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Behavioral-level performance modeling of analog and mixed-signal system using support vector machines

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Introduction

Selection of the performance modeling method is one of the key elements in AMS synthesis

- **Fuzzy logic and neural network method**
- **Symbolic method**
- **Simulation-based methods**

Introduction

An SVM-based approach has been introduced recently

- An alternative to fuzzy-logic and neural networks
- Limited to classical ‘good-bad’ analysis
- Full space regression model construction

Support vector machines

- **Structured risk minimization:** considers both training errors and separation hyperplane
- Right choice of the kernel function can simplify the computational cost of SVM.

1: Linear Kernel: $k(x, x^{'}) = \vec{x} \cdot \vec{x}^{'}$
2: Polynomial Kernel: $k(x, x^{'}) = (\gamma \vec{x} \cdot \vec{x}^{'} + r)^d$
3: Radial Basis Function Kernel (RBF):
$k(x, x^{'}) = exp(-\gamma ||\vec{x} - \vec{x}^{'}||^2), \gamma > 0$
4: Sigmoid Kernel: $k(x, x^{'}) = tanh(\gamma \vec{x} \cdot \vec{x}^{'} + r)$

Support vector machines

Compared to traditional neural network models, SVM models have:

- Superior generalization capability
- Higher execution speed

However, suitable modeling techniques are essential to utilise the potential offered by SVMs.

Linearly graded performance models

To provide effective and accurate modeling of AMS systems

- Partition the entire performance space into sub-spaces
- Construct regression models of each sub-space

Reduces the complexity of performance space exploration.

