Data Analytics Application Series I: Wind Energy Part III

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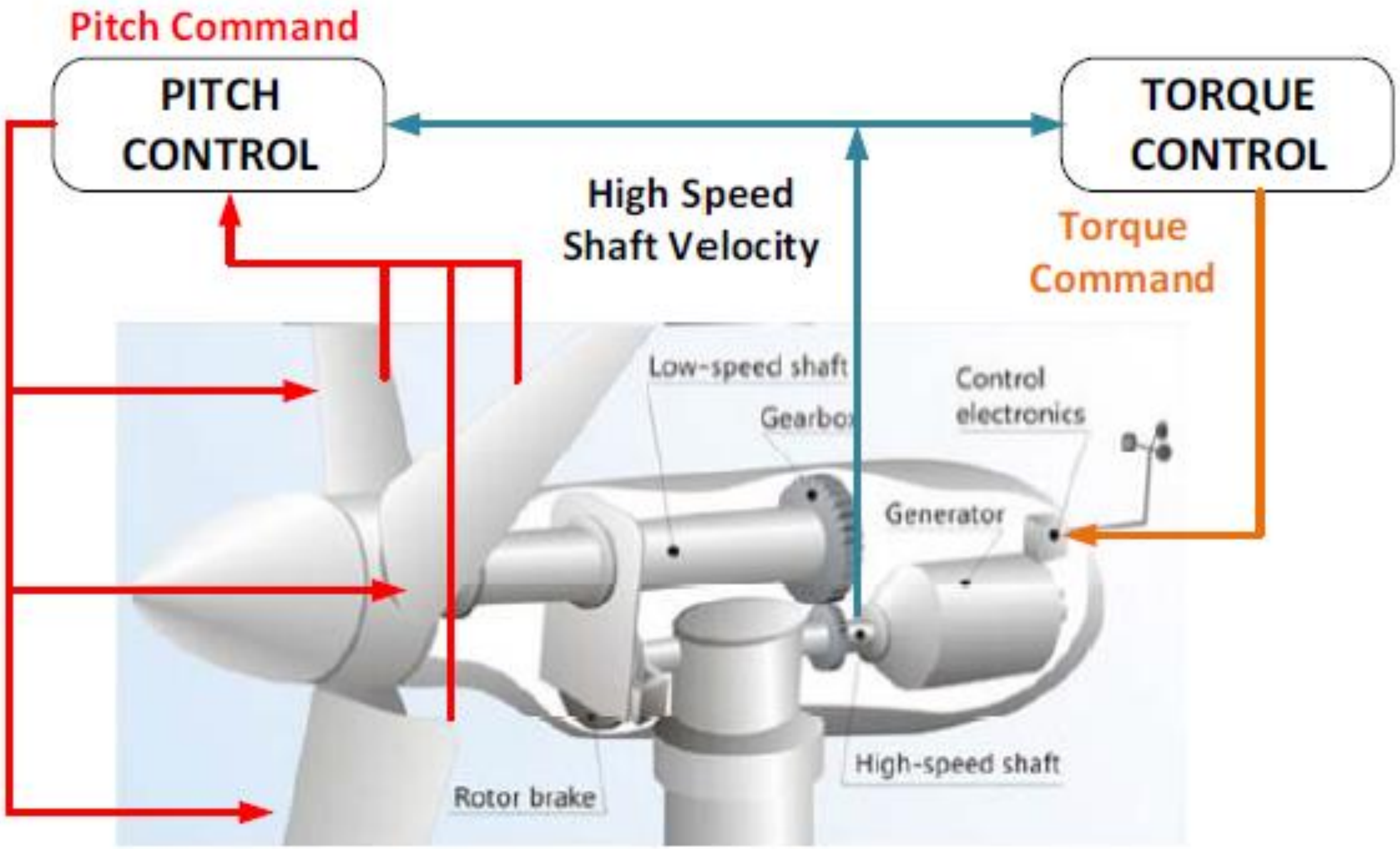
Outline

“Machine Learning + Others” Analytics Framework

- Data-driven wind turbine intelligent control
- Data-driven wind farm operational optimization
- Data-driven wind turbine condition monitoring

Data-driven Wind Turbine Intelligent Control

Data-driven Wind Turbine Intelligent Control



High speed shaft velocity is highly correlated with the power output

Ref: A. Kusiak, Z. Song, and H. Zheng, "Anticipatory Control of Wind Turbines with Data-Driven Predictive Models," IEEE Trans on Energy Conversion, Vol. 24, No. 3, pp. 766-774, 2009.

