Black-box modelling of analogue and mixed-signal circuits in the time domain

↪ public defence ↩

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Outline

1. Introduction

2. Black-box modelling framework
   - Selection of the features and training data points - **FTSR**
   - Selection of the modelling method - **ALSVR**
   - Checking and improving stability - **CISB**
   - Selection of the model type - **TDMA/PMA models**

3. Conclusion

1. INTRODUCTION

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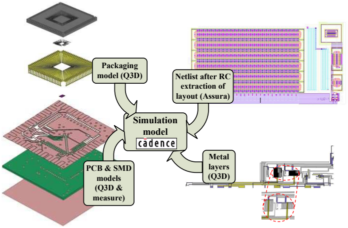
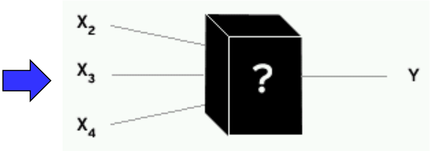
3. CONCLUSION

- Black box - a device, circuit or a system that is observed in terms of its input, output or transfer characteristics without any knowledge of its internal workings.

- Black-box modelling - behavioural modelling of such devices, circuits or systems.

1. Hiding the circuit/system details
2. Simulation models at transistor-level can be slow to simulate
3. Extraction of models from measured data is difficult and slow





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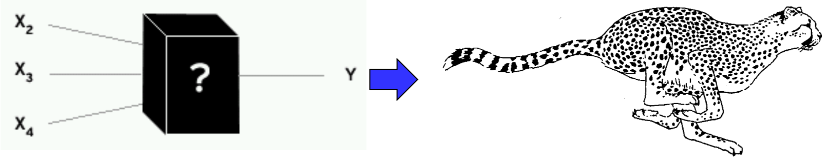

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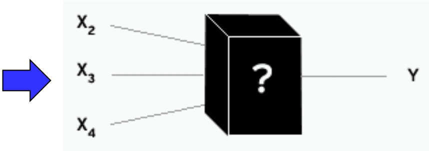

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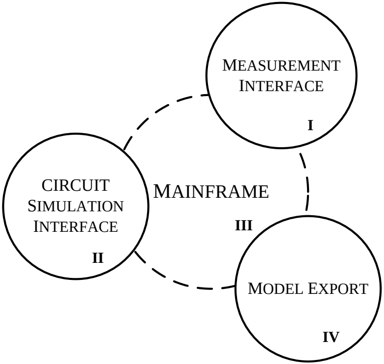
3 CONCLUSION

I Measurement interface
II Circuit simulation interface
III Mainframe
IV Model export module



III.A Data acquisition
III.B Data processing
III.C Selection of the input-output variables and training data points.
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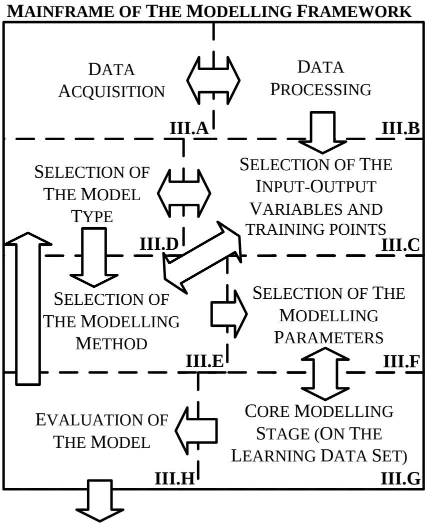
III.G Core modelling stage.
III.H Evaluation of the model.