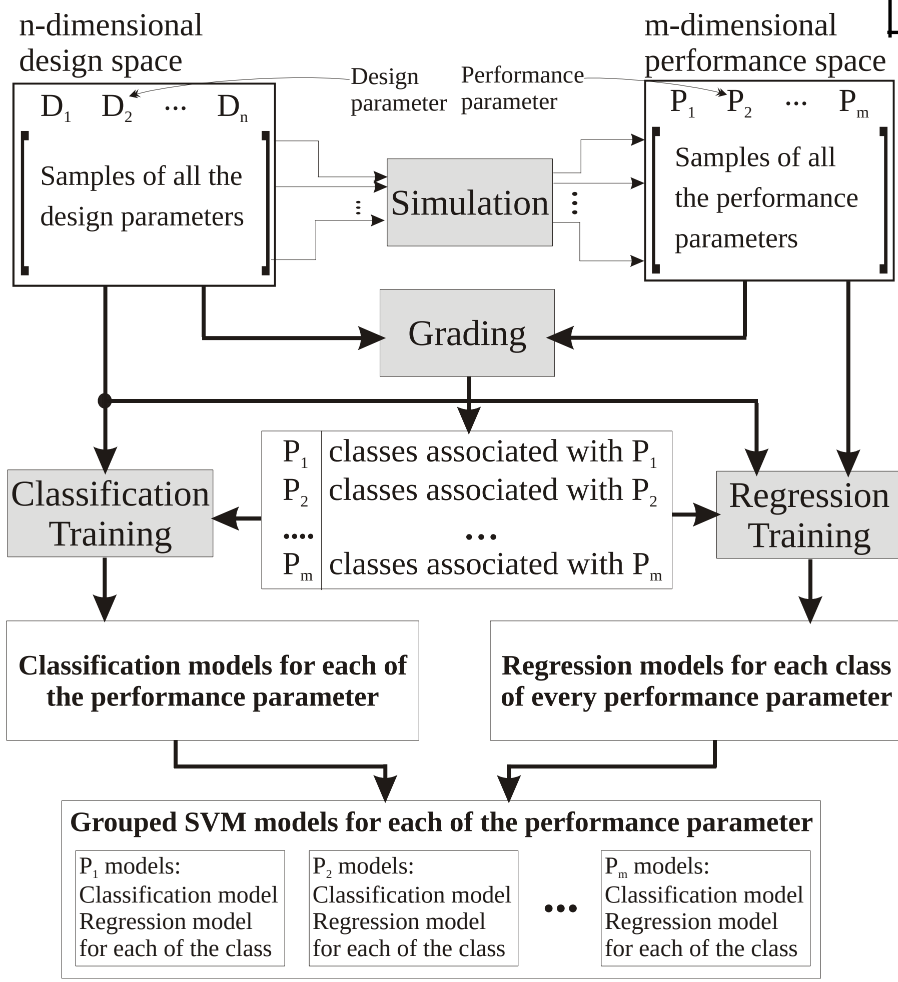
Linearly graded performance models

Data

- Design space
- Performance space

Operations

- Simulation
- Grading
- Classification training
- Regression training



Linearly graded performance models

- **Design space**

  each design parameter represents a dimension

- **Performance space**

  each performance parameter represents a dimension

- **Grading**

  Each performance parameter is automatically graded into sub-ranges. Combined sub-ranges form hypercubes in the performance space and are linked with corresponding subspaces in the design space.

Linearly graded performance models

Intermediate results

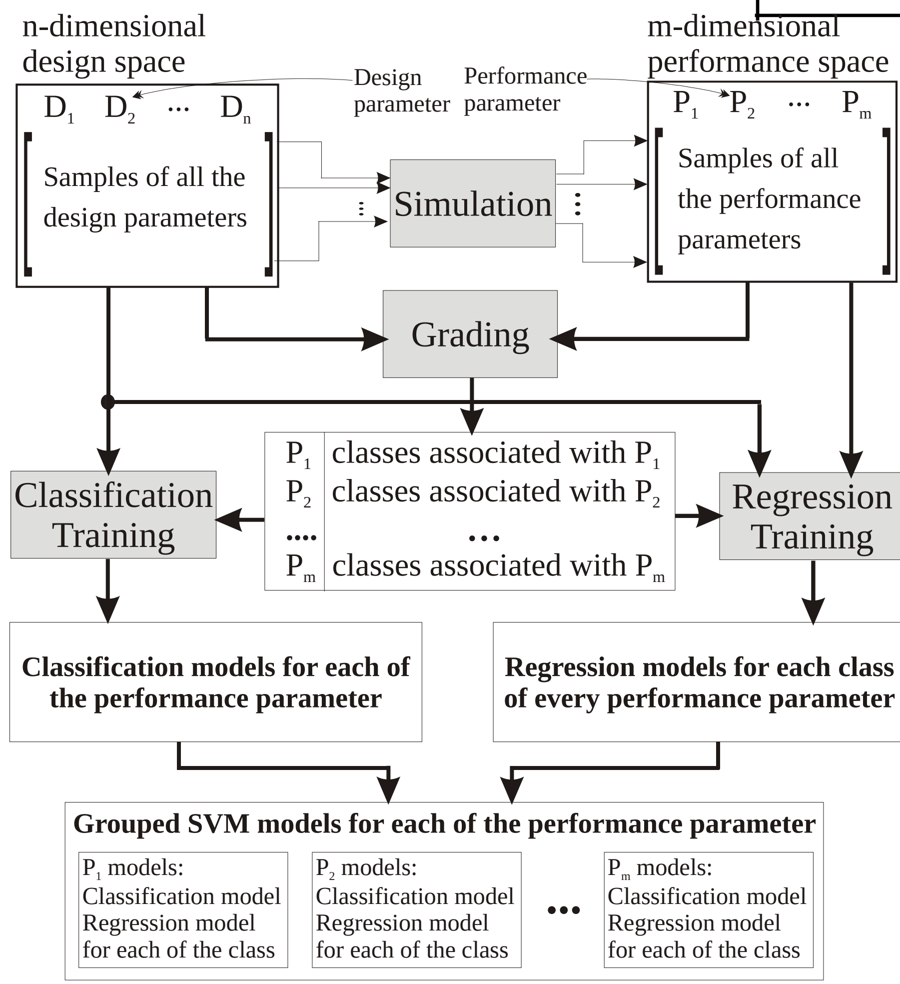
•Class matrix related with each performance parameter

•Classification models

•Regression models

results

•Grouped classification and regression models for each parameter.



