Data-Driven Fault Diagnosis and Fault Tolerant Control of Wind Turbines

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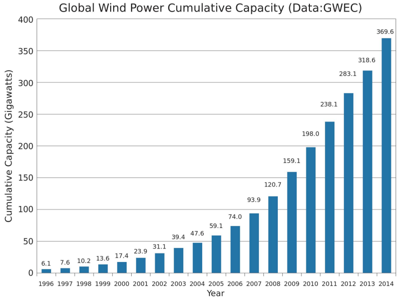
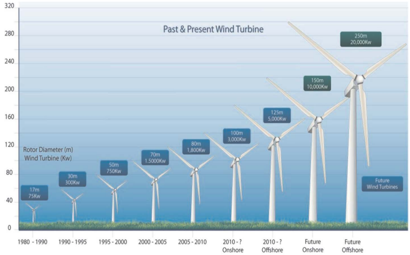
Motivations: Statistics



The global wind energy installed capacity has increased by 400% in the last decade.



Size and complexity of wind turbines are expected to widely grow in the near future.

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Motivations: Requirements of Offshore Installations

- **Efficiency**: in the generation of electrical power;
- **Reliability**: reduce Operation and Maintenance services;
- **Safety**: reduce risk of endangering people, equipment, and environment.

In one word:

Sustainability (Sustainable Control)

- In case of fault occurrence, the energy production cost can increase up to 30%,

Nomenclature: Signals and Tasks

- **Fault**: an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable, usual, or standard conditions;
- **Residual**: a fault indicator, based on a deviation between measurements and model-equation-based computations.
- **Fault Detection**: determination of the presence of faults and the time of occurrence;
- **Fault Isolation**: determination of the kind, location and time of detection of a fault;
- **Fault Diagnosis (FDD)**: determination of the kind, size, location and time of detection of a fault;
- **Fault Tolerance**: capability to automatically manage the faults affecting the system;

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Objectives and Methods

Sustainable control of wind turbines:

Design of a Fault Tolerant Control (FTC) system, able to guarantee the tracking of the desired power reference, even in presence of system faults.

Design

- **Active FTC**: includes a FDD system;
- **FDD**: data-driven approaches:
  - Fuzzy Takagi Sugeno models;
  - Artificial Neural Network models.

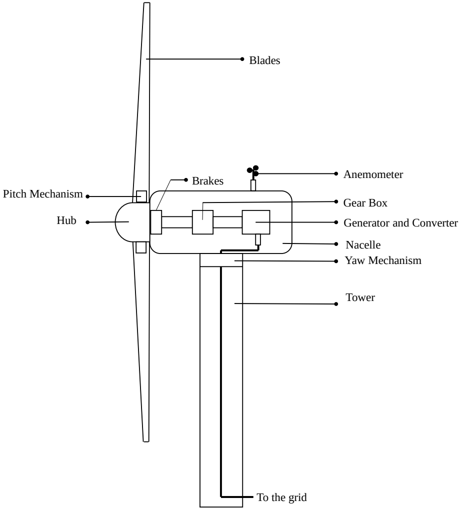
Simulation

- Single wind turbine benchmark
- Wind farm benchmark
- Comparative Analysis

Validation

- Monte Carlo analysis
- Hardware In the Loop (HIL) test

Wind Turbine Components

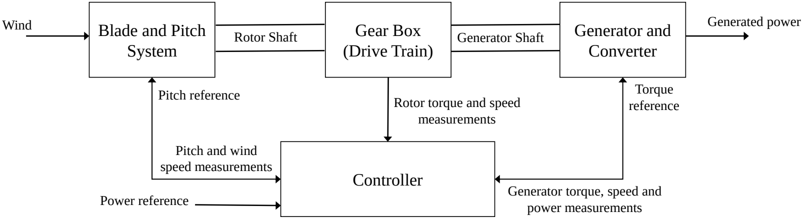


Characteristics:

- upwind;
- three-bladed;
- horizontal axis;
- variable speed;
- pitch controlled;
- full converter configuration.

Wind Turbine Benchmark System: Submodels

Odgaard, P. F., Stoustrup, J., and Kinnaert, M. (2013). Fault-tolerant control of wind turbines: A benchmark model. *Control Systems Technology, IEEE Transactions on*, 21(4):1168-1182.



Turbine submodels:

- Wind;
- Blade and pitch;
- Drive-train;
- Generator;
- Controller;
- Load-carrying structure neglected.

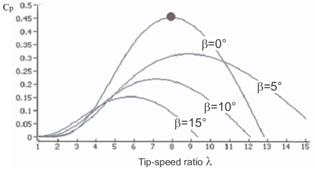
Measurements:

- Redundant Sensors;
- Additive White Gaussian Noise.