Data-driven Wind Turbine Intelligent Control

- Wind power generation process can be represented by a triplet (**x**, **v**, **y**)

- **x** is a vector of controllable parameters
- **v** is a vector of non-controllable parameters
- **y** is a vector of response parameters

- **y** = f(**x**, **v**) and f(·) needs to be identified, traditionally based on studying system dynamics and now from data

Data-driven Wind Turbine Intelligent Control

Dynamic Equations:

$$y_1(t) = f_1(y_1(t-1), x_1(t), x_1(t-1), x_2(t), x_2(t-1), v(t), v(t-1)) \quad (1)$$

$$y_2(t) = f_2(y_2(t-1), x_1(t), x_1(t-1), x_2(t), x_2(t-1), v(t), v(t-1)) \quad (2)$$

Predictive Models:

$$y_1(t+1) = f_1(y_1(t), x_1(t+1), x_1(t), x_2(t+1), x_2(t), v(t+1), v(t)) \quad (3)$$

$$y_2(t+1) = f_2(y_2(t), x_1(t+1), x_1(t), x_2(t+1), x_2(t), v(t+1), v(t)). \quad (4)$$

Data-driven Wind Turbine Intelligent Control

Future state of non-controllable parameters needs to be predicted. A simple time-series model can be applied:

$$v(t) = g(v(t-1), v(t-2), \ldots, v(t-n_v)) \qquad (5)$$

Data-driven Wind Turbine Intelligent Control

- The first question we have is the identification of those f(·)

- Data-driven modeling process discussed in the previous lecture
  - Feature selection – domain knowledge
  - Model selection – a comparative analytics

- Such modeling process is identical to all individual wind turbines

Data-driven Wind Turbine Intelligent Control

Data-driven models serve as a based for studying a control problem

Wind turbine power output optimal control

$$y_1^*(t) = f_1(y_1(t-1), x_1^*(t), x_1(t-1), x_2^*(t), \\ x_2(t-1), v(t), v(t-1))$$

$$y_1^*(t+1) = f_1(y_1^*(t), x_1^*(t+1), x_1^*(t), x_2^*(t+1), \\ x_2^*(t), v(t+1), v(t)).$$

Wind turbine rotor speed optimal control

$$y_2^*(t) = f_2(y_2(t-1), x_1^*(t), x_1(t-1), x_2^*(t), \\ x_2(t-1), v(t), v(t-1))$$

$$y_2^*(t+1) = f_2(y_2^*(t), x_1^*(t+1), x_1^*(t), x_2^*(t+1), \\ x_2^*(t), v(t+1), v(t)).$$

Data-driven Wind Turbine Intelligent Control

Recast optimal control problem into an optimization problem with first designing the objective functions

$$J_{\text{power}} = w_{y_1} \left| y_1^*(t) - 1600 \right| + (1 - w_{y_1}) \left| y_1^*(t+1) - 1600 \right|$$

$$J_{\text{rotor}} = w_{y_2} \left| y_2^*(t) - y_2(t) \right| + (1 - w_{y_2}) \frac{\left| y_2^*(t+1) - y_2^*(t) \right|}{h}$$

Integrate two objective functions into one

$$J = wJ_{\text{power}} + (1 - w)J_{\text{rotor}}$$

Data-driven Wind Turbine Intelligent Control

Refining objective functions by integrating the estimation from the aerodynamics model

$$
\begin{aligned}
J_{\text{power}} = &\, w_{y_1} \left| y_1^*(t) - \min\{1600, 2.625 v(t)^3\} \right| \\
&+ (1 - w_{y_1}) \left| y_1^*(t+1) - \min\{1600, 2.625 v(t+1)^3\} \right|.
\end{aligned}
$$

Data-driven Wind Turbine Intelligent Control

Complete optimization model formulation

$$\min_{x_1^*(t), x_2^*(t), x_1^*(t+1), x_2^*(t+1)} J(\bullet)$$

subject to

$$\begin{aligned}
y_1^*(t) &= f_1(y_1(t-1), x_1^*(t), x_1(t-1), x_2^*(t), x_2(t-1), \\
&\qquad v(t), v(t-1)) \\
y_1^*(t+1) &= f_1(y_1^*(t), x_1^*(t+1), x_1^*(t), x_2^*(t+1), x_2^*(t), \\
&\qquad v(t+1), v(t)) \\
y_2^*(t) &= f_2(y_2(t-1), x_1^*(t), x_1(t-1), x_2^*(t), x_2(t-1), \\
&\qquad v(t), v(t-1)) \\
y_2^*(t+1) &= f_2(y_2^*(t), x_1^*(t+1), x_1^*(t), x_2^*(t+1), x_2^*(t), \\
&\qquad v(t+1), v(t)) \\
v(t) &= g(v(t-1), v(t-2), v(t-6)) \\
y_2^*(t+1) &\le 23, y_2^*(t) \le 23 \\
y_1^*(t+1) &\le \min\left\{1600, 2.625v(t+1)^3\right\}, \\
y_1^*(t) &\le \min\left\{1600, 2.625v(t)^3\right\} \\
x_2^*(t) &\le 10090, x_2^*(t+1) \le 10090, |x_2^*(t) - x_2(t)| \le 4500 \\
x_1^*(t) &\le 15, x_1^*(t+1) \le 15. \qquad (11)
\end{aligned}$$

