t-2); u(t); u(t-1)]$ as a linear input. System 2 considers only $u(t-1)$ as linear due to the condition $\mathcal{Z}^a \cap \mathcal{Z}^b = \emptyset$. First, the overall order of the system is identified using a full black-box NARX model M_0 trained with LS-SVM. The evolution

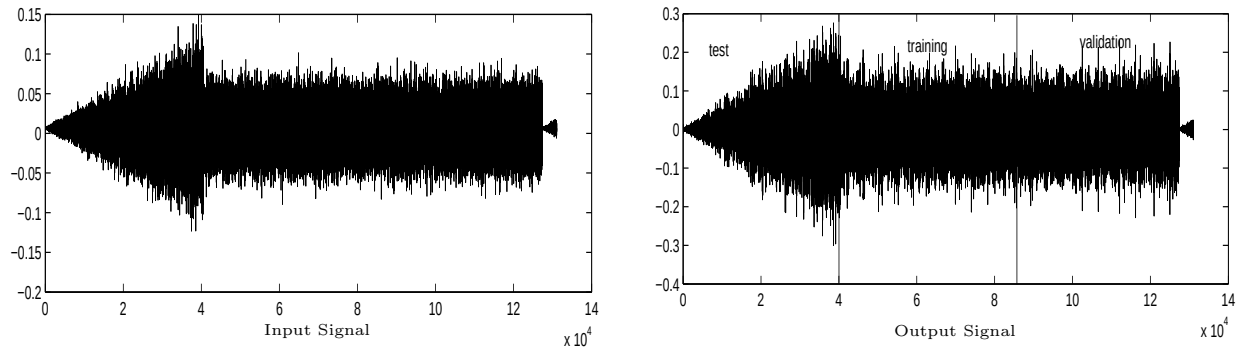


Figure 1: Input and output signal for the Silverbox data set, showing the regions for training, validation and testing.

of the $CV(M_0)$ over different model orders for System 1, where for simplicity we assume $p = q + 1$, gives an optimum at $p = 2$, which corresponds to the regression vector defined as $\boldsymbol{z}(t) = [y(t-1); y(t-2); u(t); u(t-1)]$. The same situation happens for System 2. Once the regression vector has been identified, a sequential application of (3) is performed. We see that even if the original M_0 model was estimated optimally, it is still possible to improve the performance by using a PL-LSSVM correctly specified. For System 1, we have CV-MSE$(M_0) = 2.32 \times 10^{-4}$, which is reduced to CV-MSE$(M_a) = 1.20 \times 10^{-4}$; for System 2, we have CV-MSE$(M_0) = 2.31 \times 10^{-4}$ reduced to CV-MSE$(M_a) = 1.67 \times 10^{-4}$. The effective number of parameters, measured as the trace of the equivalent smoother matrix [8], for System 1 is reduced from 41 to 5.5. For System 2, it is reduced from 39 to 24. We then compute the one-step-ahead error and the simulation error [7] for the original black-box model M_0 and the PL-LSSVM model M_a. The results are reported in Table 1. In addition, the model that minimizes the CV-MSE correctly identifies the linear coefficients. For System 1 we obtain $\hat{\boldsymbol{\beta}} = [-0.4996; 0.3002; -0.2002]$. For System 2, $\hat{\boldsymbol{\beta}} = 0.1996$.

4.3 Example 2: The Silverbox Data

The real-life nonlinear dynamical system that was used in the NOLCOS 2004 Special Session benchmark [10] consists of a sequence of 130,000 inputs and outputs measured from a real physical system, shown in Figure 1 with the definition of the data that was used for training and final testing. The final test consists on computing a simulation for the first 40,000 datapoints (the "head of the arrow"), which requires the models to generalize on a region of larger amplitude than the one used for training. A full black-box LS-SVM model reached excellent levels of performance [1] using 10 lags of inputs and outputs. We obtained a root mean squared error (RMSE) of 3.24×10^{-4} in simulation mode. Figure 2 shows the errors obtained in simulation mode when testing the generalization performance of the model in the "head of the arrow" for the full nonlinear black-box LS-SVM. Now the objective is to check if the knowledge of the existence of linear regressors can improve further on the simulation performance. A partially linear model using $p = q = 10$ is formulated using past and current inputs as linear regressors,

