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Support Vector Machine (SVM) based general model building algorithm for production control

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Abstract: The paper introduces an algorithm for building up the general system model applying the Support Vector Machine (SVM) modeling approach. It finds that input/output configuration of the system model that realizes the most accurate estimation and explores the maximum of dependencies among the related system parameters. Its performance is tested and evaluated under various conditions: after the basic testing using simple mathematical equations a field specific analysis was performed applying the classical equations from the cutting control theory. Experiments were done also for cutting control based on real measured parameters under varying conditions. These validations showed good empirical performance and practical applicability of the algorithm introduced. This model building approach was generalized to various model types having learning capabilities.

1. INTRODUCTION

The paper introduces an algorithm for building up the general system model applying the Support Vector Machine (SVM) approach. System models are extremely important in control solutions e.g. in production control systems, too. Reliable process models are extremely important in different fields of computer integrated manufacturing (Merchant, 1998). Difficulties in modeling manufacturing processes are manifold: the great number of different machining operations, multidimensional, nonlinear, stochastic nature of machining, partially understood relations between parameters, lack of reliable data, etc. A number of reasons back the required models: the design, optimization, control and simulation of processes and the design of equipment. However, in spite of progress being made in fundamental process modeling, accurate models are not yet available for many manufacturing processes. Heuristic models are usually based on the rules of thumb gained from experience, and used for qualitative evaluation of decisions. Empirical models derived from experimental data still play a major role in manufacturing process-modeling (Yerramareddy, et al., 1993). Developments and trends in control and monitoring of machining processes shows the necessity of sensor integration, sophisticated models, multimodel systems, and learning ability (Tönshoff, et al., 1988).

SVMs were introduced first by Cortes and Vapnik for training linear machines efficiently (Cortes, et al., 1995). One of the simplest tasks for such models is the linear separation of various, multidimensional vectors representing two classes. SVMs find the hyper plane having one dimension less than the original dimensionality of the vectors separating the two classes. The target of the separation is to maximizing the distance of the elements of the classes from the hyper plane on the different sites of it. The closest class elements from the two classes are called support vectors (Hamel, et al., 2009).

One of the most effective tools of the SVMs is using kernel functions. The idea to ensure higher class separation capability is to transform the input space into another space having usually higher dimensionality. This space is called as feature space. When an appropriate transformation is found for the problem analyzed, typically it results better modeling accuracy and usually it results no significant increase in computational time. Another very important feature of SVMs is that the target function of their training for building up its kernel is quadratic and convex having no local but a global extreme (Cristianini, et al., 2000). These features and their promising applications result that SVMs are very popular in machine learning applications.

SVMs were further developed and extended to handle much more complex assignments, e.g. multiclass classification even if when the classes are not linearly separable. In this case the target of the SVM is to minimize the number of misclassified class elements together with the maximization of the distance between the separating hyper plane and the support vectors (Hamel, et al., 2009).

Based on the promising results in classification assignments SVMs were extended to realize also estimation tasks. Similar to the classification their estimation capabilities are considered also successful even if the dimensionality of the input space is very high (Hamel, et al., 2009). Variety of further SVM improvement research activities were done and are under development also today, one of such a very important result is the introduction of the SVM type called Least Squares SVM that is able to solve the model fitting through solving a linear equation set instead of the original extreme search algorithm included in SVMs (Suykens, et al., 2002, Valyon, et al., 2005).

The input-output configuration strongly influences the accuracy of the developed model especially if dependencies between parameters are non-invertable. In various stages of production (e.g. in planning, optimisation or control) different tasks arise; consequently, the estimation capabilities of the related applied models are different even if the same set of parameters is used.

One of the main goals of the research to be reported here was to find a general model for a set of assignments, which can satisfy accuracy requirements. A similar algorithm was already developed by the authors using artificial neural networks (ANNs) as models (Viharos, et al., 1999, Monostori, et al., 2000) but the promising results of SVMs in aspect of learning accuracy and training speed drove them to redefine and adapt the original input-output search algorithm to SVMs. This adaptation and the related testing results in the field of production control is the main aim of the paper presented here.