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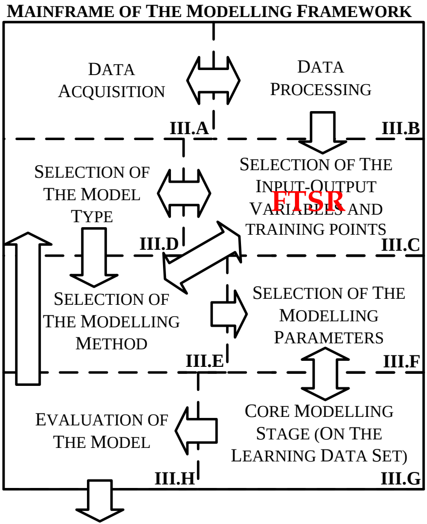

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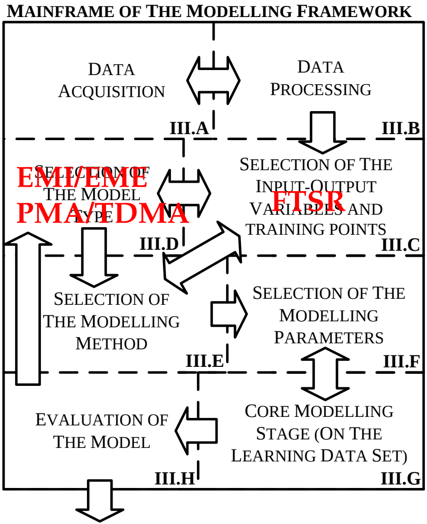

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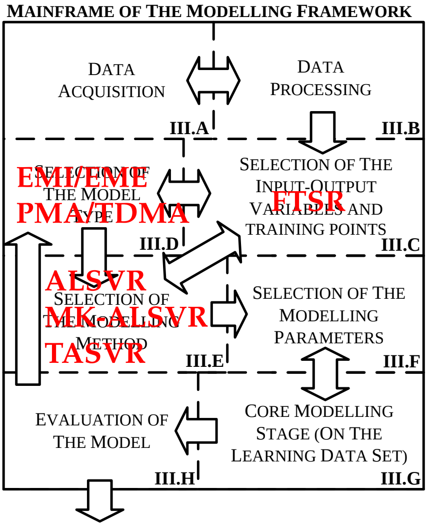

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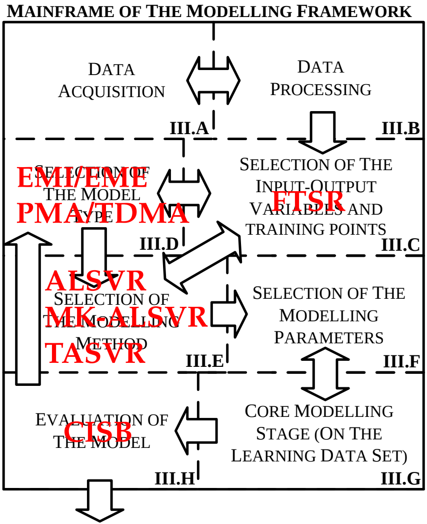
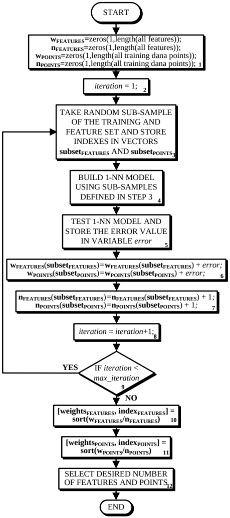


1) Simulate or measure the circuit signals under desired operation of the circuit
2) Generate additional model inputs in order to capture the dynamic behaviour of the electronic circuit
   - Derivatives as in (Cao, Ding, and Zhang 2006).
   - Delays as in (Ceperic and Baric 2004a).
   - Wavelets as in (Barford et al. 2005).
   - Moving average filters with various computation lengths as in (Ceperic and Baric 2004b).
3) Automated **selection of model inputs and training data points**:
   - Reduces overall model building time.
   - Reducing the complexity of computation for prediction.
   - Removing information redundancy.
   - Enhanced generalisation by reducing overfitting.
   - Easier interpretation.

↪ Selection of the features and training data points - FTSR

- FTSR - an algorithm for feature and training data point selection and ranking (FTSR) designed specifically for black-box modelling of electronic circuits.
    - Selection and ranking of recurrent and non-recurrent inputs and training data points.
    - Ranking is important due to setting of accuracy to complexity ratio which is often required by circuit designers.
- Algorithm identifies inputs and training data points that contribute most to the model accuracy by repeating fast 1-NN evaluations with random number of inputs and training data.