$$y(t) = \boldsymbol{\beta}^T[u(t); u(t-1); u(t-2); \ldots; u(t-p)] + \boldsymbol{w}^T\boldsymbol{\varphi}([y(t-1); y(t-2); \ldots; y(t-p)]) + e(t)$$

and estimated with PL-LSSVM. Due to the large sample size, a fixed-size PL-LSSVM in primal space is used. It improves the simulation performance over the full black-box model, as it is shown in Figure 2. Table 2 shows a comparison between both models in terms of their in-sample accuracy, their validation performance, the simulation accuracy and the model complexity. By imposing a linear structure we decrease the simulation root mean squared error to 2.7×10^{-4}. Moreover, when considering only the last 10,000 points of the test data, the improvement is more important, as shown in Table 3. Using the full black-box model, the maximum absolute error is 0.0081, which is reduced to 0.0037 with the PL-LSSVM. The mean absolute error for the full black-box model is 2.3×10^{-4}; for the partially linear model, it is 2.02×10^{-4}. The effective number of parameters is reduced from 490 to 190.

	Black-Box model	Partially Linear Model
RMSE_{val}	1.05×10^{-4}	0.45×10^{-4}
$\text{RMSE}_{\text{test}}$	1.75×10^{-4}	0.57×10^{-4}
RMSE_{sim}	3.24×10^{-4}	2.71×10^{-4}
N_{eff}	490	190

Table 2: Performance comparison between the models for the Silverbox data in terms of RMSE for validation, testing and simulation.

Case	Indicators	Black-Box model	Partially Linear Model
Case I	$\max(\lvert e_i \rvert)$	0.0081	0.0037
	$\text{mean}(\lvert e_i \rvert)$	2.30×10^{-4}	2.02×10^{-4}
	$\text{RMSE}(e_i)$	3.24×10^{-4}	2.71×10^{-4}
Case II	$\max(\lvert e_i \rvert)$	0.0081	0.0037
	$\text{mean}(\lvert e_i \rvert)$	3.72×10^{-4}	2.31×10^{-4}
	$\text{RMSE}(e_i)$	5.86×10^{-4}	3.34×10^{-4}

Table 3: Simulation errors for the Silverbox data, over the full test set (Case I) and only for the last 10,000 points of the test set (Case II).

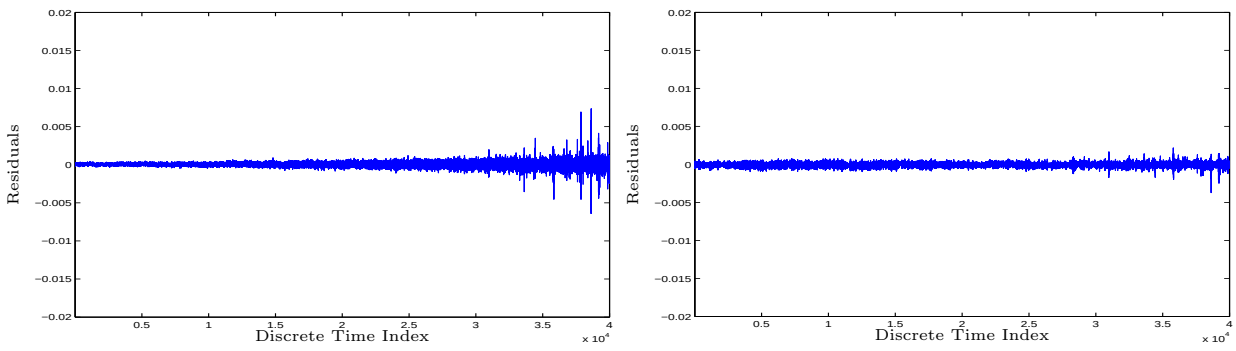


Figure 2: Simulation errors in the test region of the Silverbox data. Full black-box LS-SVM model (Left), PL-LSSVM (Right).

5 Conclusion

In this paper we illustrated that it is possible to use a partially linear model with least squares support vector machines to successfully identify a model containing a linear part and a nonlinear component, with better performance results than a full nonlinear black-box model. The structured model may show a better generalization ability, and a lower model complexity, than a full nonlinear black-box model. In the real-life example of the Silverbox benchmark data, an existing nonlinear black-box model can be further improved by imposing a linear structure, as it is illustrated in the simulation performance.

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