The paper is organised as follows: after a short description of the original input-output search algorithm using ANNs, a generalized approach of the solution is defined applicable for any modelling systems having learning capabilities. It is followed by the SVM based method introduction and the description of the implementation environment and tools. Related test cases are grouped in three levels: first the new algorithm was tested using simple linear mathematical equations; it is followed by the analysis based on empirical and non-linear equations from the cutting control theory and practice and the last test-application case already takes real turning processes and the related measured signal values as database for the model building. Finally, some features of the introduced algorithm are described and the paper is closed by the conclusion, acknowledgement and references.

2. BUILDING UP THE GENERAL SYSTEM MODELL FOR PRODUCTION CONTROL: INPUT-OUTPUT SEARCH

A lot of effort has been made to apply ANNs for modelling manufacturing operations (Monostori, et al., 1996). The assignments to be performed determined the input-output configurations of the models, i.e. the parameters to be considered as inputs and the ones as outputs. Considering the input and output variables of a given task together as a set of parameters, the ANN model estimates a part of this parameter set based on the remaining part. This partitioning strongly influences the accuracy of the developed model especially if dependencies between parameters are non-invertable. In different stages of production (e.g. in planning, optimisation or control) tasks are different, consequently, the estimation capabilities of the related applied models are different even if the same set of parameters is used. It should be stressed that in a classical application the input-output configuration of the applied model is determined by the given assignment, namely known parameters serves as inputs and unknown parameters serves as outputs. The estimation capabilities of the applied ANN models are determined as results after the model building and testing stage. The breakthrough of the original, ANN based algorithm was not to determine the input-output configuration before the model building stage but the model building and training algorithm has to define the appropriate and best input-output configuration of the model automatically (Viharos, et al., 1999).

2.1 Input-output search based on artificial neural networks

The input-output search algorithm based on artificial neural networks was developed before (Viharos, et al., 1999). By building up of this general model the algorithm does not have any regard to the given assignment of engineers its target is to satisfy accuracy requirements and build up the most useful system model, e.g. for control aspects. The automatic generation of the general process model, i.e. model, which is expected to work accurately enough in different assignments, consists of the following steps:

- Determination of the (maximum) number of output parameters (No) from the available N parameters which can be estimated using the remaining Ni = N - No input parameters within the prescribed accuracy.
- Ordering of the available parameters into input and output parameter sets having Ni and No elements, respectively.
- Training the network whose input-output configuration has been determined in the preceding steps.

For the realization of these steps a search algorithm combined with the ANN training is needed to select all the possible outputs from the given set of parameters with regard to the accuracy demands. From the user point of view the learning data set is given in the form of N dimensional vectors. First, the search algorithm chooses only one parameter form the N parameters to be output of the model. To select the first output parameter, N ANNs are generated, each having one different output and N-1 input parameters. After generating the ANNs, learning begins by all ANNs, concurrently. First, each ANN performs M learning step. The evaluation follows for checking whether the ANN with the smallest estimation error had reached the required estimation accuracy. If not, another learning phase is started with M epoch again. If yes, then this means that an output was found which can be estimated with the given accuracy based on the remaining input parameters. The next step of the algorithms is to order this variable to the output set of parameters and to select a further output parameter. This selection is realised by the same method as for the previous output(s). For searching the second output, N-1 ANNs are generated because one output is already fixed, consequently, there are N-1 different possibilities to add another output to the set of output parameters. The remaining N-2 parameters are used as inputs. After finding the second output, two outputs are fixed and a search starts to find a third output etc. This indicates that for adding a new output to the set of output parameters successful learning is required. Learning is successful if an ANN configuration can learn the dependencies between input and output variables with a given accuracy. The algorithm stops if after a large number of learning steps, none of the ANNs, being in their learning stages can achieve the given accuracy. During this search algorithm the largest number of outputs can be found, the accuracy demands are satisfied and the ANN model is built up. It is called as the general model of the system because it is built up without considering any assignments related to the parameters analysed. Another algorithm was built up to solve various assignments using the same general model (Monostori, et al., 2000).