Linearly graded performance models

- **Classification training**

  uses points in the design space and their corresponding classes

- **Regression training**

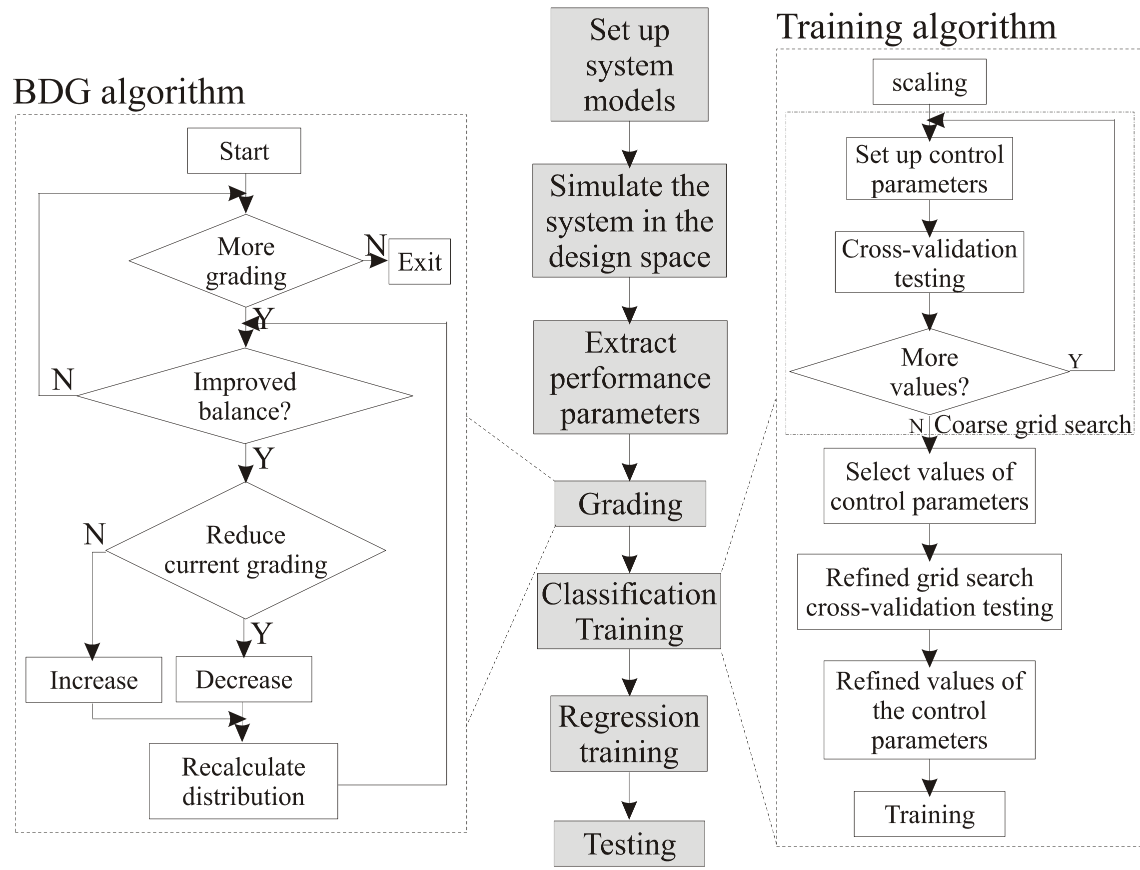
  uses points in the design and performance spaces and their corresponding classes

- **Grouped models**

  each performance parameter has a set of models including the classification models for classes and the regression models for each of the class

Model construction process

- Major operations
  - simulation
  - grading
  - training
  - testing
- Balanced Data Grading (BDG) algorithm
- Training algorithm