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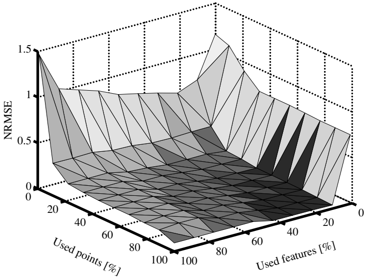
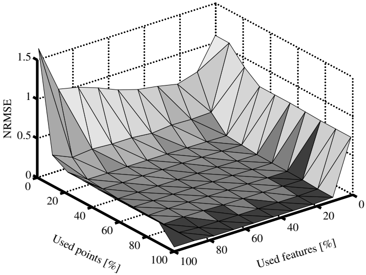
- Performance of the **1-NN** model made from inputs and training data points indexed by FTSR (1000 points, 100 non-recurrent and 15 recurrent inputs).
- Voltage bandgap reference circuit with offset compensation (242 transistors).

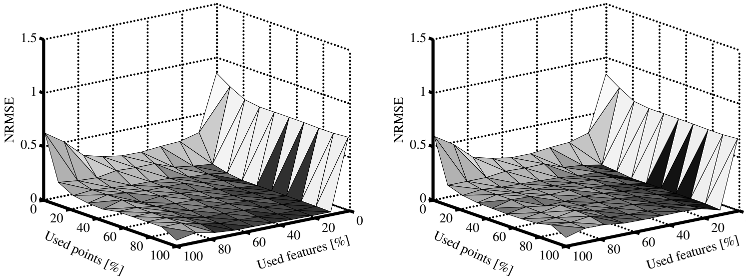


(a) 1-NN model error on the validation data set



(b) 1-NN model error on the testing data set

- Performance of the ε-**SVR** model made from inputs and training data points indexed by FTSR (1000 points, 100 non-recurrent and 15 recurrent inputs).
- SVR evaluations are approximately two orders of magnitude slower than 1-NN evaluations.



(a) ε-SVR model error on the validation data set

(b) ε-SVR model error on the testing data set

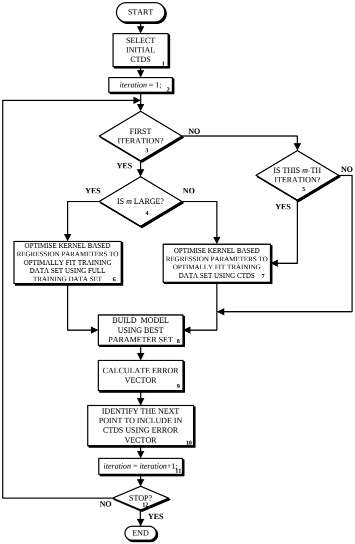
- The performance of the FTSR algorithm on the test data set.

	FTSR	**"Expert" (manual selection)**	**GA**	**PSO**
NRMSE:	0.045	0.18	0.11	0.15

- Next step: model the data using machine learning
- The selection of the appropriate approximation method depends on two basic factors:
  - Signal complexity.
  - Number of IC pins.
- **Support vector regression machines** -
  - Support vector machines, due to their favourable properties, can show better performance in modelling electronic circuits and devices, when compared to ANNs.
    - Ceperic and Baric [15] - first usage of support vector regression machines for modelling of analog circuits.
    - Xu et al. in [47] - conventional equivalent circuit model + support vector machine regression for modelling of MESFET devices.
    - Karsmakers et al. in [48] - least-squares support vector machines.

- Variants of support vector regression machines designed specifically for black-box modelling of electronic circuits:
  - ALSVR - application of active learning for ε-tube SVR.
  - MK-ALSVR - application of active learning for multi-kernel SVR.
    - V. Ceperic, G. Gielen, and A. Baric (2012d). „Sparse multikernel support vector regression machines trained by active learning". In: *Expert Systems with Applications* 39.12, pp. 11029–11035.
  - TASVR - application of active learning in the time domain using time horizon.
    - V. Ceperic, G. Gielen, and A. Baric (2012c). „Recurrent sparse support vector regression machines trained by active learning in the time-domain". In: *Expert Systems with Applications* 39.12, pp. 10933–10942.
  - Patent application: Vladimir Ceperic and Adrijan Baric (Jan. 2012). „System, Method and Computer Program Product for Modelling Electronic Circuits". Patent application 13,353,701 (US) (Appendix A).