Wind Turbine Benchmark System: Power flow

Aerodynamics:

$$P_r(t) = \frac{\rho \pi R^2 C_P(\lambda(t), \beta(t)) v_w^3(t)}{2}$$



Drive-Train:

$$J_r \dot{\omega}_r = \tau_r(t) - K_{dt}\theta_\Delta(t) - (B_{dt} + B_r)\omega_r(t) + \frac{B_{dt}}{N_g}\omega_g(t)$$

$$J_g \dot{\omega}_g = \frac{\eta_{dt} K_{dt}}{N_g}\theta_\Delta(t) + \frac{\eta_{dt} B_{dt}}{N_g}\omega_r(t) - (\frac{\eta_{dt} B_{dt}}{N_g^2} + B_g)\omega_g(t) - \tau_g(t)$$

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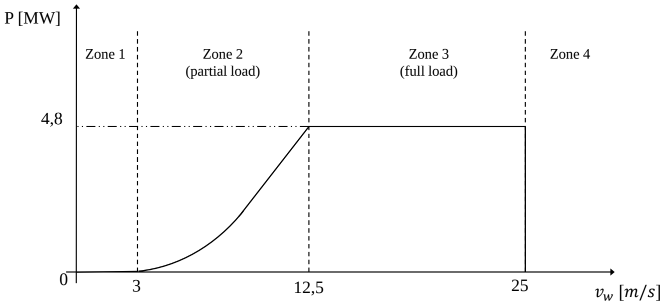
Wind Turbine Benchmark System: Controller



- Cut-in, cut-out: turbine shutdown;
- Partial load: maximized power, τ_g regulation;
- Full load: constant power, β regulation;
- Bumpless transfer mechanism between region 2 and 3.

Wind Turbine Benchmark System: Faults

Fault	Description	Type
1	Fixed value of the blade 1 pitch sensor 1	Sensor fault
2	Scaling error of the blade 2 pitch sensor 2	Sensor fault
3	Fixed value of the blade 1 pitch sensor 1	Sensor fault
4	Fixed value of the rotor speed sensor 1	Sensor fault
5	Combined scaling error of the rotor speed sensor 2 and the generator speed sensor 2	Sensor fault
6	Pitch system changed response for the pitch actuator of the blade 2 due to air content in oil	Actuator fault
7	Pitch system changed response for the pitch actuator of the 3 due to low pressure	Actuator fault
8	Fixed value of the converter torque control signal	Actuator fault
9	Changed dynamics of the drive-train	System fault

Wind Turbine Benchmark System: Overall Model

State-space description:

$$\begin{cases} \dot{\mathbf{x}}_{wt}(t) = \mathbf{f}_{wt}(\mathbf{x}_{wt}, \mathbf{u}(t)) \\ \mathbf{y}(t) = \mathbf{x}_{wt}(t) \end{cases}$$

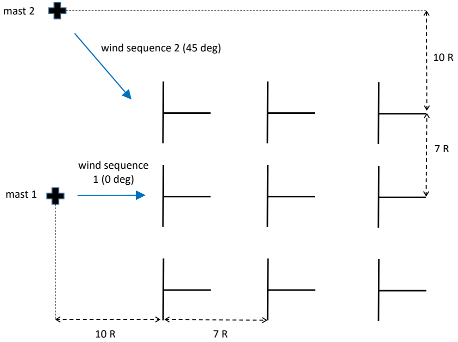
$$\mathbf{x}_{wt}(t) = \mathbf{y}(t) = [\omega_{g,m1}, \omega_{g,m2}, \omega_{r,m1}, \omega_{r,m2}, P_{g,m}]$$

$$\mathbf{u}(t) = [\beta_{1,m1}, \beta_{1,m2}, \beta_{2,m1}, \beta_{2,m2}, \beta_{3,m1}, \beta_{3,m2}, \tau_{g,m}]$$

- Nonlinear behavior;
- Disturbances and uncertainty;
- Faults.

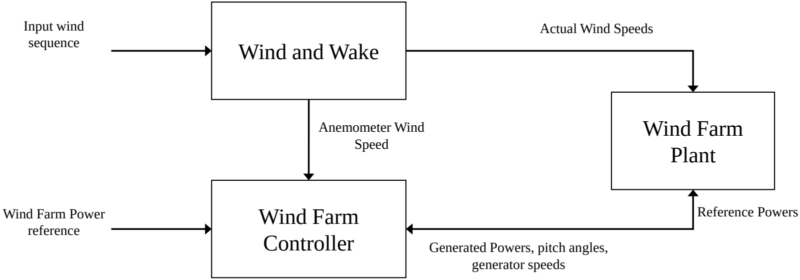
Wind Farm Benchmark System: Layout

Odgaard, P. F. and Stoustrup, J. (2013). Fault tolerant wind farm control. A benchmark model. In *Control Applications (CCA), 2013 IEEE International Conference on*, pages 412-417. IEEE.