2.2 Generalized input-output search algorithm

After the introduction of the ANN based input-output search algorithm the methodology can be generalized to be applicable for all modelling methods having learning capabilities. In a case of a system having N variables it is as follows:

- A training data set is given having many vectors with N parameters.
- At the start N pieces of the training models are set up having one different output parameter and the remaining N-1 parameters are the inputs of the models.
- The N different models are trained parallel and they are ordered according to their estimation accuracy and the output parameter with the smallest error is selected as the first, fixed output variable of the final model.
- In the next steps at every epoch a new output parameter is targeted to add to the list of already given output parameters while the number of input parameters are decreasing continuously according to the new output variable. In a general case when the number of already found and fixed outputs is O then N-O training models are set up having the same output variables plus one but at every model different additional output parameter. These models have N-O-1 inputs they are those parameters that are not on the output side.
- The N-O models are trained using the same data set and the same number of training steps and they are ordered according to their estimation accuracies (average estimation error of their outputs based on the whole training data set) and the O+1 outputs of most accurate model are selected as the new, fixed set of output parameters. This process increased the number of output parameters from O to O+1 and the estimation accuracy of the new model is determined. This type of approach is called as sequential forward selection in the search theory.
- The two previous steps are repeated continuously until two alternative possible criteria: In the first case the estimation errors of any the $(O+1)^{th}$ models are above a prescribed acceptable limit the algorithm can be stopped and the most accurate model having in the previous step O output parameters is the final, resulted system model. In a second case the increase of the output parameters can be continued until the system configuration having N-1 outputs and 1 input is reached. In this case for all the (most accurate) models from 1 to N-1 output parameters and also their estimation accuracy is given and these models can be ordered according to their estimation error. This ordered accuracy parameter values can be used to select the appropriate models with the appropriate number of outputs. As it will be seen later in the paper typically a significant (relative) increase in the estimation error represents a limit where adding and additional output parameter to the model is not worth because it results significant decrease in the model estimation accuracy. This seems to be appropriate criteria for selecting the appropriate model, however further; field and system specific criteria can be also applied.

This general approach was also applied for the SVM based model building, too, as it is described in the next paragraph.

3. SVM BASED GENERAL MODEL BUILDING

The algorithm described in the previous paragraph was realized based on SVMs with the criteria for searching for all the appropriate N-1 models and representing the estimation errors of these cases. The software realization environment was served by MATLAB® that has incorporated SVM models and the related training algorithms. The SVM algorithm is included in the LSSVMLab add-on of published at June, 2010 with the version number 1.6. The included Least Squares SVM algorithm was applied in the developments and experiments (Brabanter, et al., 2010). The Gauss kernel was applied in the model having the variable σ^2. This together with the related SVM regularization parameters they are tuned during the model training process by using the 'tunelssvm' function of MATLAB®.

In the tests the applied data set is cut randomly into three parts and in all of the task cases two third is used for the training and one third is applied for testing the model estimation capabilities, this is a typical cross validation test. The model estimation error is measured as the quadratic error between estimated (y) and target (t) value of the testing data set calculated using average through outputs, testing data vectors and the three validation data sets:

$$E = \frac{\overline{\sum_{i=1}^{n}\sum_{j=m}^{m}\left(y_{ij} - t_{ij}\right)^2}}{n \cdot m} \quad (1)$$

The number of output parameters is 'n' and the number of the testing data vectors is 'm'. Test on one validation set was performed once not in a repeated manner, consequently the average in (1) concerns to the average calculation of the results based measured on the three validation data sets.

4. ALGORITHM TESTING EXPERIMENTS

The SVM based general model building algorithm capabilities were tested in three levels: first the new algorithm was tested using simple linear mathematical equations; it is followed by the analysis based on empirical and non-linear equations from the cutting control theory and practice and the last test-application case already takes real turning processes and the related measured signal values as database for the model building.

5.1Experiments with simple linear mathematical equations

In the first test case 99 data values were randomly generated for the parameters x_1 and x_2 in the range between 0.1 and 0.9 and the related $x_1 + x_2$, $x_1 * x_2$ values were calculated. Four dimensional data vectors were generated indicating that the SVM based models may have one, two or three outputs identified during the model search algorithm. Naturally, in this test case there are two independent parameters, consequently it is expected to have two input and two output values. The resulted estimation errors are shown in Fig. 1 representing that the search the algorithm found at first the $x_1 + x_2$ and then the $x_1 * x_2$ parameters as model outputs. When forcing to go forward to appoint a next possible output the x_2 parameter was selected as the third output, however, it is known that it is independent from the input x_1 parameter. A positive aspect of the SVM based search is when selecting the third output the estimation error increased dramatically showing to the user that this parameter cannot be estimated with an acceptable accuracy, consequently, e.g. the maximal relative increase in the estimation error when adding a new output parameter to the model is a promising trigger to appoint that this extension of the output parameter set is not worth anymore.