Data-driven Wind Turbine Intelligent Control

Solving the previous optimization model is challenging due to

- Data-driven models are non-parametric and nonlinear
- Existing exact solution methods are not applicable

Solving via the heuristic search which does not require explicit form of the optimization model

Data-driven Wind Turbine Intelligent Control

Evolutionary strategy algorithm – Description of the set-up

The general form of the jth individual in the evolutionary strategy algorithm is defined as $(\boldsymbol{z}^j, \boldsymbol{\sigma}^j)$, where $\boldsymbol{z}^j$ and $\boldsymbol{\sigma}^j$ are two vectors with four entries, i.e., $\boldsymbol{z}^j = (x_1^{*,j}(t), x_1^{*,j}(t+1), x_2^{*,j}(t), x_2^{*,j}(t+1))^T$ and $\boldsymbol{\sigma}^j = (\sigma_1^j, \sigma_2^j, \sigma_3^j, \sigma_4^j)^T$.

Each element of $\boldsymbol{\sigma}^j$ represents a standard deviation of the normal distribution with zero mean. Parameter $\boldsymbol{\sigma}^j$ is used to mutate the solution $\boldsymbol{z}^j$. The initial population $\boldsymbol{\sigma}^j$ $(j = 1, \ldots, \mu_{Child})$ is generated by uniformly sampling from the range $[\boldsymbol{\sigma}_{\text{low}}, \boldsymbol{\sigma}_{\text{up}}]$, where $\boldsymbol{\sigma}_{\text{low}}$ and $\boldsymbol{\sigma}_{\text{up}}$ are the lower and upper bounds for the standard deviation vector. Here, $\boldsymbol{\sigma}_{\text{low}}$ and $\boldsymbol{\sigma}_{\text{up}}$ are set as: $\boldsymbol{\sigma}_{\text{low}} = [0.1, 0.1, 5, 5]^T$, $\sigma_{\text{up}} = [2, 2, 200, 200]^T$, based on the data analysis.

Data-driven Wind Turbine Intelligent Control

Bi-objective optimization

$$\min\left\{\mathrm{Obj}_1, \mathrm{Obj}_2\right\}$$

subject to

$$\begin{aligned}
y_1^*(t) &= f_1(y_1(t-1), x_1^*(t), x_1(t-1), x_2^*(t), x_2(t-1), \\
&\qquad v(t), v(t-1)) \\
y_1^*(t+1) &= f_1(y_1^*(t), x_1^*(t+1), x_1^*(t), x_2^*(t+1), x_2^*(t), \\
&\qquad v(t+1), v(t)) \\
y_2^*(t) &= f_2(y_2(t-1), x_1^*(t), x_1(t-1), x_2^*(t), x_2(t-1), \\
&\qquad v(t), v(t-1)) \\
y_2^*(t+1) &= f_2(y_2^*(t), x_1^*(t+1), x_1^*(t), x_2^*(t+1), x_2^*(t), \\
&\qquad v(t+1), v(t)) \\
v(t) &= g(v(t-1), v(t-2), v(t-6)) \\
x_2^*(t) &\le 10\,090, x_2^*(t+1) \le 10\,090, \\
&\qquad |x_2^*(t) - x_2(t)| \le 4500 \\
x_1^*(t) &\le 15, x_1^*(t+1) \le 15 \qquad (12)
\end{aligned}$$

where $\mathrm{Obj}_1 = J$ and

$$\begin{aligned}
\mathrm{Obj}_2 = {} & \max\{0, y_2^*(t+1) - 23\} + \max\{0, y_2^*(t) - 23\} \\
& + \max\{0, y_1^*(t+1) - \min\{1600, 2.625v(t+1)^3\}\} \\
& + \max\{0, y_1^*(t) - \min\{1600, 2.625v(t)^3\}\}.
\end{aligned}$$

Data-driven Wind Turbine Intelligent Control

Strength Pareto Evolutionary Algorithm

Step 1) Initialize three empty sets *Parent*, *Offspring*, and *Elite*. Randomly generate μ_{Child} individuals (solutions) to form the initial children population and place them in the *Offspring* set.

Step 2) Repeat until the stopping criterion is satisfied.

- Step 2.1) Find nondominated solutions in *Offspring* and copy them into *Elite*. Remove dominated solutions from *Elite*. Reduce the size of *Elite* by clustering, if necessary.
- Step 2.2) Fitness assignment: Assign fitness to individuals in *Offspring* and *Elite*.
- Step 2.3) Selection: Use tournament selection to select μ_{Parent} individuals from $Offspring \cup Elite$ and store them in *Parent*.
- Step 2.4) Recombination: Generate a new population *Offspring* by selecting two parents in *Parent*.
- Step 2.5) Mutation: Mutate the individuals in *Offspring*.
- Step 2.6) Assign fitness to the individuals in *Offspring*.