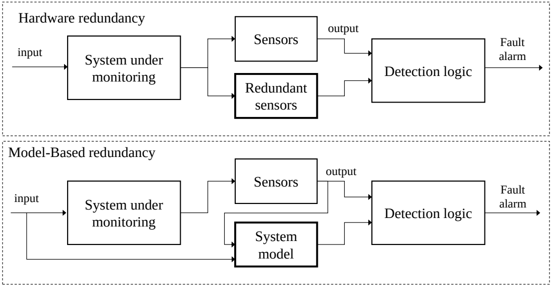
- 9 turbines;
- square grid;
- 2 anemometers;
- 2 wind sequences;

Wind Farm Benchmark System: Submodels and Faults



Fault	Description
1	Pitch actuator signal change
2	Rotor speed sensor bias
3	Generator torque control offset

Data-Driven, Model-Based Fault Diagnosis



Model-Based approach:

- cheapness;
- equipment reduction.

Data-Driven modeling and identification:

- enhanced analytical knowledge limitations;
- manage disturbance and uncertainty;
- fuzzy Takagi-Sugeno (TS) and neural network (NN) models.

Fuzzy Modeling and Identification: TS Models

Fuzzy inference:

$$R_i : \text{IF} \quad x \quad \text{is} \quad A_i \quad \text{THEN} \quad y_i = f_i(x)$$

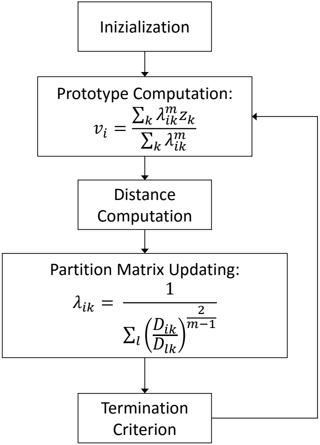
$$y_i = a_i x + b_i$$

Defuzzification

$$y = \frac{\sum_{i=1}^{K} \lambda_i(x) y_i}{\sum_{i=1}^{K} \lambda_i(x)}$$

- Membership functions $\lambda_i \longrightarrow$ *c-means* clustering
- Affine Parameters $a_i, b_i \longrightarrow$ identification procedure

Fuzzy Modeling and Identification: *c-means* Clustering



- Data matrix: $\mathbf{Z} = [\mathbf{z}_k]$
- Partition Matrix: $\mathbf{U} = [\lambda_{ik}]$
- Prototypes: $\mathbf{v} = [\mathbf{v}_i]$
- Distance: $D_{ik}^2 = (\mathbf{z}_k - \mathbf{v}_i)^T (\mathbf{z}_k - \mathbf{v}_i)$
- Goal Function: $J = \sum_{i=1}^{K} \sum_{i=1}^{N} \lambda_{ik}^m D_{ik}^2$

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Fuzzy Modeling and Identification: Parameter Identification

Error In Variable (EIV) model:

Noisy data:

$$u_k = u_k^* + \tilde{u}_k \quad y_k = y_k^* + \tilde{y}_k$$

Regressor:

$$\mathbf{x}_k = [y_{k-1}, \ldots, y_{k-o}, u_{k-1}, \ldots, u_{k-o}]$$

Regressand:

$$\mathbf{a}_i = [\alpha_1, \ldots, \alpha_o, \delta_1, \ldots, \delta_o]$$

Data Matrix:

$$\mathbf{X}^{(i)} = \begin{bmatrix} y_k & \mathbf{x}_k^T & 1 \\ \vdots & \vdots & \vdots \\ y_{k+N_i} & \mathbf{x}_{k+N_i}^T & 1 \end{bmatrix}$$

Frisch scheme:

Covariance Data Matrix:

$$\mathbf{\Sigma}^{(i)} = \mathbf{X}^{(i)^T} \mathbf{X}^{(i)} = \mathbf{\Sigma}^{(i)^*} + \bar{\tilde{\mathbf{\Sigma}}}^{(i)}$$

Covariance Noise Matrix:

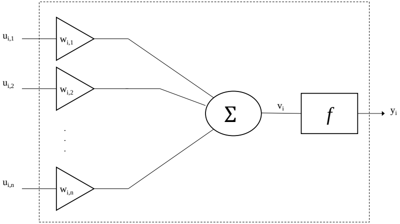
$$\bar{\tilde{\mathbf{\Sigma}}}^{(i)} = \mathbf{diag}\left[\bar{\tilde{\sigma}}_y \mathbf{I}, \bar{\tilde{\sigma}}_\mathbf{u} \mathbf{I}, 0\right]$$

Optimization problem:

$$\left(\mathbf{\Sigma}^{(i)} - \bar{\tilde{\mathbf{\Sigma}}}^{(i)}\right)\mathbf{a}_i = 0$$

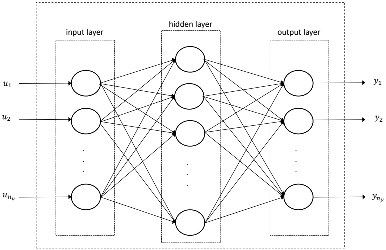
NN Modeling and Identification: Architecture

Neuron:



- $y_i = f_i(\sum_k w_{ik} u_k)$;
- f sigmoidally shaped.