- ALSVR - application of active learning for ε-tube SVR.
- ALSVR iteratively constructs training data set for ε-tube SVR thus liming model complexity. Training data points are selected by using active learning principle.



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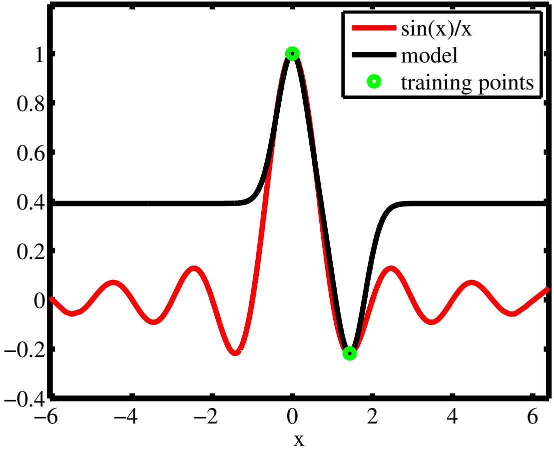
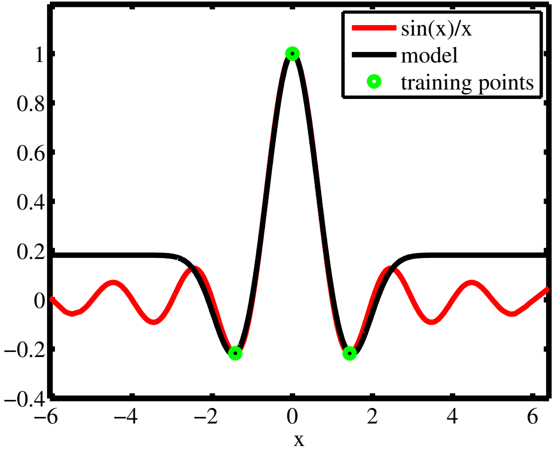
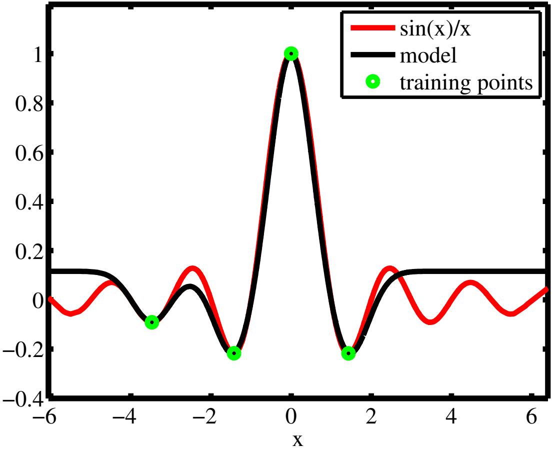
- ALSVR - application of active learning for ε-tube SVR. (2000 training points)
- 2 training and support vectors. SSE = 176.6



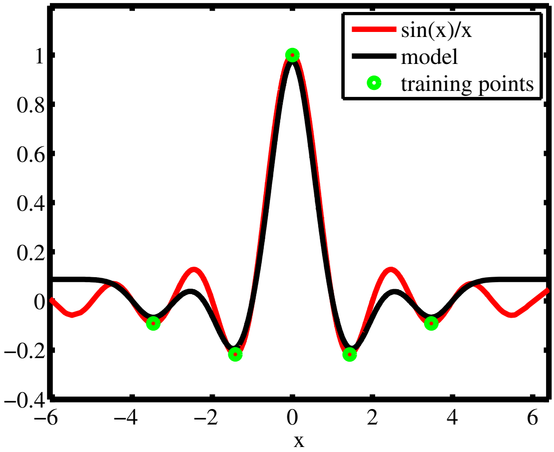
- ALSVR - application of active learning for ε-tube SVR. (2000 training points)
- 3 training and support vectors. SSE = 14.7