Data-driven Wind Turbine Intelligent Control

Mutation process:

First

$$\boldsymbol{\sigma}^j = \boldsymbol{\sigma}^j \bullet \\ (e^{N(0,\tau')+N_1(0,\tau)}, e^{N(0,\tau')+N_2(0,\tau)}, e^{N(0,\tau')+N_3(0,\tau)}, \\ e^{N(0,\tau')+N_4(0,\tau)}) \qquad (13)$$

Next

$$\boldsymbol{z}^j = \boldsymbol{z}^j + N(\mathbf{0}, \boldsymbol{\sigma}^j) \qquad (14)$$

Data-driven Wind Turbine Intelligent Control

Selection and recombination of parents

$$\left(\frac{\sum_{j \in SeletedParents} \boldsymbol{z}^j}{2}, \frac{\sum_{j \in SeletedParents} \boldsymbol{\sigma}^j}{2} \right) \tag{15}$$

Tournament Selection

Initial Population Generation and Constraints Handling

Data-driven Wind Turbine Intelligent Control

Continuous optimization

- A rolling forward process

In this section, in order to simulate the actual implementation of the anticipatory control for the wind speed scenario, continuous optimization is used, i.e., the optimal control settings solved at time t will be passed to the next sampling time. For example, at time t, based on wind turbine status $\{y_1(t-1), y_2(t-1), x_1(t), x_1(t-1), x_2(t), x_2(t-1), v(t), v(t-1)\}$, model (12) is solved, and an optimal solution $x_1^*(t), x_1^*(t+1), x_2^*(t), x_2^*(t+1)$ is determined and implemented at the time stamp t. The corresponding optimized power output and rotor speed are $y_1^*(t)$ and $y_2^*(t)$. At the next sampling time $t+1$, assume the optimal control settings from t are applied; in other words, the wind turbine status at $t+1$ becomes $\{y_1^*(t), y_2^*(t), x_1^*(t+1), x_1^*(t), x_2^*(t+1), x_2^*(t), v(t+1), v(t)\}$ as the optimal control settings from the previous sampling times are implemented. Then, based on this new turbine status, model (12) is solved again to generate optimal control settings at the time stamp $t+1$, and this process is repeated. In this way, the scenario of controlling a wind turbine is emulated.

Data-driven Wind Turbine Intelligent Control

Visualization of optimization results

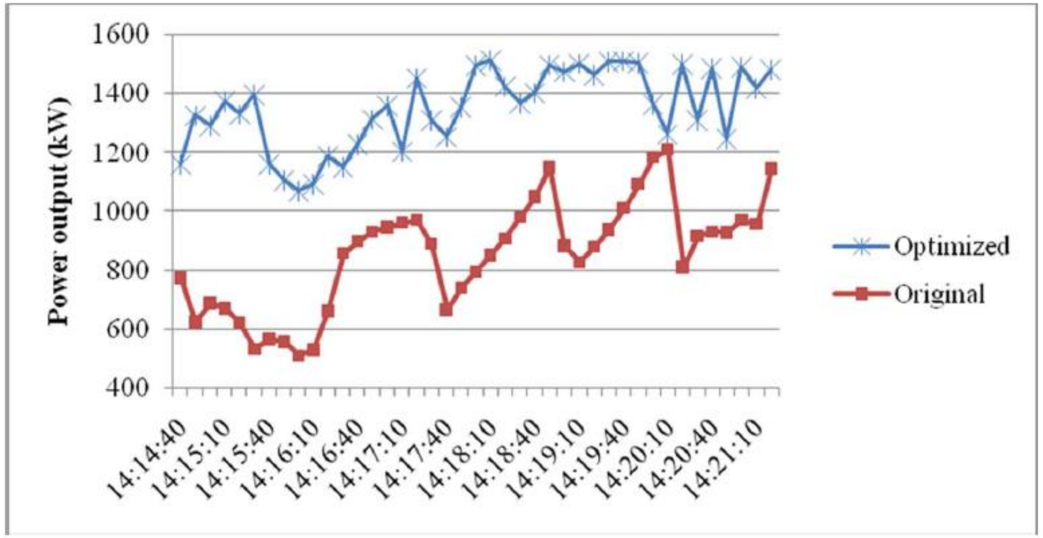


Fig. 7. Continuous optimization of power output for the time period "2:14:40 P.M."–"2:21:20 P.M."