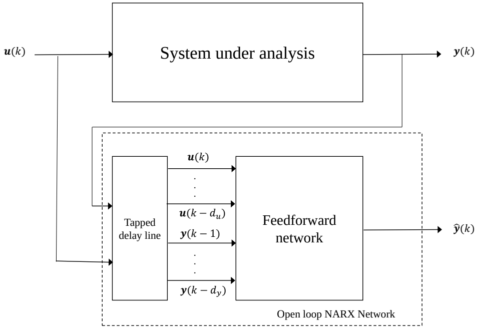
Multilayer Network:



- Three-layer networks;
- Feedforward architecture.

NN Modeling and Identification: NARX Network

Recurrent Network with tapped delay line:



- Trade-off between the delay number and the accuracy of the output reconstruction

NN Modeling and Identification: Training

Problem:

Given a set of P example patterns $(\mathbf{u}_i, \mathbf{t}_i)$, and the network architecture, minimize the cost function $E(\mathbf{w}) = \frac{1}{P}\sum_{p=1}^{P}(\mathbf{t}_i - \hat{\mathbf{y}}_i)^2$, by adjusting the weight vector $\mathbf{w}$

Methods:

- Levenberg-Marquardt (LM) iteration:
  $\mathbf{w}_{k+1} = \mathbf{w}_k - \left(\mathbf{J}_k^T \mathbf{J}_k + \mu \mathbf{I}\right)^{-1} \mathbf{J}_k \bar{\mathbf{e}}_k$
- Backpropagation: Jacobian $\mathbf{J}_k$ computation

Fault Mode and Effect Analysis (FMEA)

- Faults modeled as actuator or output (sensor) additive unknown signals
- Execution of a set of single-fault simulations
- Computation of the sensitivity index $S_x = \frac{\|x_f[k] - x_n[k]\|}{\|x_n[k]\|}$
- Selection of the most affected input and output signals;
- Reduction of FDI complexity.

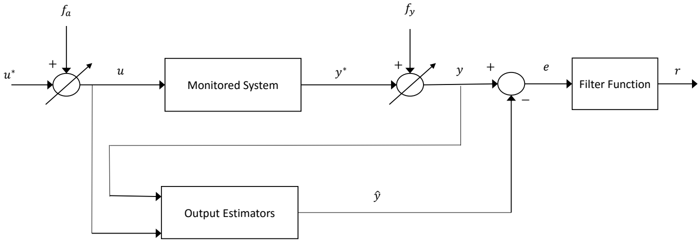
Wind Turbine:

Fault	Sel. Inputs	Sel. Outputs
1	$\beta_{1,m1}$, $\beta_{1,m2}$	$\omega_{g,m2}$
2	$\beta_{1,m2}$, $\beta_{2,m2}$	$\omega_{g,m2}$
3	$\beta_{1,m2}$, $\beta_{3,m1}$	$\omega_{g,m2}$
4	$\beta_{1,m2}$	$\omega_{g,m2}$, $\omega_{r,m1}$
5	$\beta_{1,m2}$	$\omega_{g,m2}$, $\omega_{r,m2}$
6	$\beta_{1,m2}$, $\beta_{2,m1}$	$\omega_{g,m2}$
7	$\beta_{1,m2}$, $\beta_{3,m2}$	$\omega_{g,m2}$
8	$\beta_{1,m2}$, $\tau_{g,m}$	$\omega_{g,m2}$
9	$\beta_{1,m2}$	$\omega_{g,m1}$, $\omega_{g,m2}$

Wind Farm:

Fault	Sel. Measurements
1	β_2, $P_{g,2}$, β_7, $P_{g,7}$, $v_{w,m}$
2	β_1, $\omega_{g,1}$, β_5, $\omega_{g,5}$, $v_{w,m}$
3	β_6, $P_{g,6}$, β_8, $\omega_{g,8}$, $v_{w,m}$

Fault Detection

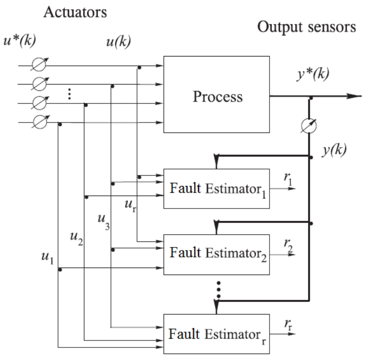


- Error computation: $e = y - \hat{y}$;
- Residual generation $r = f(e)$;
- Threshold logic:

