Study Committee C4

Power System Technical Performance

Paper 10817

Non-invasive testing of performance and stability of frequency containment reserves through machine-learning classification

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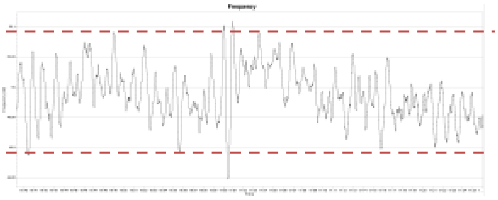
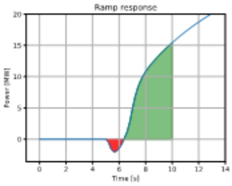
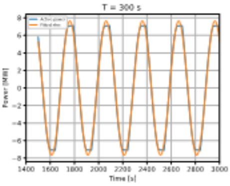
Motivation

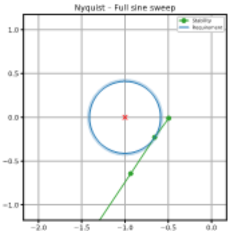
- The frequency quality has over time been deteriorating in the Northern European synchronous area, leading to increased time out of the standard range, and super-imposed oscillations
- Caused by several factors, incl. badly tuned governors and decreasing system inertia
- Remedy is new technical requirements, including more cumbersome and time-consuming testing
- This paper has investigated the possibility to instead apply non-invasive testing through machine-learning classification of data from normal operation
- The method should keep physical interpretability and transparency



Performance circles	Performance sensitivity	Performance Bode
[illegible]	[illegible]	[illegible]
Stability circles	**Stability sensitivity**	**Stability Nyquist**
[illegible]	[illegible]	[illegible]

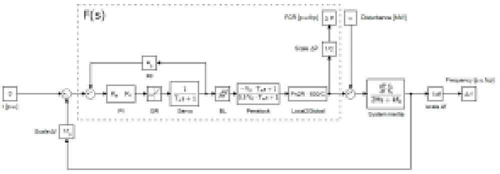






Modelling and simulations

- Not-enough real world data was available, so a simulated hydro power plant was used for data generation
- The properties of the plant and the governor were varied, to generate a distribution of allowed and non-allowed responses.
- The impact of varying quality of measurements, e.g. sampling rate and noise, were also studied through the model



Machine-learning classification

- Five ML-methods investigated
  - Decision tree
  - Random forest
  - Adaboost of decision tree
  - Support vector machine
  - Deep neural network
- Hyper-parameter tuning applied
- KPIs in time and frequency domain developed to use as features for the ML classifiers
- Feature selection investigated

Standard deviation of the power signal	$\sigma_p = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\Delta P_i - \overline{\Delta P})}$	Quotient arc length P(t), arc length f(t)	$\frac{l_p}{l_f}$
Standard deviation of the frequency signal	$\sigma_f = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\Delta f_i - \overline{\Delta f})}$	Correlation coefficient P(t), f(t)	$r = \frac{\mathrm{Cov}(\Delta P, \Delta f)}{\sqrt{\mathrm{Var}(\Delta P)\cdot \mathrm{Var}(\Delta f)}}$
Quotient σ_p and σ_f	$\frac{\sigma_p}{\sigma_f}$	Cross correlation P(t), f(t)	$(f \star g)(\tau) = \int_{-\infty}^{\infty} f^*(t)\cdot g(t+\tau)dt$
Relative arc length f(t)	$l_f = \frac{1}{(t_1-t_0)}\int_{t_0}^{t_1}\sqrt{1+\left(\frac{d\Delta f}{dt}\right)^2}\,dt$	R^2 value for regression	$R^2 = 1 - \frac{\sum_{i=1}^{N}(\Delta P_i - \hat{\Delta P}_i)^2}{\sum_{i=1}^{N}(\Delta P_i - \overline{\Delta P})^2}$
Relative arc length P(t)	$l_p = \frac{1}{(t_1-t_0)}\int_{t_0}^{t_1}\sqrt{1+\left(\frac{d\Delta P}{dt}\right)^2}\,dt$		