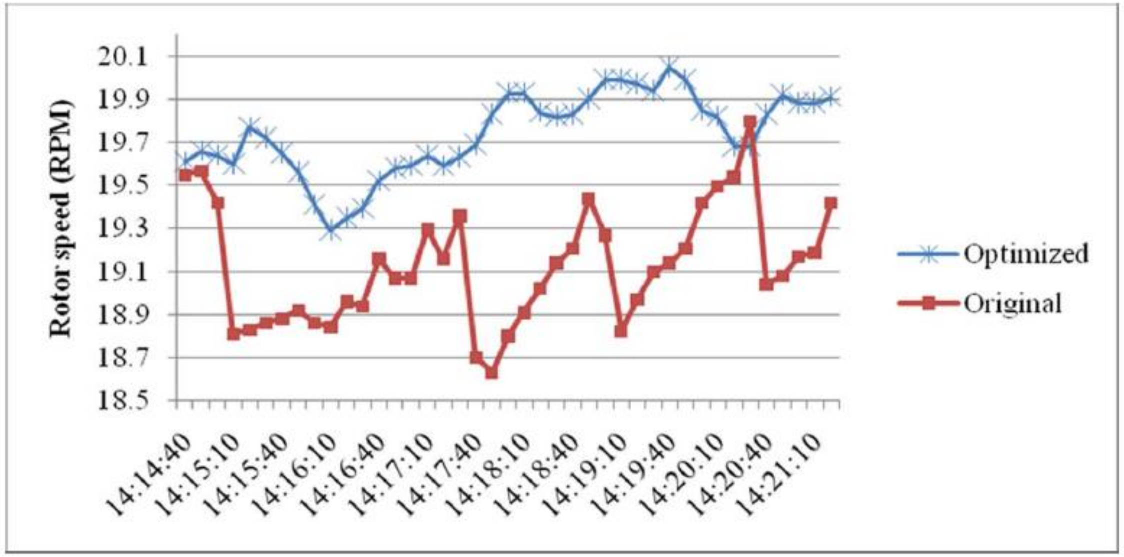


Fig. 8. Continuous optimization of the rotor speed for the period "2:14:40 P.M."–"2:21:20 P.M."

Data-driven wind farm operational optimization

Data-driven wind farm operational optimization

Optimizing control of all wind turbines in a wind farm simultaneously means the wind farm operational optimization

However, more factors need to be considered

- Operations concern costs and power production can be converted into costs
- Wind farm operational decisions – system on/off and control settings
- Uncertain factors handling formulation – stochastic v.s. robust optimizations

Ref1: A. Kusiak, Z. Zhang and G. Xu, "Minimization of Wind Farm Operational Cost Based on Data-Driven Models," IEEE Trans on Sustainable Energy, Vol. 4, No. 3, pp. 756-764, 2013
Ref2: H. Long, Z. Zhang, M. Sun and Y. Li, "The data-driven schedule of wind farm power generations and required reserves," Energy, Vol. 149, pp. 485-495, 2018

Data-driven wind farm operational optimization

Operational decisions

Definition 1: The decision variable is a vector $\boldsymbol{s}_t = [s_{1,t}, s_{2,t} \ldots, s_{I,t}]$, $s_{i,t} \in \{0, 1\}$ and $i = 1, 2, 3, \ldots, I$, determining the operational status (ON/OFF) of wind turbines in the wind farm at time window t.

Definition 2: The control variable is represented as a 2-tuple $(\boldsymbol{\tau}_t, \boldsymbol{\beta}_t)$. In this 2-tuple, $\boldsymbol{\tau}_t = [\tau_{1,t}, \tau_{2,t}, \ldots, \tau_{I,t}]$ and $\boldsymbol{\beta}_t = [\beta_{1,t}, \beta_{2,t}, \ldots, \beta_{I,t}]$, $\tau_{i,t}, \beta_{i,t} \in R^I$ and $i = 1, 2, 3, \ldots, I$, are two vectors representing the settings of the generator torque and the blade pitch angle of wind turbines at time window t.

Data-driven wind farm operational optimization

Optimization Objective - Cost

Definition 3: The cost of operating a wind farm in power generation includes the power shortage cost, operations and maintenance (O&M) cost, and the idle turbine cost.

Definition 4: The opportunity cost reflects the potential revenue of selling the amount of electric power equivalent to the power shortage, i.e., the product of the electricity price and the electric power shortage at a given time window.

Definition 5: The compensation cost is the penalty paid to activate backup power generation systems or purchase power from the third agent to compensate for the amount of power shortage.

Data-driven wind farm operational optimization

Formulation of objective function

$$
\begin{aligned}
TC &= \sum_{t=T_0}^{T_e} C_{oc,t} + C_{cc,t} + C_{om,t} + C_{ic,t} \\
&= \sum_{t=T_0}^{T_e} B_t \Delta P_t + \sum_{t=T_0}^{T_e} p_t \Delta P_t + \sum_{t=T_0}^{T_e} \sum_{i=1}^{I} c P_{i,t} s_{i,t} \\
&\quad + \sum_{t=T_0}^{T_e} \sum_{i=1}^{I} B_t K_{i,t} (1 - s_{i,t}). \qquad (2)
\end{aligned}
$$

Data-driven wind farm operational optimization

Computation of wind power output in the objective function – data-driven models

$$P_{i,t} = f_i(\tau_{i,t}, \beta_{i,t}, \hat{v}_t) I_{(v_{ci}, v_{co})}(\hat{v}_t). \qquad (3)$$