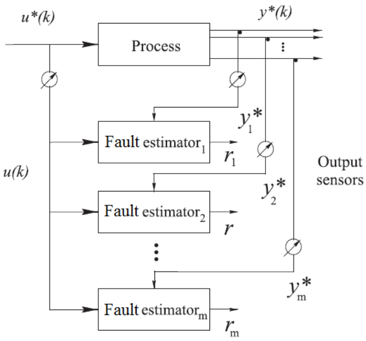
$$\begin{cases} \bar{r}_i - \delta\sigma_{r_i} \leq r_i \leq \bar{r}_i + \delta\sigma_{r_i} & \text{fault-free} \\ r_i < \bar{r}_i - \delta\sigma_{r_i} \text{ or } r_i > \bar{r}_i + \delta\sigma_{r_i} & \text{faulty} \end{cases}$$

Fault Isolation

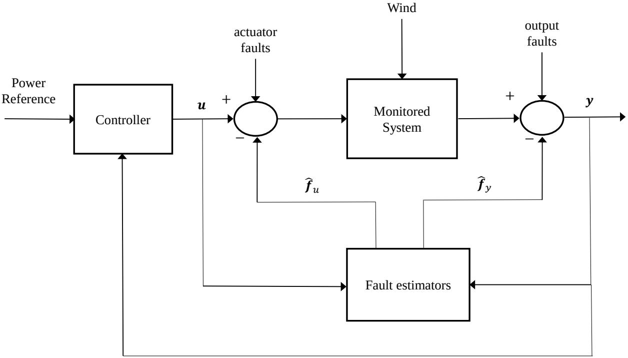
Actuator fault isolation, generalized observer scheme:



Output fault isolation, dedicated observer scheme:

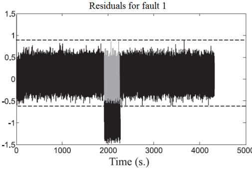


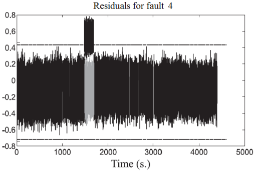
Fault Tolerant Control

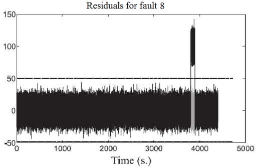


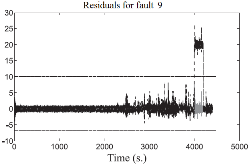
- Fault accommodation;
- Controller designed in fault-free conditions.

Wind Turbine FDD: Fuzzy Residual





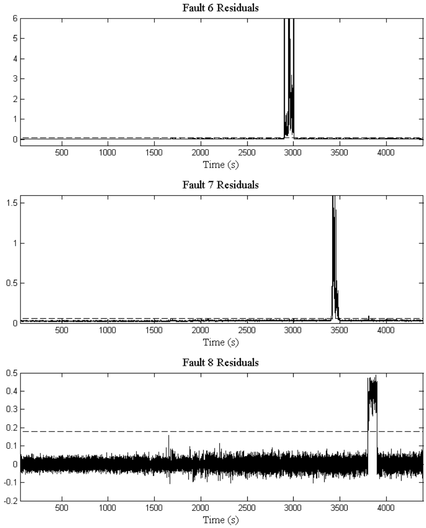




$$\textbf{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y-\hat{y})^2}$$

Fault	RMSE
1	0.016
2	0.023
3	0.021
4	0.020
5	0.019
6	0.021
7	0.017
8	0.021
9	0.019

Wind Turbine FDD: NN Residual



Fault	RMSE
1	0.009
2	0.009
3	0.009
4	0.012
5	0.011
6	0.011
7	0.009
8	0.009
9	0.014

Monte Carlo Analysis

Typical parameter variations:

Parameter	Nominal Value	Min. Error	Max. Error
ρ	$1.225\,\mathrm{Kg/m^3}$	$\pm 0.1\%$	$\pm 20\%$
J	$7.794 \times 10^6\,\mathrm{Kg/m^3}$	$\pm 0.1\%$	$\pm 30\%$
C_p	C_{p0}	$\pm 0.1\%$	$\pm 50\%$

Performance indices:

- False Alarm Rate (FAR);
- Missed Fault Rate (MFR);
- True FDI Rate (TFR);
- Mean FDI Delay (MFD).

Comparative Analysis: Related Works

Gaussian Kernel Support Vector machine (GKSV):

Laouti, N., Sheibat-Othman, N., and Othman, S. (2011). Support vector machines for fault detection in wind turbines. In *Proceedings of IFAC world congress*, volume 2, pages 7067-707.

Estimation-Based (EB):

Zhang, X., Zhang, Q., Zhao, S., Ferrari, R. M., Polycarpou, M. M., and Parisini, T. (2011). Fault detection and isolation of the wind turbine benchmark: An estimation-based approach. In *Proceedings of IFAC world congress*, volume 2, pages 8295-8300.