- ALSVR - application of active learning for ε-tube SVR. (2000 training points)
- 4 training and support vectors. SSE = 5.9



- ALSVR - application of active learning for ε-tube SVR. (2000 training points)
- 5 training and support vectors. SSE = 4.47



- ALSVR - application of active learning for ε-tube SVR. (2000 training points)
- 11 training and support vectors. SSE = 0.13

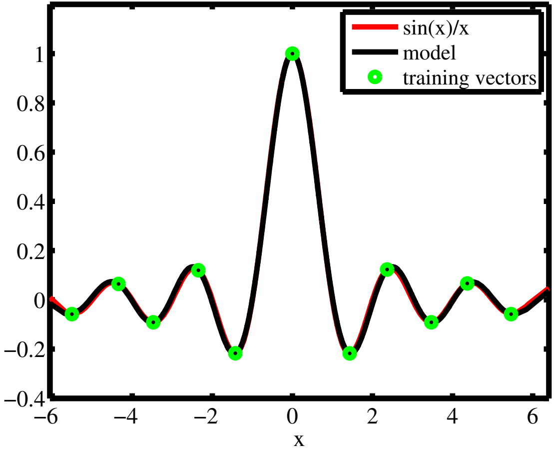


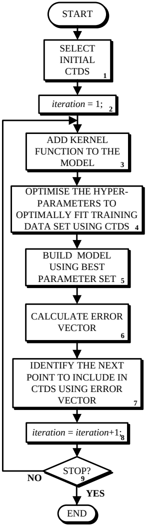
Table : Voltage bandgap reference with offset compensation - modelling of the **voltage at the VBG pin as a function of the supply voltage** - ALSVR vs. ε-SVR model: model accuracy on the training and testing data set

Model	SVs	NRMSE (training data set)	NRMSE (testing data set)
ε-SVR	167	0.0694	0.0809
ALSVR	30	0.0389	0.0343

Table : Voltage bandgap reference with offset compensation - modelling of the **voltage at the VBG pin as a function of temperature** - ALSVR vs. ε-SVR model: model accuracy on the training and testing data set

Model	SVs	NRMSE (training data set)	NRMSE (testing data set)
ε-SVR	62	0.00242	0.00245
ALSVR	30	0.00259	0.00259

- MK-ALSVR - application of active learning for multi-kernel SVR.
- In each iteration another SV with independent kernel is added.



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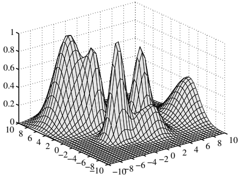
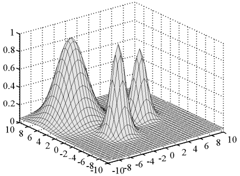
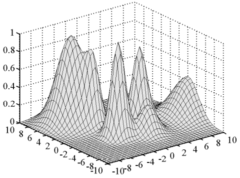
- MK-ALSVR - application of active learning for multi-kernel SVR. (3362 training data points).



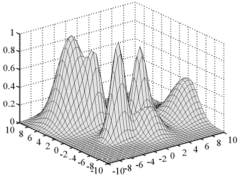
(c) original data set



(d) MK-ALSVR model with 4 SV



(e) MK-ALSVR model with 7 SV



(f) MK-ALSVR model with 10 SV

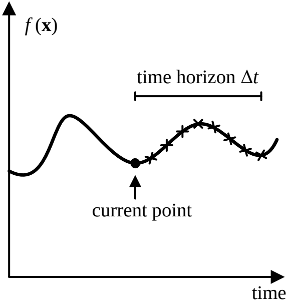
Table : Voltage bandgap reference with offset compensation - modelling of the **voltage at the VBG pin as a function of the supply voltage** - ALSVR and MK-ALSVR vs. ε-SVR model: model accuracy on the training and testing data set