Data-driven wind farm operational optimization

Base model

$$
\begin{aligned}
&\min_{s,\tau,\beta} TC \\
&\text{s.t.} \\
&TC = \sum_{t=T_0}^{T_e} B_t \Delta P_t + \sum_{t=T_0}^{T_e} p_t \Delta P_t + \sum_{t=T_0}^{T_e} \sum_{i=1}^{I} c P_{i,t} s_{i,t} \\
&\quad + \sum_{t=T_0}^{T_e} \sum_{i=1}^{I} B_t K_{i,t} (1 - s_{i,t}) \\
&\Delta P_t = \max \left\{ 0, D_t - \sum_{i=1}^{I} P_{i,t} s_{i,t} \right\} \\
&P_{i,t} = f_i(\tau_{i,t}, \beta_{i,t}, \hat{v}_t) I_{(v_{ci}, v_{co})}(\hat{v}_t) \\
&P_{i,t} \leq \min \left\{ 1500, 2.625 \hat{v}_t^3 \right\} \\
&\hat{v}_t = f(v_{t-Q}, v_{t-2Q}, v_{t-3Q}, \ldots, v_{t-7Q}) \\
&s_{i,t} \in \{0, 1\} \\
&\tau_{1,t} \in [1.5, 100.78], \tau_{2,t} \in [1.23, 100.63], \\
&\tau_{3,t} \in [1.14, 100.68], \\
&\tau_{4,t} \in [1.55, 100.63], \tau_{5,t} \in [1.8, 100.62] \\
&\beta_{1,t} \in [-0.07, 76.14], \beta_{2,t} \in [-0.07, 76.12], \\
&\beta_{3,t} \in [-0.07, 84.23], \\
&\beta_{4,t} \in [-0.08, 80.51], \beta_{5,t} \in [0.04, 359.6]
\end{aligned} \tag{9}
$$

Data-driven wind farm operational optimization

Stochastic Formulation – Which is uncertain? Wind speed

Wind scenario construction – Markov model

$$\partial_1 \in (0,4), \partial_2 \in [4,6), \partial_3 \in [6,8), \partial_4 \in [8,10),$$
$$\partial_5 \in [10,12), \partial_6 \in [12,14), \partial_7 \in [14,24), \partial_8 \in [24,113). \quad (10)$$

Transition matrix

$$A = \begin{bmatrix} \Pr(v_{t+Q} \in \partial_1 | v_t \in \partial_1), \ldots, \Pr(v_{t+Q} \in \partial_8 | v_t \in \partial_1) \\ \vdots, \ddots, \vdots \\ \Pr(v_{t+Q} \in \partial_1 | v_t \in \partial_8), \ldots, \Pr(v_{t+Q} \in \partial_8 | v_t \in \partial_8) \end{bmatrix}. \quad (11)$$

Data-driven wind farm operational optimization

Objective function

$$TC = \sum_{t=1}^{T} \sum_{\partial_h \in \partial} \Pr(\upsilon_t \in \partial_h | \upsilon_{t-Q} \in \partial') \cdot (C_{oc,\partial_h} + C_{cc,\partial_h} + C_{om,\partial_h} + C_{ic,\partial_h}). \quad (13)$$

Expectation of power production

$$\Delta P_t = \max \left\{ 0, D_t - \sum_{i=1}^{I} E_{\partial_h}(P_{i,t}) s_{i,t} \right\}. \quad (14)$$

$$\begin{aligned} E_{\partial_h}(P_{i,t}) &= \int_{\upsilon_t \in \partial_h} P_{i,t} f_{\upsilon_t \in \partial_h}(\upsilon_t) d\upsilon_t \\ &= \int_{\upsilon_t \in \partial_h} f_i(\tau_{i,t}, \beta_{i,t}, \upsilon_t) f_{\upsilon_t \in \partial_h}(\upsilon_t) d\upsilon_t \\ &\approx \sum_{\partial_S \in \partial_h} f_i(\tau_{i,t}, \beta_{i,t}, \bar{\upsilon}_{\partial_S}) \Pr(\bar{\upsilon}_{\partial_S}) \end{aligned} \quad (15)$$

Data-driven wind farm operational optimization

Full optimization model

$$\min_{s,\tau,\beta} TC$$

s.t.

