

Comparison of performance for PLSR and neural net modelling on process data

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Introduction

Multivariate techniques can be applied to detect bias changes, drift and higher levels of noise in process instruments and sensors. Principal components analysis (PCA), partial least squares regression (PLSR) and neural net modelling are examples of such techniques. Multiple sensor failures is however a problem, since one failure (or process disturbance) can mask another. Different techniques, recalibration with a reduced data set and "replacement matrices", have been proposed as a remedy to these obstacles¹⁻². Another approach is to use robust process models for sensor failure detection such as neural nets. These models will degrade more gradually when exposed to multiple sensor failures or process disturbances.

Objective, measurement data and software

The objective of this study was to compare different modelling techniques, PLS-regression and feed-forward neural nets, with regard to "robustness" to systematic or random errors in the input data.

Process modelling was based on measurement data from three different solid-fuel combustion units. The amount of process variables varied between 10-30 and the total number of measurement values were about 150000. For each facility PLSR1- and feed-forward neural net models were calculated for a number of important process and emission variables, such as load, temperatures and the content of oxygen, carbon dioxide, carbon monoxide, ammonia and nitrogen oxides in the flue gas.

PLSR modelling was performed using *The Unscrambler*TM from CAMO A/S, and neural nets with *NeuroShell 2* from Ward Systems Group, Inc. Robust PLSR-models was developed using the macro system in combination with the extensive data editing functions in *The Unscrambler*TM. Modelling was in both cases done on a PC, but the neural nets were trained using an accelerator board with a DSP-RISC-processor.

Results - standard PLSR1-model and neural net

This presentation will focus on only one variable in one of the plants, the furnace temperature in a waste-to-energy plant. The general results and conclusions are comparable for the other investigated variables and plants.

PLSR1- and neural net models (test set validated) could explain between 80-90% of the variance in furnace temperature based on measurements for the other 22 process variables. Prediction results based on recorded and undisturbed process data were comparable for all the investigated modelling techniques, figure 1.

To investigate the sensitivity to disturbances two simulations were done. First noise (5% proportional) was added to all of the independent variables, and secondly a strong systematic disturbance was introduced to another correlating temperature measurement (200° C).

Both models were affected by the simulated noise and systematic error, but the neural net was more robust and could still be used while the PLSR1-model deteriorated completely.

Results - comparison to a robust PLSR1-model

A standard PLSR-model can be made somewhat more robust by introducing noise in the calibration phase, but in the investigated processes this improvement was of minor importance. On the other hand, by introducing and combining both different non-linear transformations and signal filtration techniques it was possible to calculate a "robust" PLSR1-model that had least the same performance as the neural net model. Standard deviations of residuals and biases are compared in table 1, both for the normal situation and with the simulated noise and error.

Table 1

Comparison of modelling techniques.

	SED_{norm}	SED_{noise}	SED_{syst}	$Bias_{syst}$
Standard PLSR1	25.1	511	25.1	-54.0
Neural net	18.5	46.2	34.4	-4.17
Robust PLSR1	21.0	33.5	31.7	-8.05

In figures 1-3 the behaviour of the robust PLS-model is shown for normal data as well as with simulated noise and systematic errors.

Conclusions and acknowledgement

Multivariate techniques can be used for the detection of sensor and instrument failures. Multiple failures can be complicated to handle in practice, but robust models offer a direct and simple way since no recalibration or recalculation will be needed to begin with.

Robust PLS-models can be calculated with an industry standard software, *The UnscramblerTM*, and have shown comparable performance and robustness to feed-forward neural nets.