Up-Down Counters (UDC):

Ozdemir, A. A., Seiler, P., and Balas, G. J. (2011). Wind turbine fault detection using counter-based residual thresholding. In *Proceedings of IFAC world congress*, volume 18, pages 8289-8294.

Combined Observer and Kalman filter (COK):

Chen, W., Ding, S. X., Sari, A., Naik, A (2011). Observer-based FDI schemes for wind turbine benchmark. In *Proceedings of IFAC world congress*, volume 18, pages 7073-7078.

General Fault Model (GFM):

Svard, C., Nyberg, M., and Stoustrup, J. (2011). Automated design of an FDI system for the wind turbine benchmark. *JCSE-Journal of Control Science and Engineering*, 2012:19.

Comparative Analysis: Results -1-

Fault	Index	GKSV	EB	UDC	COK	GFM	Fuzzy	Neural
1	FAR	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	MFR	0.002	0.003	0.002	0.003	0.002	0.001	0.001
	TFR	0.978	0.977	0.987	0.977	0.982	0.999	0.999
	MFD (s)	0.03	0.03	0.04	10.32	0.05	0.02	0.01
2	FAR	0.234	0.224	0.123	0.003	0.235	0.001	0.228
	MFR	0.343	0.333	0.232	0.029	0.532	0.003	0.001
	TFR	0.657	0.667	0.768	0.971	0.468	0.997	0.999
	MFD (s)	47.24	44.65	69.03	19.32	13.74	0.08	0.08
3	FAR	0.004	0.141	0.123	0.056	0.135	0.003	0.001
	MFR	0.006	0.132	0.241	0.128	0.232	0.008	0.001
	TFR	0.974	0.868	0.769	0.872	0.768	0.992	0.999
	MFD (s)	0.05	0.54	0.05	19.32	0.74	0.02	0.01
4	FAR	0.006	0.005	0.123	0.056	0.236	0.004	0.001
	MFR	0.005	0.006	0.113	0.128	0.333	0.004	0.001
	TFR	0.975	0.994	0.887	0.872	0.667	0.996	0.999
	MFD (s)	0.15	0.33	0.04	19.32	17.64	0.02	0.69
5	FAR	0.178	0.004	0.234	0.256	0.236	0.002	-
	MFR	0.223	0.005	0.254	0.329	0.242	0.003	-
	TFR	0.777	0.995	0.746	0.671	0.758	0.997	-
	MFD (s)	25.95	0.07	0.04	31.32	9.49	0.03	-

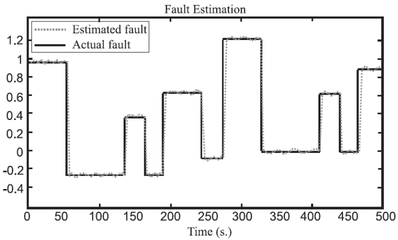
Comparative Analysis: Results -2-

Fault	Index	GKSV	EB	UDC	COK	GFM	Fuzzy	Neural
6	FAR	0.897	0.173	0.334	0.156	0.096	0.042	0.001
	MFR	0.987	0.234	0.257	0.129	0.042	0.033	0.001
	TFR	0.013	0.766	0.743	0.871	0.958	0.967	0.999
	MFD (s)	95.95	11.37	12.94	34.02	9.49	3.03	0.01
7	FAR	0.899	0.044	0.134	0.134	0.123	0.047	0.676
	MFR	0.899	0.035	0.121	0.101	0.098	0.023	0.001
	TFR	0.101	0.965	0.879	0.899	0.902	0.977	0.999
	MFD (s)	99.95	26.17	13.93	35.01	29.79	5.07	6.87
8	FAR	0.004	0.045	0.144	0.109	0.099	0.003	0.466
	MFR	0.007	0.011	0.101	0.032	0.124	0.002	0.001
	TFR	0.993	0.989	0.899	0.968	0.876	0.998	0.999
	MFD (s)	0.07	0.08	0.09	0.06	8.94	0.05	0.20
9	FAR	-	-	-	-	-	0.134	-
	MFR	-	-	-	-	-	0.165	-
	TFR	-	-	-	-	-	0.835	-
	MFD (s)	-	-	-	-	-	0.30	-

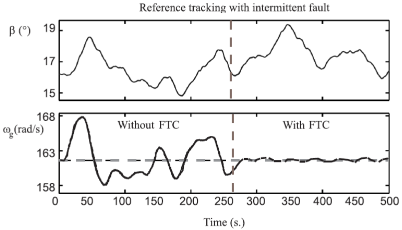
- Fuzzy: detection of fault 9, low MFD, FAR, MFR;
- NN: low MFD, neglectable MFR, medium FAR for fault 2,7,8

Wind Turbine FTC

Simulated fault:



Controller action:



Tracking capabilities:
NSSE=Normalized Sum of Squared Errors

Simulated fault	Best NSSE%	Average NSSE%	Worst NSSE%
1	8.04	11.23	15.05
2	9.01	12.23	14.74
3	7.96	10.35	13.83