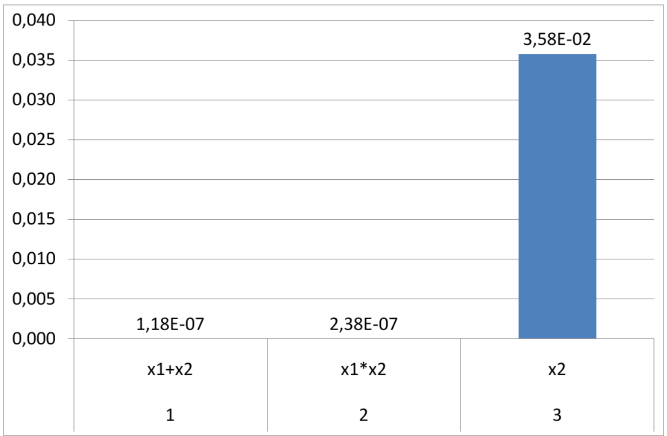

Fig. 1. significant error increase: the horizontal axis represents the order of the model output parameters (in a cumulative way, e.g. in the second step the model has already two output parameters $x_1 + x_2$ and $x_1 * x_2$) during the SVM based search and the vertical axis shows the related model estimation errors when all the remaining (not output) parameters are on the input side of the model.

5.2 Experiments with non-linear mathematical equations from the metal cutting theory and practice

The previous, simple, linear experiment showed that the maximal relative increase in the estimation error when adding a new output parameter to the model is a promising trigger to appoint that this extension of the output parameter set is not worth anymore. The current paragraph analyses a non-linear case and moves to the production control where such models are necessary to handle the cutting process efficiently. There are many variables describing a metal cutting process. The following parameters were selected for the analysis: Setting of the machine is handled through three machining parameters: depth of cut: a [mm], feed: f [mm/rev], speed: v [m/min]. The tool is presented by three tool parameters: cutting edge angle: χ [rad], corner radius: r_ε [mm], tool life: T [min]. Two monitoring parameters may be used for the turning operation: force: Fc [N] (main force component) and power: P [kW]. The customer demand is determined by the required roughness: Ra [mm].

In cutting theory and practice the following dependencies are applied among these parameters (F. Krupp Gmbh, 1985):

$$\begin{aligned} F_c &= 1560 \cdot f^{0.76} \cdot a^{0.98} \cdot (\sin(\chi))^{-0.22} \\ P &= 0.039 \cdot f^{0.79} \cdot a \cdot v \\ T &= 1.85 \cdot 10^{10} \cdot f^{-0.7} \cdot a^{-0.42} \cdot v^{-3.85} \\ R_a &= 8.5 \cdot f^{1.8} \cdot a^{0.08} \cdot v^{-0.9} \cdot r_\varepsilon^{-0.5} \end{aligned} \quad (2)$$

The equations represent four dependencies among parameters; consequently, it is expected to find a model with four outputs.

In the experiments 999 random values were selected for the parameters on the right side of these equations in the following ranges:

$$\begin{aligned} &f: 0.1...0.4[\text{mm/rev}], a: 1...4[\text{mm}], \\ &\chi: 1.3...1.66[\text{rad}], v: 75...200[\text{m/min}], \\ &r_\varepsilon: 0.4...1.2[\text{mm}], T: 5...60[\text{min}], \\ &\text{consequently}, Fc \approx: 800...3000[\text{N}], \\ &P \approx: 3.8..13.5[\text{kW}], \\ &R_a \approx: 0.0015...0.023[\text{mm}] \end{aligned} \quad (3)$$

The introduced SVM based model building algorithm was applied for the data set generated and as result, the Fig. 2. represents the errors of the models generated. The picture shows that after identifying four outputs the maximal increase in the estimation error is at the fifth parameter, consequently, as it was expected the best model identified during search has five input and four output parameters, moreover, those four outputs were selected that are on the left side of the equations above.