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References

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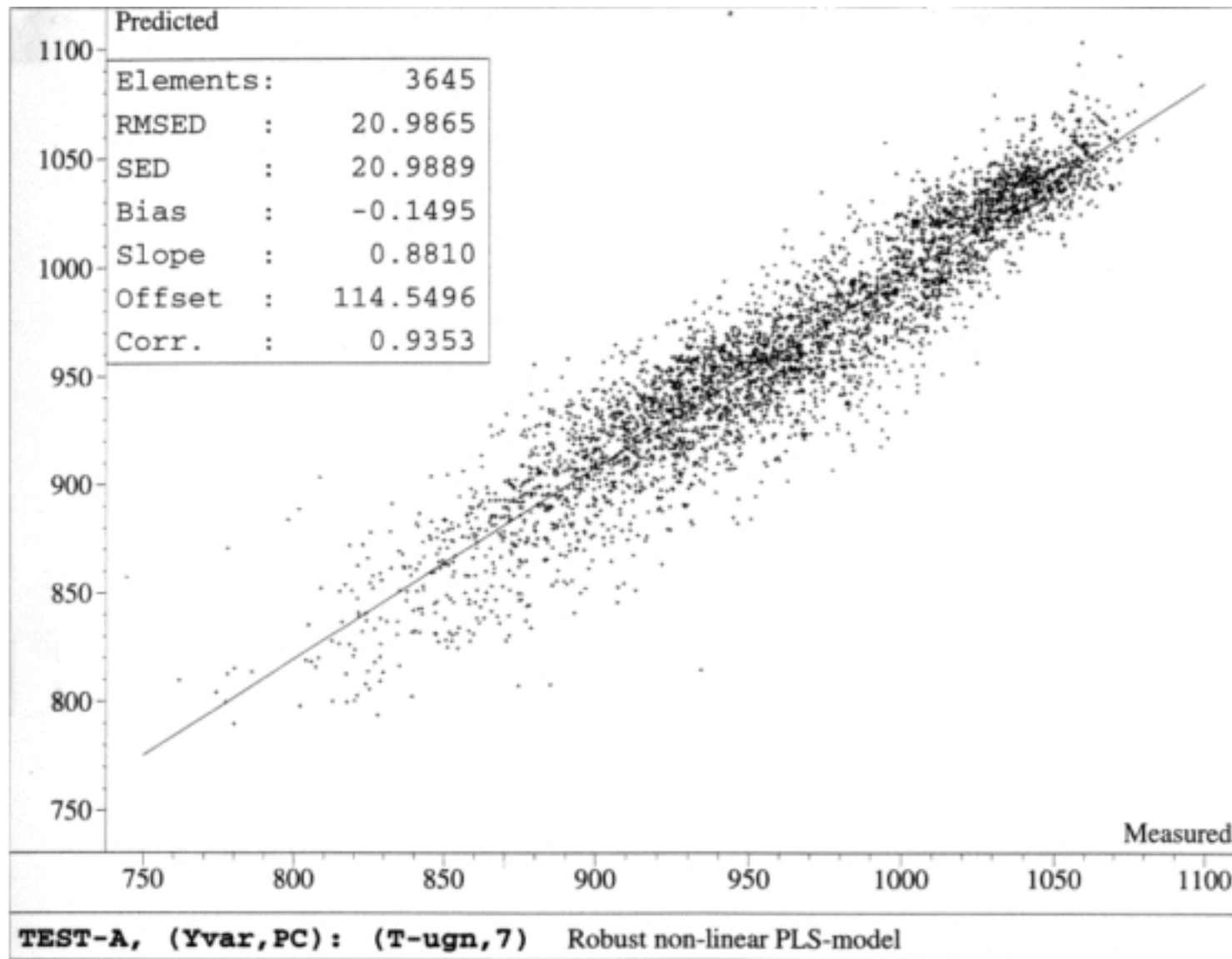


Figure 1
Prediction results for robust PLSR1-model, normal process data.