$$TC = \sum_{t=T_0}^{T_e} \sum_{\partial_h \in \partial} \Pr(v_t \in \partial_h | v_{t-Q} \in \partial') \cdot (B_t \Delta P_t + p_t \Delta P_t$$
$$+ \sum_{i=1}^{I} cE_{\partial_h}(P_{i,t}) s_{i,t} + \sum_{i=1}^{I} B_t K_{i,t}(1 - s_{i,t}))$$
$$\Delta P_t = \max \left\{ 0, D_t - \sum_{i=1}^{I} E_{\partial_h}(P_{i,t}) s_{i,t} \right\}$$
$$E(P_{i,t}) = \left(\sum_{\partial_S \in \partial_h} f_i(\tau_{i,t}, \beta_{i,t}, \bar{v}_{\partial_S}) \Pr(\bar{v}_{\partial_S}) \right)$$
$$\cdot I_{(v_{ci}, v_{co})}(\bar{v}_{\partial_S})$$
$$f_i(\tau_{i,t}, \beta_{i,t}, \bar{v}_{\partial_S}) \le \min \left\{ 1500, 2.625(\bar{v}_{\partial_S})^3 \right\}$$
$$s_{i,t} \in \{0, 1\}, \tau_{1,t} \in [1.5, 100.78], \tau_{2,t} \in [1.23, 100.63],$$
$$\tau_{3,t} \in [1.14, 100.68], \tau_{4,t} \in [1.55, 100.63],$$
$$\tau_{5,t} \in [1.8, 100.62],$$
$$\beta_{1,t} \in [-0.07, 76.14], \beta_{2,t} \in [-0.07, 76.12],$$
$$\beta_{3,t} \in [-0.07, 84.23],$$
$$\beta_{4,t} \in [-0.08, 80.51], \beta_{5,t} \in [0.04, 359.6]. \tag{16}$$

Data-driven wind farm operational optimization

Solving the optimization problem is a MINLP with data-driven components

We develop a specific Migrated Particle Swarm Optimization to solve it

- Migration via GA operator
- Introduce diversity in the search route to escape local optima

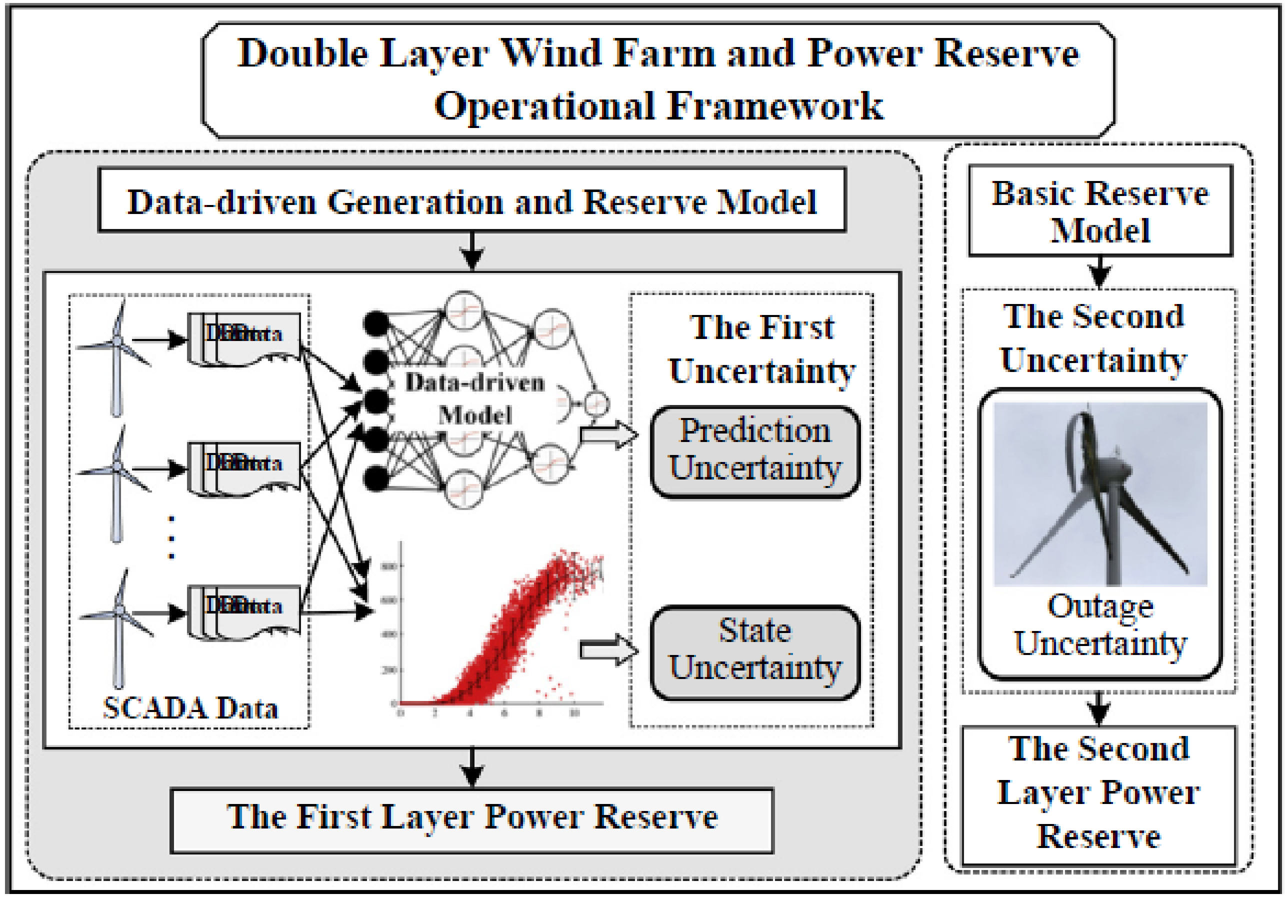
Data-driven wind farm operational optimization