In the same way as it was identified during the previous experiment, also in the non-linear case the maximal relative increase in the estimation error when adding a new output parameter to the model is a promising trigger to appoint that this extension of the output parameter set is not worth anymore.

It is worth to compare these results also with the cases of the ANN based model building algorithm (Viharos, et al., 1999). The same data set was tested and the related results showed the same tendency in the error increase of the searched ANN models according to the Fig. 3.

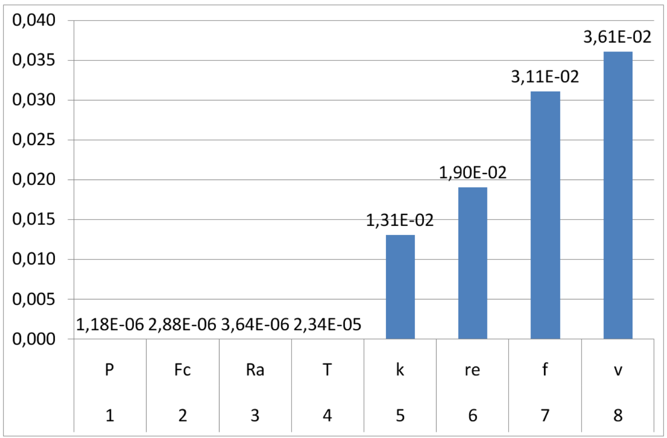

Fig. 2. significant error increase in non-linear case of the cutting theory: the horizontal axis represents the order of the model output parameters during the SVM based search and the vertical axis shows the related model estimation errors when all the remaining (not output) parameters are on the input side of the model.

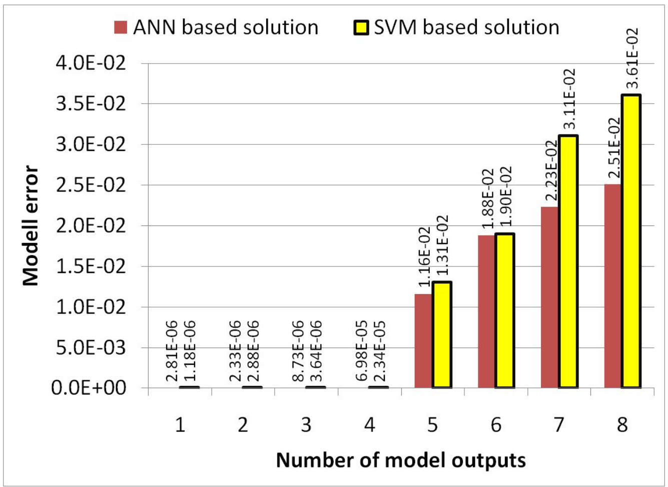

Fig. 3. same tendency in the error increase in non-linear case of the cutting theory on ANN based and also on SVM based model building: the horizontal axis represents the order of the model output parameters during the model building search and the vertical axis shows the related model estimation errors when all the remaining parameters are on the input side of the model. This similarity proves that the above, general, learning model independent algorithm produces the same characteristics in the model build search, moreover the maximal increase in the estimation error is a learning model type independent trigger.

5.3 Experiments with real, measured cutting data having typically non-linear and noisy features

The last experiment was done using real, measured data from the turning process. All of the machining parameters were varied and the roughness of the produced surface and the tool wear was measured while performing these cutting experiments, moreover the temperature (T) of the cutting was measured in process, through changes of the resistance of the machine-tool-material-machine loop. When the tool wear condition reached the wear-out phase, it was replaced by a new tool. Circumstances of cuttings were: material: 42CrMo4, machine: NC, Voest-Alpine, Nr. 085064, Type: WNC500S/1, tool: CNMG12040843, cp 3, 1820091, p15, k20, radius: 0.8 mm, without cooling. The speed was varied form 2.12 to 4.89 m/s, the depth of cut form 0.25 to 1.75 mm and the feed from 0.1 to 0.45 mm/revolution. All of the combinations of the parameters were set-up, the parameter ranges was split equally in these intervals. 5 different feed values were selected together with 4 depth of cut and 6 speed set-ups, consequently, data from 120 measurements are available. The data vectors consist of 7 parameters: $a\ f\ v\ VB\ \Delta VB\ R_a\ T$. VB and ΔVB mean the tool wear and the changes in the tool wear during one turning experiment respectively and T is the measured cutting temperature at the edge of the tool.