Model construction process

Grading with the BDG algorithm

- Grading along a parameter dimension with approximately similar amount of data material in the performance space
- Algorithm avoids sparse or over-concentrated distributions of data

The process starts with the user provided grading requirements and calculates balanced grading vectors;

Performance model construction process

SVM training: construction of the models

- Grid search

  coarse grid search (CGS) with low grid resolution

  refined grid search (RGS) with high grid resolution

  - to enhance the model construction efficiency

- Cross-validation

  - to enhance accuracy and generality (occurs also in neural networks)

Testing: validation of the models

Case study – a 2nd order Sigma Delta Modulator

- Design space

  amplifier gains, etc.

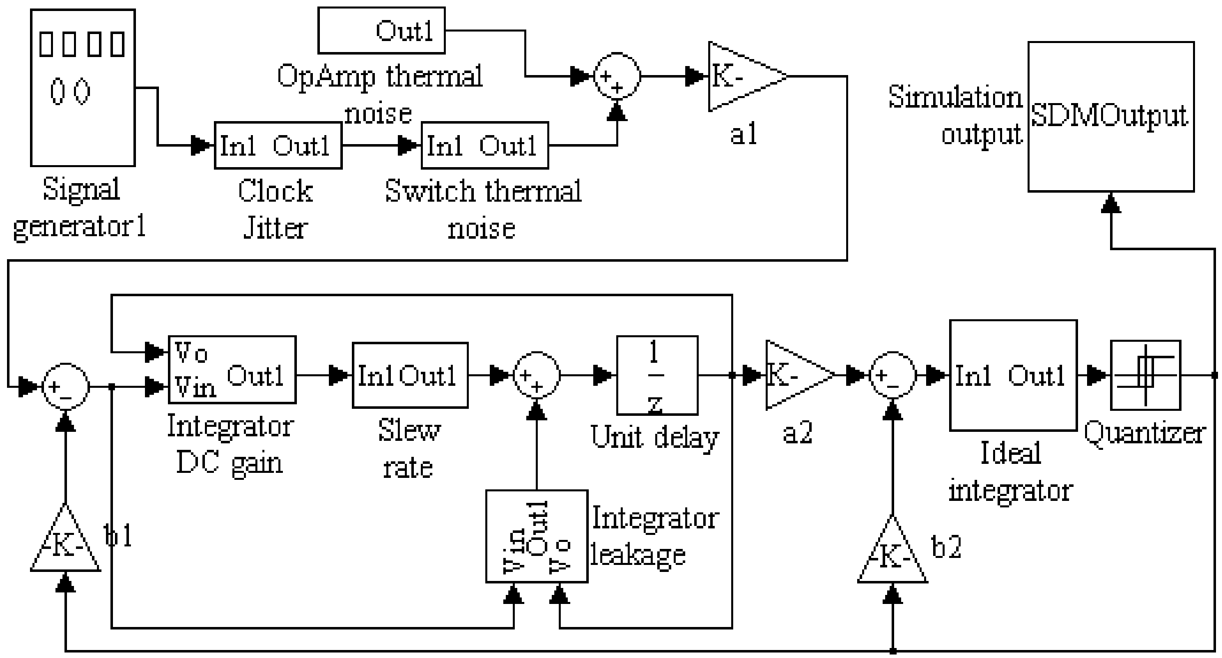
- Performance space

  SNR

  Output dynamic range (DR)