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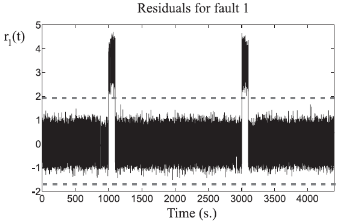
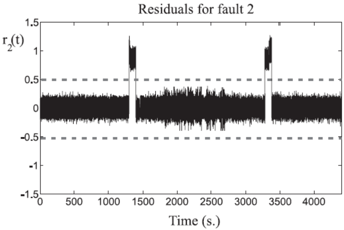
Wind Farm FDD: Fuzzy Residual





PPCRE=Predicted PerCent Reconstruction Error

Data Set	**PPCRE** (%)		
	Fault 1 Estimator	Fault 2 Estimator	Fault 3 Estimator
Estimation	0.90	0.87	0.92
Validation	2.80	1.80	2.10
Test	4.20	3.50	4.00

Comparative Analysis: Related Works and Results

CUmulative SUM (CUSUM):

Borchersen, A., Larsen, J. A., and Stoustrup, J. (2014). Fault detection and load distribution for the wind farm challenge. In *Proceedings of the 19th IFAC World Congress 2014*, pages 4316-4321

Interval Parity Equation (IPE):

Blesa, J., Puig, V., Saludes, J., and Fernandez-Canti, R. M. (2014). Set membership parity space approach for fault detection in linear uncertain dynamic systems. *International Journal of Adaptive Control and Signal Processing*.

MFD

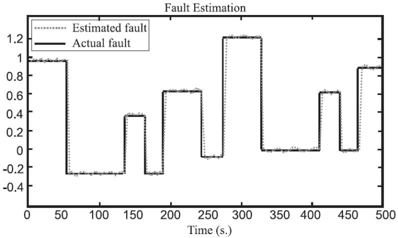
Method	F. 1 (s)	F. 2 (s)	F. 3 (s)
CUSUM	2.2	-	1
IPE	0.8	6.3	1.4
Fuzzy	0.75	0.95	0.60

MFR

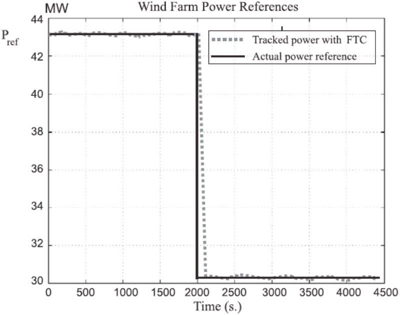
Method	F. 1 (%)	F. 2 (%)	F. 3 (%)
CUSUM	0	-	0
IPE	30	30	60
Fuzzy	0.1	0.3	0.1

Wind Farm FTC

Simulated fault:



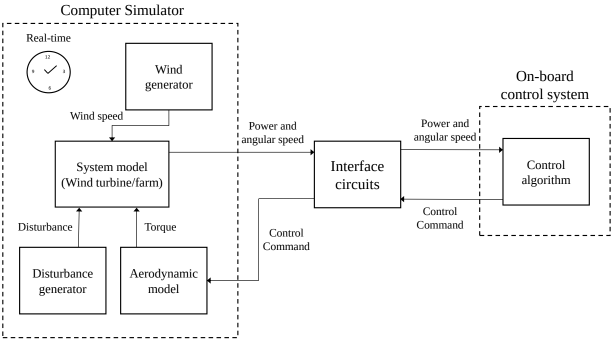
Controller action:



Tracking capabilities: NSSE=Normalized Sum of Squared Errors

Simulated fault	Best NSSE%	Average NSSE%	Worst NSSE%
1	11.14	12.63	14.05
2	12.31	13.63	15.74
3	10.46	11.55	12.73

Hardware In the Loop (HIL) Test: Set-Up



- kk-electronic implementation;
- Computer simulator interacting with on-board electronics;
- Simulated wind, plant, faults and disturbances;
- Real-time scenario.

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HIL Test: Results

Wind Turbine FDD

Fault	FAR	MFR	TFR	MFD
1	0.005	0.005	0.995	0.07
2	0.004	0.004	0.996	0.49
3	0.004	0.004	0.996	0.08
4	0.005	0.005	0.995	0.07
5	0.003	0.004	0.997	0.06
6	0.004	0.005	0.996	0.76
7	0.005	0.004	0.995	0.64
8	0.005	0.004	0.995	0.06
9	0.004	0.005	0.996	0.18

Wind Farm FTC

Fault	Average NSSE%
1	13.74
2	14.37
3	15.01

- Consistency with Monte Carlo analysis;
- Deviations due to numerical accuracy and AD/DA conversions.

Conclusions and further investigations

Conclusions:

- Development of sustainable data-driven FDD, FTC modules;
- Simulation on benchmark systems;
- Validation of the obtained performances.