The same, SVM based model building search was applied in this real data set and the estimation errors are presented in the Fig. 4.

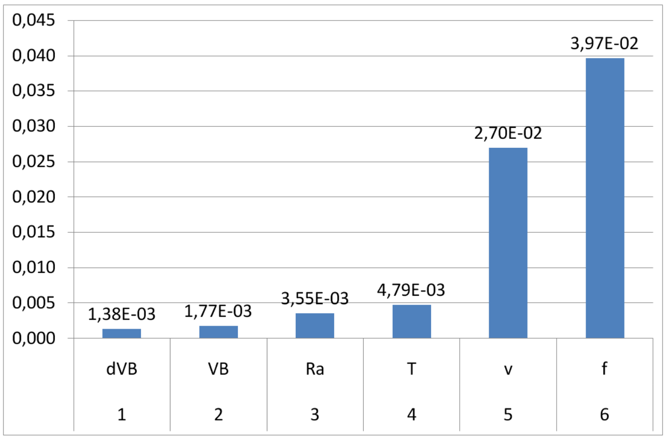

Fig. 4. significant error increase based on real measurements: the horizontal axis represents the orders of the model output parameters during the SVM based search and the vertical axis shows the related model estimation errors when all the remaining (not output) parameters are on the input side of the model.

The figure prove clearly that similar to the previous two cases there exists a maximal relative increase in the estimation error when adding a new output parameter to the model, consequently, in this real, practical experiment the parameters $VB\ \Delta VB\ R_a$ and T are the appropriate outputs of the SVM model. This result fully matches with the idea of cutting modelling experts, proving also that the approach and the algorithm works well in practical, typically noisy situations, too.

5. COMPARISON OF THE ANN BASED AND THE SVM BASED MODEL BUILDING APPROACH

The ANN and SVM based solutions were compared based on the estimation accuracies measured on the three experiments introduced. When comparing the estimation accuracies of the

ANN based and SVM based solutions in Fig. 3., it is seen that the ANN based models have the same level of accuracy than the SVM based solutions. However, in the case of SVM, the Gauss kernel function was selected that is not necessarily the best kernel function for the system modelled. This represents that the appropriate selection of the kernel function for the SVMs is one of the key questions and it needs sometimes apriori knowledge from the system analyzed and controlled. Another aspect of the comparison is the required calculation time of the SVM and ANN based model building technique. The Table 1. shows the calculation times needed to realize the model building search algorithm in MATLAB® environment. These experiments take the same order of calculation times then in the case of an ANN based solution, however, the ANN application in implemented in Ms Visual C++ environment. As conclusion, no significant changes were measured in the model building times; however better calculation speed is expected having also the SVM model in Ms Visual C++ environment.

Table 1. Models search computational times of the SVM based solution

Experiments	x_1, x_2, x_1+x_2, x_1*x_2	cutting with measured data	cutting with generated data
Time (min)	3	15	25

5. CONCLUSIONS

The paper introduced an algorithm for building up the general system model applying the Support Vector Machine (SVM) modelling approach. The solution is a transfer of the previously introduced Artificial Neural Network (ANN) based model building method into one that uses SVMs. It finds that input/output configuration of the system model that realizes the most accurate estimation and explores the maximum of dependencies among the related system parameters. Its capabilities were tested and evaluated under various conditions and these validations showed good empirical performance and practical applicability of the algorithm introduced in the field of production control. The SVM based solution showed the same modelling features as the previously introduced ANN based algorithm, it was empirically proven that the maximal relative increase in the estimation error when adding a new output parameter to the model is a good trigger to appoint that the extension of the output parameter set is not worth anymore, independently from the learning model type. The ANN and the SVM based solutions were compared and showed similar magnitude of modelling accuracy capabilities, too. This impulse that the earlier introduced, ANN based submodel decomposition algorithm (Viharos, 2005) can be realized also on SVM basis.

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