  Stability

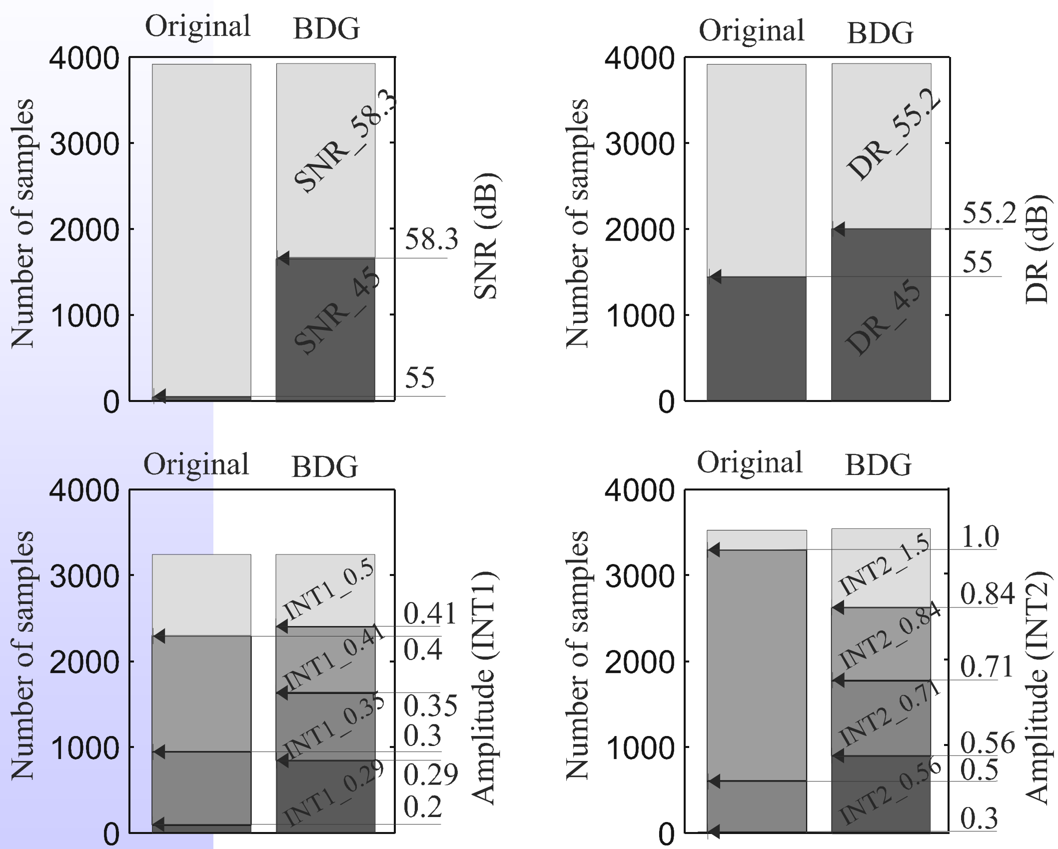
  Intgrator DR (INT1, INT2)



Results – kernel comparison

SVM method	Sample parameters	Linear kernel	RBF kernel	Sigmoid kernel
Classification	Stability - accuracy	82.98%	99.58%	99.05%
	Stability – CPU time	16:48:09	00:34:17	08:22:00
	SNR - accuracy	82.01%	98.77%	98.22%
	SNR – CPU time	22:30:40	00:53:54	17:13:37
Regression	SNR- CPU time	02:48:31	31:49:49	17:13:37

Results - BDG

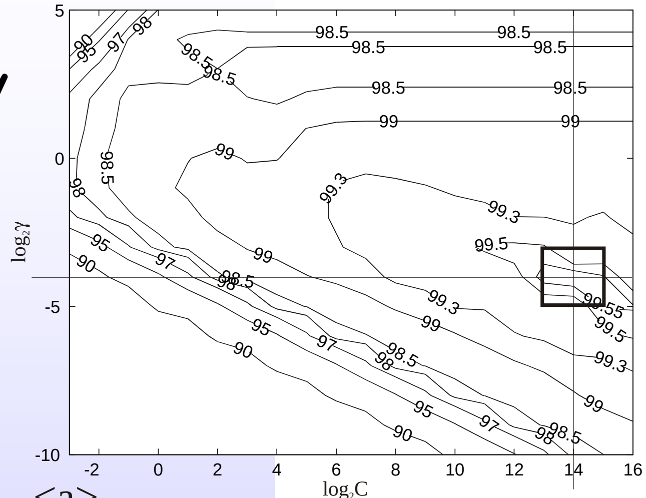


Original
BDG
4000
3000
2000
1000
0
Number of samples
SNR_58.3
SNR_45
58.3
55
SNR (dB)
DR_55.2
DR_45
55.2
55
DR (dB)
INT1_0.5
INT1_0.41
INT1_0.35
INT1_0.29
0.41
0.4
0.35
0.3
0.29
0.2
Amplitude (INT1)
INT2_1.5
INT2_0.84
INT2_0.71
INT2_0.56
1.0
0.84
0.71
0.56
0.5
0.3
Amplitude (INT2)