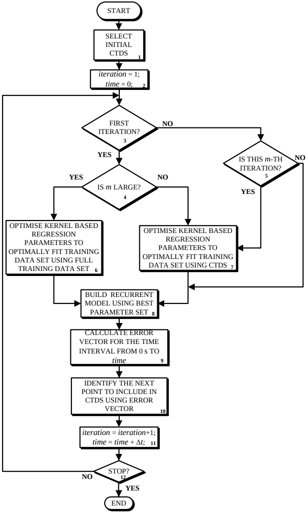
Model	SVs	NRMSE (training data set)	NRMSE (testing data set)
ε-SVR	167	0.0694	0.0809
ALSVR	30	0.0389	0.0343
MK-ALSVR	5	0.0182	0.0189

Table : Voltage bandgap reference with offset compensation - modelling of the **voltage at the VBG pin as a function of temperature** - ALSVR and MK-ALSVR vs. ε-SVR model: model accuracy on the training and testing data set

Model	SVs	NRMSE (training data set)	NRMSE (testing data set)
ε-SVR	62	0.00242	0.00245
ALSVR	30	0.00259	0.00259
MK-ALSVR	20	0.00243	0.00245

- TASVR - application of active learning in the time domain using time horizon.
- Active learning adapted for time domain modelling with recurrent inputs.





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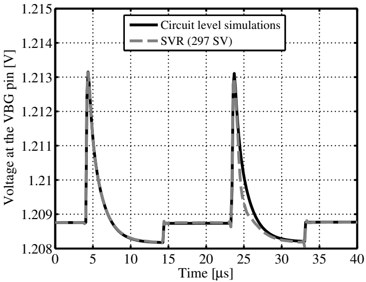
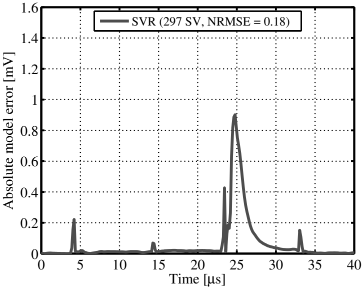
- Voltage bandgap reference with offset compensation (**242 transistors**): modelling of the voltage at the VBG pin in the time domain - ε-SVR model.

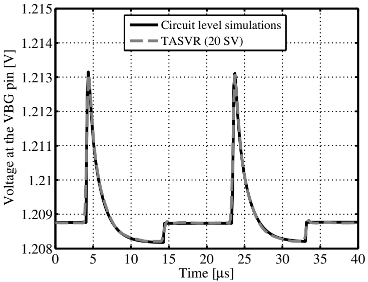


(a) ε-SVR **(297 SVs)** vs. circuit level simulations

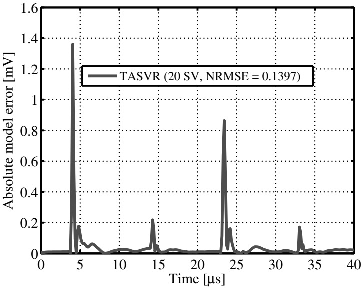


(b) ε-SVR **(297 SVs)** model error (NRMSE = 0.18)

- Voltage bandgap reference with offset compensation (**242 transistors**): modelling of the voltage at the VBG pin in the time domain - TASVR model.



(a) TASVR **(20 SVs)** vs. circuit level simulations



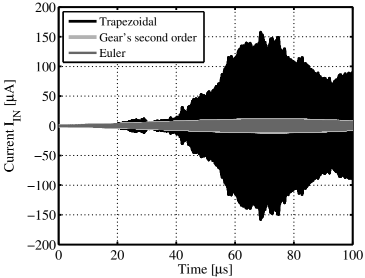
(b) TASVR **(20 SVs)** model error (NRMSE=0.1397)

Table : Voltage bandgap reference with offset compensation: modelling of the voltage at the VBG pin in the time domain - TASVR vs. ε-SVR model: model accuracy on the training and testing data sets