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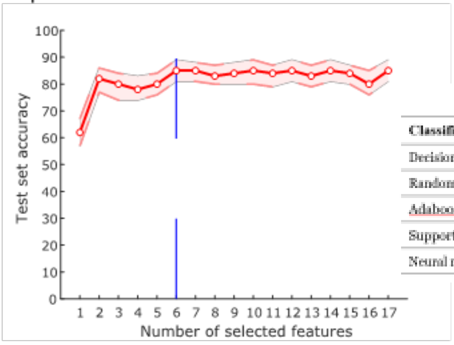
Classification accuracy

Classifier	Linear	Non-linear	Non-linear with noise	Sub-sampled with noise (1 s)	Sub-sampled with noise (3 s)
Decision tree	79	80	74	72	76
Random forest	85	82	78	78	77
Adaboost	83	80	74	72	73
Support vector machine	87	82	80	80	79
Neural network	88	80	78	78	78

Discussion: Classification accuracy

- General trend is decreasing accuracy as modelling complexity increases
- Accuracy not so sensitive to sub-sampling of data
- Adaboost and Decision tree consistently performing worse
- Random forest, Support vector machine, and the neural network taken to be about equally promising
- Similar accuracies for the latter 3, combined with confidence interval widths of about 7%, indicates that the amount of training data has been limiting during the training process

Impact of feature selection on test set accuracy



Classifier	After feature selection: Accuracy (%)	After feature selection: 95 % CI (%)	Before feature selection: Accuracy (%)	Before feature selection: 95 % CI (%)
Decision tree	74	70-77	71	67-75
Random forest	78	75-82	76	72-79
Adaboost	74	70-77	75	72-79
Support vector machine	80	77-83	75	71-78
Neural network	78	74-82	78	73-81

Discussion: Feature selection

- The feature selection resulted in a drastically reduced number of selected features for all classifiers and over all the models.
- The 18 features were reduced to at the most 9 selected features at the higher end.
- At the lower end, 3 selected features were enough for the neural network to achieve 88 % accuracy on the linear model.
- The effect of feature selection on classification accuracy has been quite small as indicated above, mostly increasing the accuracy slightly.

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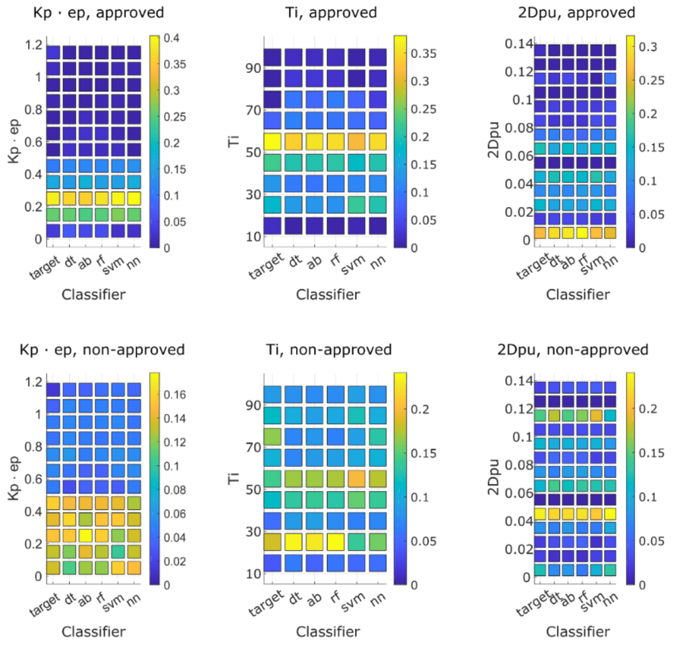
Normalized parameter distributions after classification
(Δt = 3 s)



Discussion: Parameter distributions

- The ability to preserve the distribution of the physical parameters K_p, T_i, ep, b was investigated
- Mostly small deviations appearing in the data relative to the target
- All methods have had some problems with T_i in the general region of 40-80 s

Conclusion

- The examined methods were to be non-invasive while keeping the physical interpretability and transparency
- The classification accuracy started at up to 88 % on the linear model, steadily declining through increasing model complexity to end at up to 79 % on the non-linear model with noise and 3 s sample interval
- The methods have all been shown to be slightly too generous with classification in the sense that more samples that should have been approved actually did become classified as such
- The parameter distributions have indicated that the errors from the classifiers are to be seen mostly as random
- The general conclusion is that the proposed methodology has potential to act as a complement to the evaluation process