Results - training

stability

INT1_0.35



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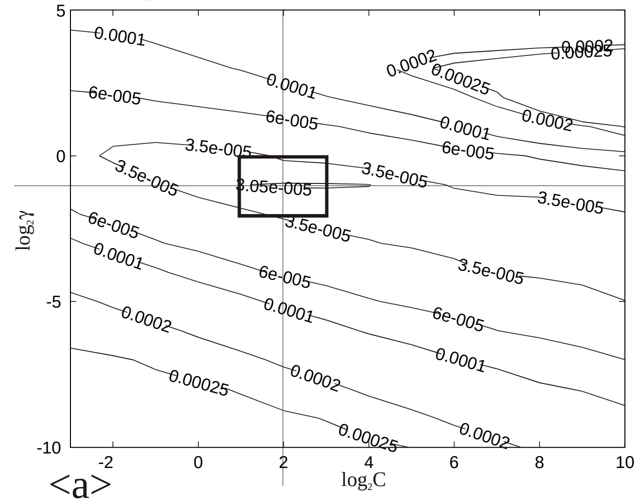

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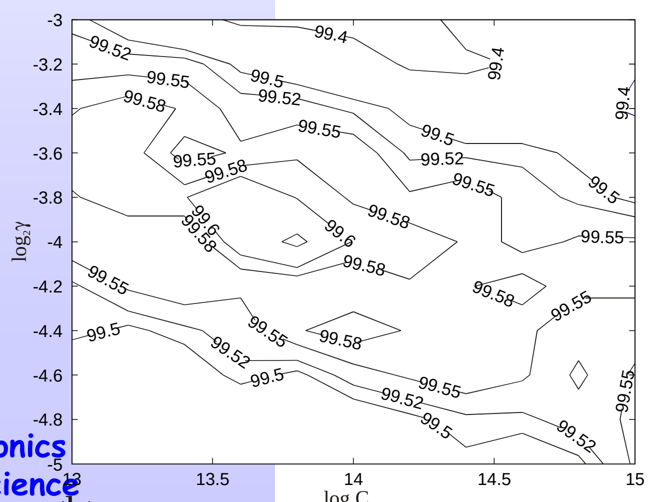

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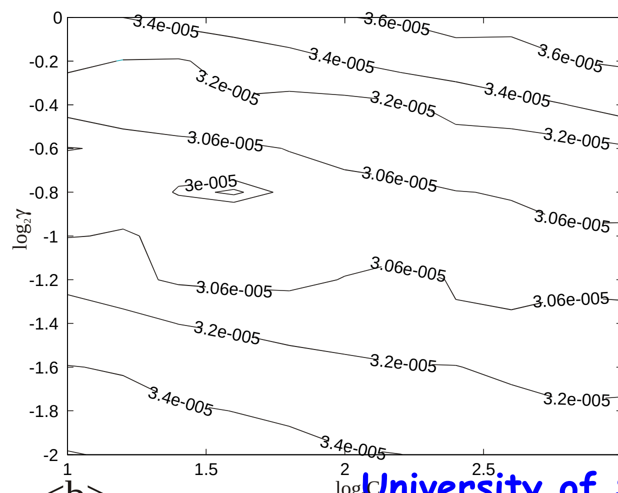