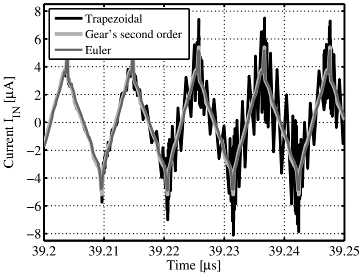
Model	SVs	NRMSE (training data set)	NRMSE (testing data set)
ε-SVR	297	0.0181	0.18
TASVR	20	0.1348	0.1397
TASVR	10	0.1551	0.1654

- **Serious issue: model works well in Matlab/Python/etc, but fails in circuit simulator!**

1. Illustration of the numerical problems using various integration methods within the Cadence Spectre.
   - Input current of the CMOS inverter circuit while input voltage is a frequency modulated sinusoid.
   - Simulator parameters are set to default values.

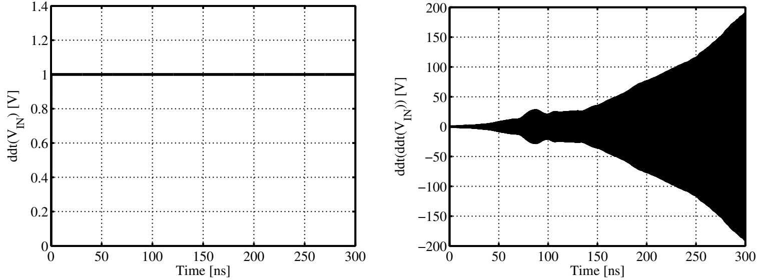


(a)



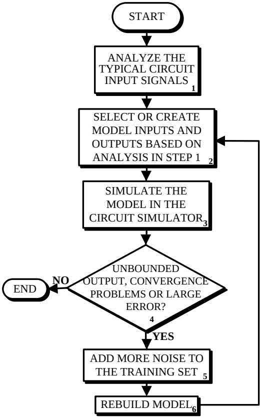
(b)

2. (a) first and (b) second derivative of the signal that linearly increases with time ($V_{IN} = time$), calculated in the circuit simulator while using default simulator parameters.



(a) (b)

- Method for **c**hecking and **i**mproving **s**tability of **b**lack-box models (CISB) is proposed.
  - Test in the circuit simulator! CISB is based on tests done in the circuit simulator!
  - CISB adds white noise to the training data set until circuit behaves well in the circuit simulator.



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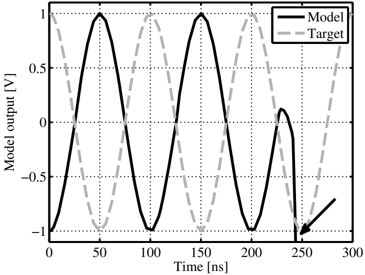
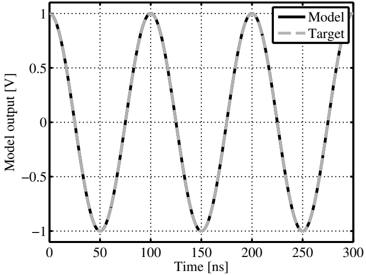
- For the test of the CISB procedure two test cases that exhibit stability issues are prepared:

1. The input is the sine signal while the output is the cosine signal. A feedback loop with zero delay is added as an additional input which will cause instability of the model within circuit simulator.
2. The CMOS inverter circuit designed in 0.35 μm high voltage I3T80 technology.
   - A small delay between the input change and output response can cause instabilities in the modelling phase.
   - Derivatives are used instead of time delays.
   - The training data set - frequency modulated sinusoid applied to the input of the circuit.
   - The testing data set - 100 MHz square wave signal with rise and fall time equal to 0.1 ns.

1. Test case 1 (ANN/Verilog A/Cadence Spectre):
    (a) The output of the model before applying CISB method.
    (b) The output of the model after applying CISB method (NRMSE = 2.1E-5). Signal to noise (SNR) ratio of the added white Gaussian noise to the feedback signal is equal to 75 dB.