Further investigations:

- Optimization of FDD modules;
- Controller Design;
- Validation on different simulators;
- Industrial application.

Journal Publications

- Simani, S., Farsoni, S., and Castaldi, P. (2015). Fault diagnosis of a wind turbine benchmark via identified fuzzy models. *Industrial Electronics, IEEE Transactions on*, 62(6):3775-3782.
- Simani, S., Farsoni, S., and Castaldi, P. (2015). Wind turbine simulator fault diagnosis via fuzzy modelling and identification techniques. *Sustainable Energy, Grids and Networks*, 1:45-52.
- Simani, S., Farsoni, S., Castaldi, P. (2014). Residual Generator Fuzzy Identification for Wind Turbine Benchmark Fault Diagnosis. *Machines*, 2(4), 275-298.

Conference Publications

- Simani, S., Farsoni, S., and Castaldi, P. (2014). Residual generator fuzzy identification for wind farm fault diagnosis. In *Proceedings of 19th IFAC World Congress 2014*, pages 4310-4315.
- Simani, S., Farsoni, S., and Castaldi, P. (2015). Fault-tolerant control of an offshore wind farm via fuzzy modelling and identification. *IFAC-PapersOnLine*, 48(21):1345-1350.
- Simani, S., Farsoni, S., and Castaldi, P. (2014). Fault tolerant control of an offshore wind turbine model via identified fuzzy prototypes. *In Control (CONTROL), 2014 UKACC International Conference on*, pages 486-491. IEEE.
- Simani, S., Farsoni, S., Castaldi, P., Mimmo, N. (2015). Active Fault-Tolerant Control of Offshore Wind Farm Installations. *IFAC-PapersOnLine*, 48(21), 1351-1356.
- Simani, S., Farsoni, S., Castaldi, P. (2014, October). Fault tolerant control design for a wind farm benchmark via fuzzy modelling and identification. In *Intelligent Control (ISIC), 2014 IEEE International Symposium on* (pp. 2208-2213). IEEE.
- Simani, S., Farsoni, S., Castaldi, P. (2013, December). Robust actuator fault diagnosis of a wind turbine benchmark model. In *Decision and Control (CDC), 2013 IEEE 52nd Annual Conference on* (pp. 4422-4427). IEEE.

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Conference Publications -2-

- Simani, S., Farsoni, S., Castaldi, P. (2013, October). Active fault tolerant control of wind turbines using identified nonlinear filters. In *Control and Fault-Tolerant Systems (SysTol), 2013 Conference on* (pp. 383-388). IEEE.
- S. Simani, S. Farsoni, M. Bonfè, and P. Castaldi, Fault Diagnosis of Offshore Wind Turbines via Identified Fuzzy Residual Generators, in Proceedings of Automatica.it 2014 - National Congress of the Italian Society of Academics and Researchers in Automatic Control, (Bergamo, Italy), pp. 1-6, University of Bergamo, 8-10 September 2014. Invited paper.
- S. Simani, S. Farsoni, and P. Castaldi, Fault-Tolerant Control of Offshore Wind Farm Installations via Adaptive Nonlinear Filters, in Proceedings of the International Conference on Systems Engineering - ICSE 2015, (Coventry, UK), Control Theory and Applications Centre, Faculty of Engineering and Computing, Coventry University Technology Park, IEEE, Sept. 8-10 2015.
- S. Simani, S. Farsoni, and P. Castaldi, Fuzzy Modelling and Identification for Sustainable Control Design of an Offshore Wind Farm, in Proc. of the 2nd International Conference on Offshore Renewable Energy - CORE 2016, vol. 2016, (Glasgow, UK), pp. 1-10, ASRANet Ltd, UK, 12th-14th September 2016 (accepted).

Other Activities

- **Biomedical Simulation**: Development of an ultrasound simulator with the inertial tracking of the probe pose
  - tracking algorithm;
  - image processing;
  - virtual reality
- **Robotics**: Quaternion-based Kalman filtering for industrial robot load dynamics compensations

Publication:

Farsoni, S., Astolfi, L., Bonfè, M., Spadaro, S. (2015). Design of an ultrasound simulator with probe pose tracking and medical dataset processing and visualization. IFAC-PapersOnLine, 48(20), 377-382.

Under Review:

Farsoni, S., Bonfè, M., Astolfi, L. A Low-Cost High-Fidelity Ultrasound Simulator with the Inertial Tracking of the Probe Pose. Submitted to *Control Engineering Practice*

Farsoni, S., Landi, C., Ferraguti, F., Secchi, C., Bonfè, M. Compensation of Load Dynamics for Admittance Controlled Interactive Industrial Robots using a Quaternion-based Kalman Filter. Submitted to the *International Conference on Intelligent Robots and Systems IROS 2016*

Thank you for your attention.

Questions?