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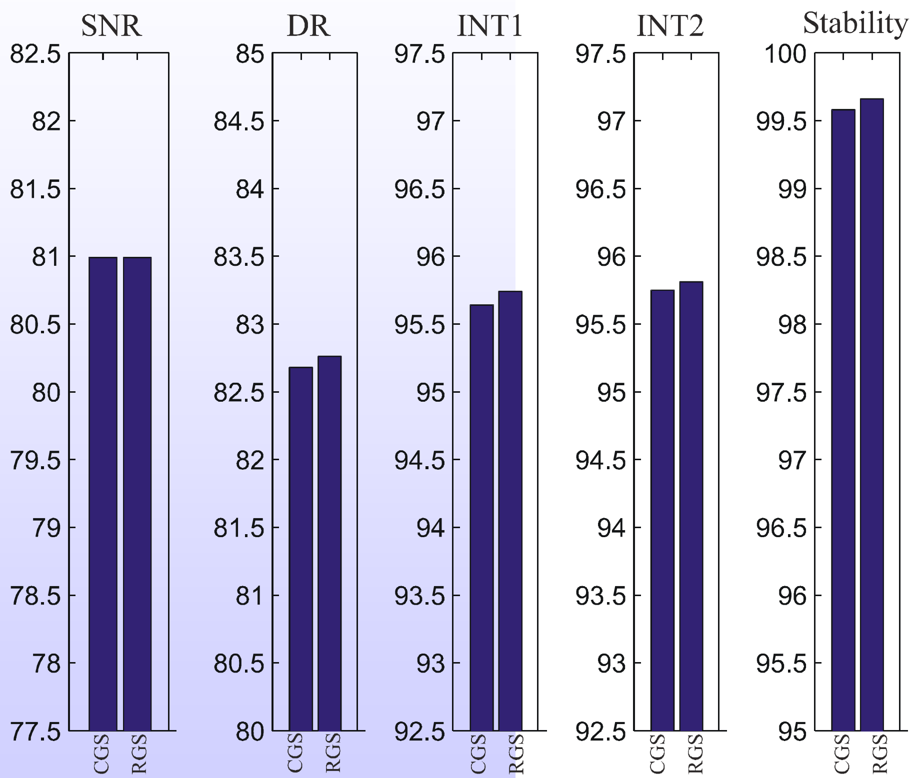
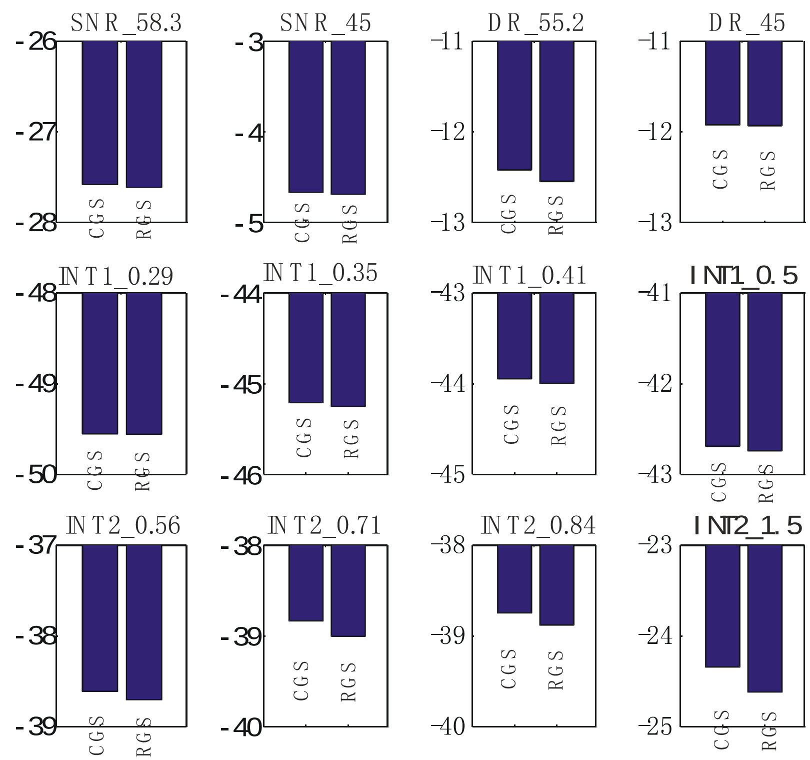
Results - training