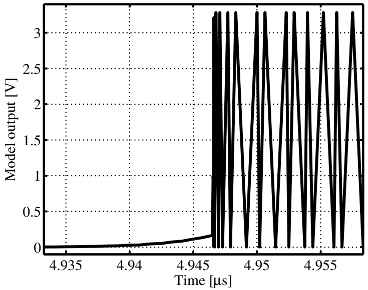


(a)

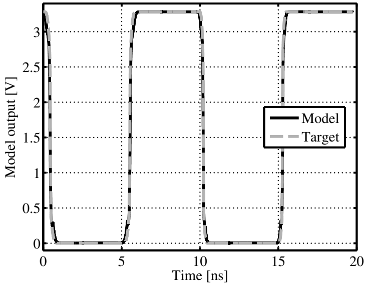


(b)

2. Test case 2 (ANN/Verilog A/Cadence Spectre):
   (a) The output of the model before applying CISB method. The signal is zoomed just before the stability and convergence problem occurred. The simulation is unable to continue after 4.958 µs.
   (b) The output of the model after applying CISB method (testing data set, NRMSE = 0.048). Signal to noise (SNR) ratio of the added white Gaussian noise to the feedback signal is equal to 50 dB.

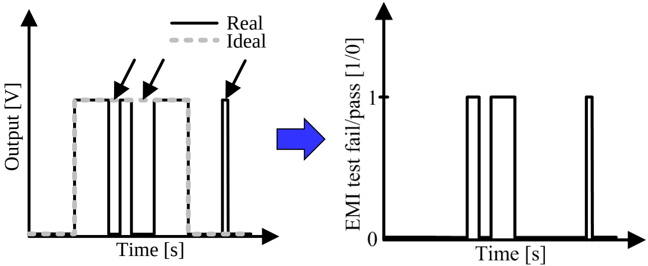


(a)

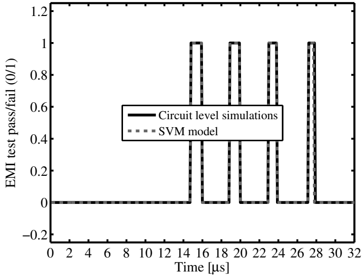


(b)

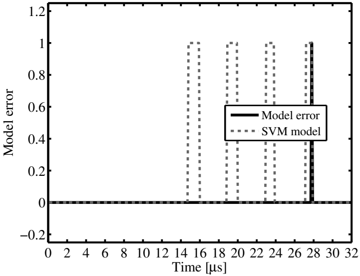
- If possible, simplify the modelling problem. Example: EMC related models TDMA-EMI-LOGIC, TDMA-EMI-FAILURE, TDMA-EME, PMA-EMI and PMA-EME.
- The problem of detecting failure of the circuit operation due to the conducted electromagnetic interferences according to DPI method is **transformed into the classification problem** solved by SVM which significantly simplifies the modelling problem.



- Test case - high voltage LIN interface (266 transistors).



(a) SPICE simulation vs. SVM model



(b) SVM model error - **99.83% of the correctly classified timesteps**

Figure : EM immunity test model (fail/pass) - LIN interface test case.

1. Introduction
2. Black-box modelling framework
   - Selection of the features and training data points - **FTSR**
   - Selection of the modelling method - **ALSVR**
   - Checking and improving stability - **CISB**
   - Selection of the model type - **TDMA/PMA models**
3. Conclusion

CONCLUSION

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- FTSR
  - Designed for black-box modelling of electronic circuits.
  - Decreases the required user input and improves the accuracy of the model.
- ALSVR, MK-ALSVR and TASVR
  - Designed for black-box modelling of electronic circuits but also perform well on benchmark data sets.
  - Enables setting of the accuracy vs. complexity ratio.
- CISB
  - Tests and improves stability of the model within circuit simulator.
  - Takes into account both the stability of the model and numerical problems within circuit simulator
- TDMA and PMA for conducted EME and EMI modelling
  - Simplifies the complex modelling problem to classification problem which enables modelling of complex circuits w.r.t. conducted EME and EMI.

PUBLICATIONS

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Patent Applications

- Vladimir Ceperic and Adrijan Baric (Jan. 2012). „System, Method and Computer Program Product for Modelling Electronic Circuits". Patent application 13,353,701 (US).

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