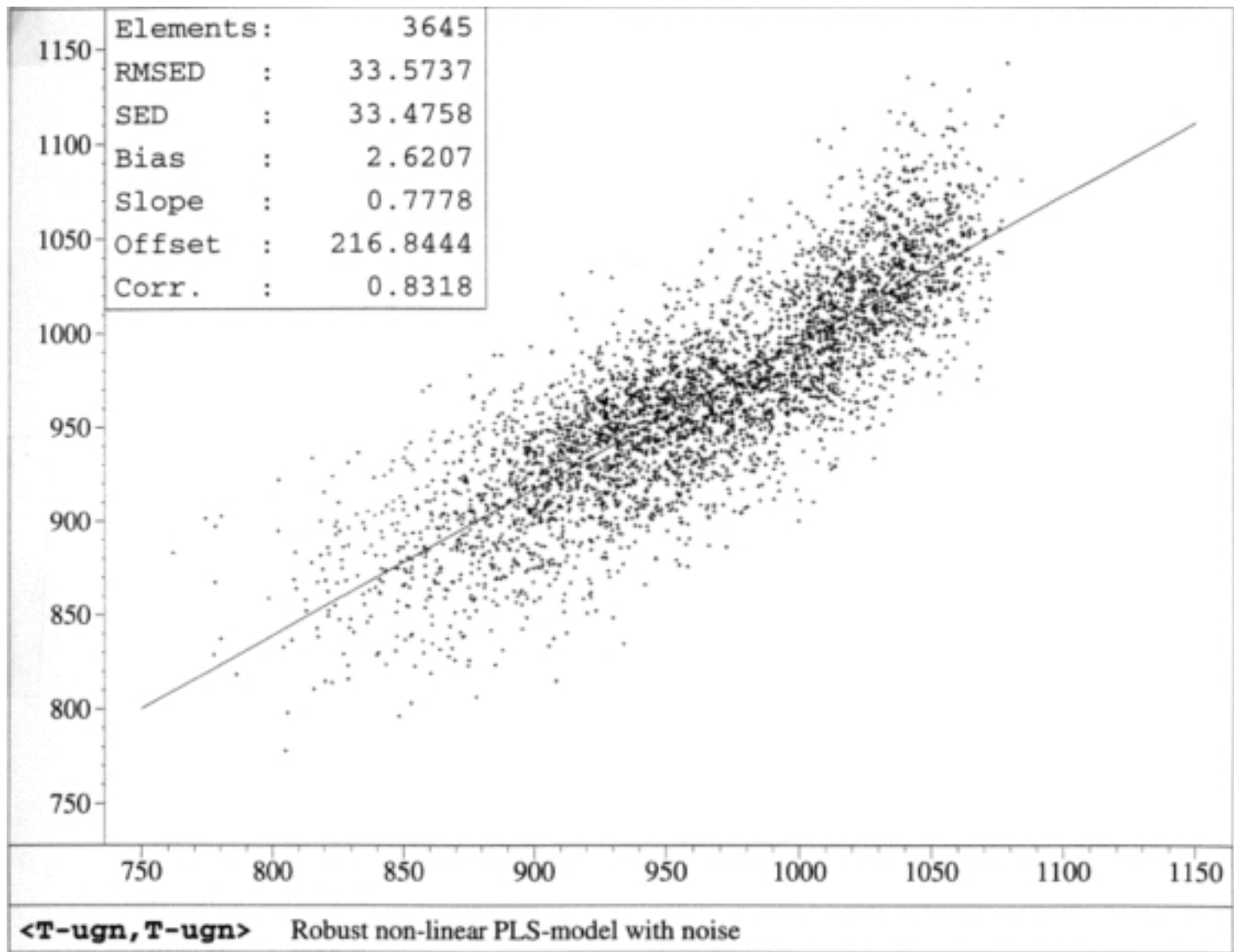


Figure 2
Prediction results for robust PLSR1-model, with noise.

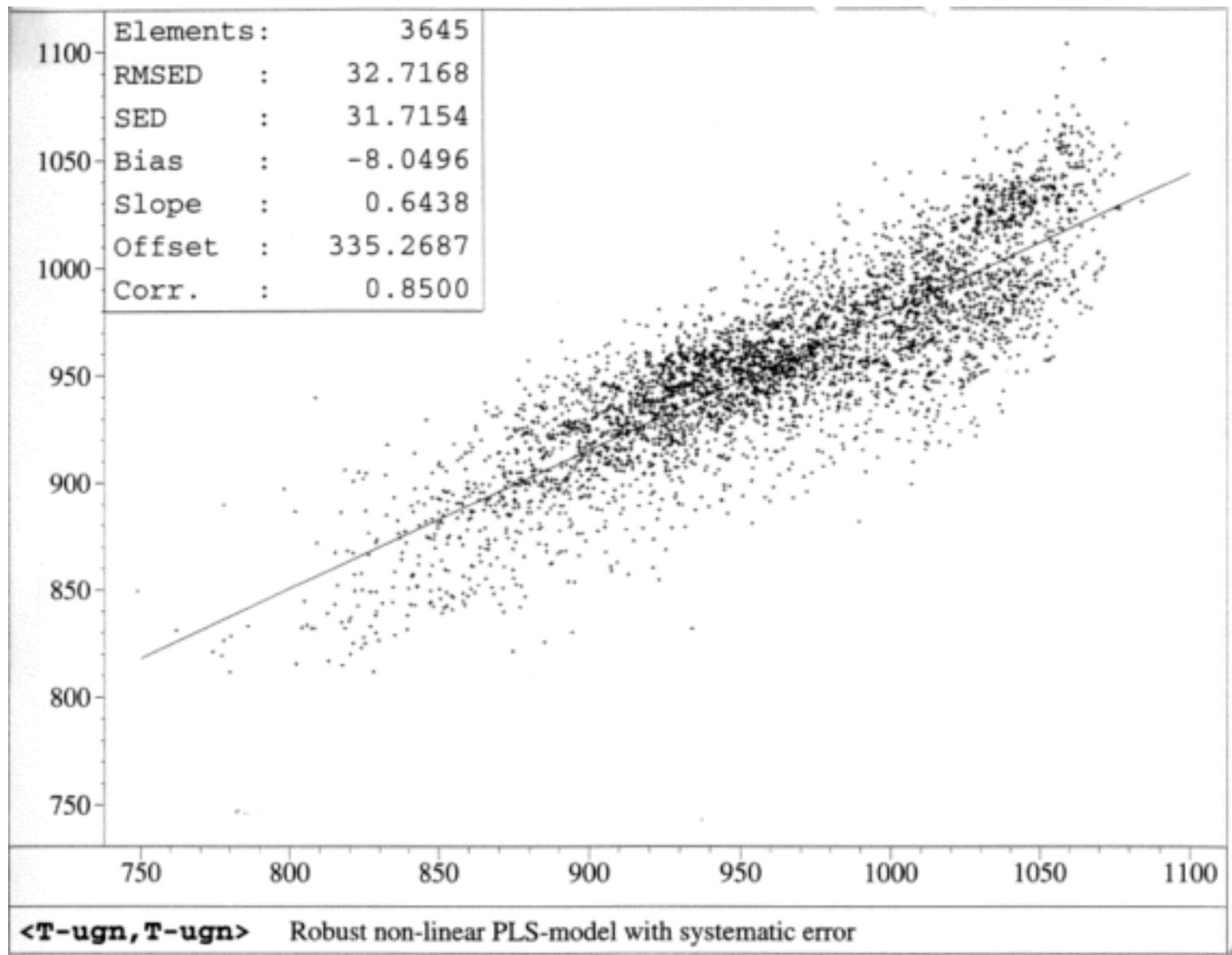


Figure 3
Prediction results for robust PLSR1-model, with systematic error.