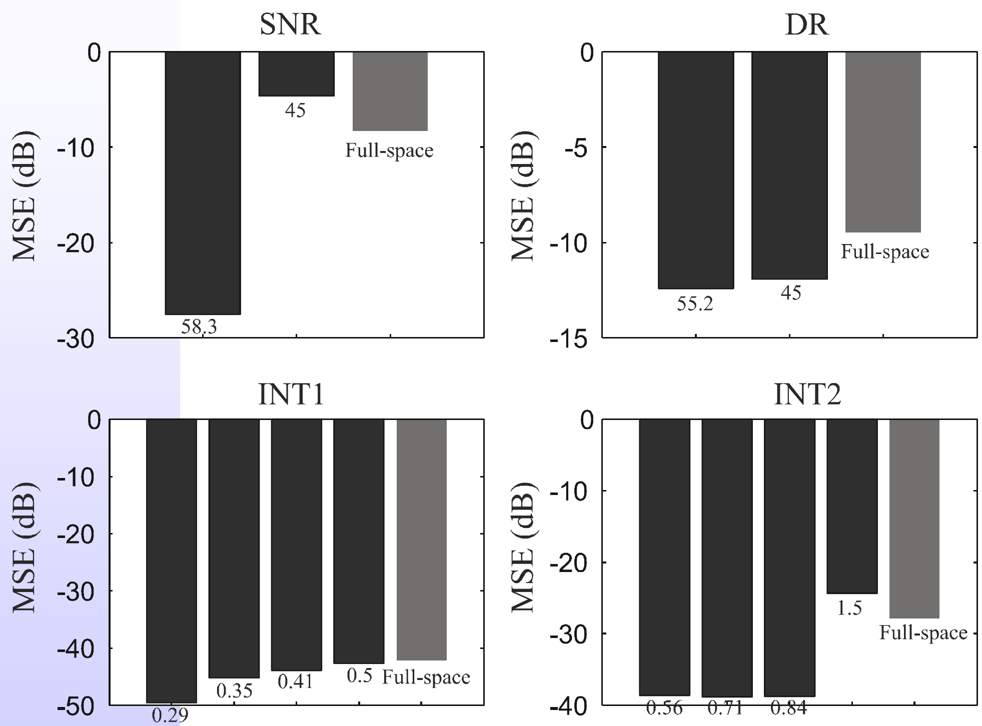


	CGS	RGS
Total time	47:50:46	02:18:04



	CGS	RGS
Total time	49:24:57	66:52:47

Results - training



Approach	Computational cost
Linearly graded	50:08:50 (classification) 49:27:57 (regression CGS)
Full-space analysis	190:44:11 (CGS only)

Results - testing

Parameter		Testing1	Testing2
SNR	Classification accuracy	66.72%	78.73%
DR		74.5%	62.7%
INT1		87.7%	97.1%
INT2		78%	99.6%
Stability		98.4%	100%
SNR_55.3	Regression accuracy (mean squared error dB)	-5	-26
SNR_45		-	-
DR_55.2		-11	-6
DR_45		-	-5
INT1_0.29		-	-29
INT1_0.35		-43	-47
INT1_0.41		-37	-50
INT1_0.5		-38	-
INT2_0.56		-28	-20
INT2_0.71		-28	-29
INT2_0.84		-26	-
INT2_1.5		-14	-

Conclusion and further work

- A new concept for performance analysis has been introduced: linearly graded performance models
- A suitable modeling process has been developed
- Demonstrated by a case study of a difficult AMS system: 2nd order SDM.

- AMS performance optimization is possible – next step towards a general AMS synthesis system.
- More work needed on grading algorithms
- More work to explore the trade-off between model construction computational cost and prediction accuracy