Result comparison

Scheduling Time Window	BES Cost (US$)	BMS Cost (US$)	SMS Cost (US$)	BS Cost (US$)
1	198.93	198.93	199.99	198.93
2	210.95	210.95	210.95	210.95
3	242.03	242.03	242.03	242.03
4	212.65	212.65	212.65	212.65
5	207.18	207.18	207.18	207.18
6	189.62	189.62	189.62	189.62
7	157.80	157.8	157.8	157.8
8	138.90	138.9	138.9	138.9
9	120.66	120.68	120.68	120.74
10	101.92	101.92	101.92	106.94
11	85.40	85.4	85.4	97.55
12	80.25	80.25	80.25	95.33
Total	1946.29	1946.31	1947.37	1978.62

Data-driven wind farm operational optimization

Robust formulation



Data-driven wind farm operational optimization

Uncertainty set construction

Operational state

$$S_t\left(\bar{\boldsymbol{s}}_t, \hat{\boldsymbol{s}}_t\right) := \Big\{\boldsymbol{s}_t \in \Re^N : s_{i,t} \in \Big[\max\Big\{0, \bar{s}_{i,t} - \hat{s}_{i,t}\Big\}, \min\Big\{1, \bar{s}_{i,t} + \hat{s}_{i,t}\Big\}\Big], \forall i \in \Omega\Big\} \quad (1)$$

Power prediction

$$\bar{p}_{i,t} = f\left(p_{i,1}, \ldots, p_{i,T-t}, v_i, \omega_i, \theta_i\right), \ \ \bar{p}_{i,t} \le P_{rated} \quad (3)$$

$$e_{i,t} = \frac{1}{Y}\sum_{y=1}^{Y}\left|\frac{p_{i,t}^y - \bar{p}_{i,t}^y}{p_{i,t}^y}\right| \quad (4)$$

$$D_t(\boldsymbol{e}_t, \Phi_t) := \Big\{\boldsymbol{d}_t \in \Re^N : \sum_{i \in N}\frac{|d_{i,t} - 1|}{e_{i,t}} \le \Phi_t, d_{i,t} \in [\max\{0, 1 - e_{i,t}\}, 1 + e_{i,t}], \forall i \in \Omega\Big\} \quad (6)$$

Data-driven wind farm operational optimization

Uncertainty set construction

$$\tilde{U}_1 = \left\{ S_t\left(\overline{\boldsymbol{s}}_t, \widehat{\boldsymbol{s}}_t\right), D_t(\boldsymbol{e}_t) \right\} = \left\{ \boldsymbol{s}_t \in \Re^N : s_{i,t} \in \left[\max\left\{0, \overline{s}_{i,t} - \widehat{s}_{i,t}\right\}, \min\left\{1, \overline{s}_{i,t} + \widehat{s}_{i,t}\right\}\right], \right.$$
$$\left. \boldsymbol{d}_t \in \Re^N : d_{i,t} \in [\max\{0, 1 - e_{i,t}\}, 1 + e_{i,t}], \forall i \in \Omega \right\} \tag{7}$$

$$\tilde{U}_2 = \left\{ S_t\left(\overline{\boldsymbol{s}}_t, \widehat{\boldsymbol{s}}_t\right), D_t(\boldsymbol{e}_t, \Phi_t) \right\} = \left\{ \boldsymbol{s}_t \in \Re^N : s_{i,t} \in \left[\max\left\{0, \overline{s}_{i,t} - \widehat{s}_{i,t}\right\}, \min\left\{1, \overline{s}_{i,t} + \widehat{s}_{i,t}\right\}\right], \right.$$
$$\left. \boldsymbol{d}_t \in \Re^N : \sum_{i \in N} \frac{|d_{i,t} - 1|}{e_{i,t}} \leq \Phi_t, d_{i,t} \in [\max\{0, 1 - e_{i,t}\}, 1 + e_{i,t}], \forall i \in \Omega \right\} \tag{8}$$

Data-driven wind farm operational optimization

Objective function

$$\begin{aligned} \min C &= \min \sum_{t=1}^{T} \left(C_{om,t} + C_{r,t} + C_{p,t} \right) \\ &= \min \sum_{t=1}^{T} \left(\alpha \sum_{i=1}^{N} s_{i,t} P_{i,t} + \beta R_t + \gamma_t \Delta P_t \right) \end{aligned} \quad (9)$$

Full optimization model

$$\begin{aligned} &\max_{\boldsymbol{d} \in D, \boldsymbol{s} \in S} \min_{\boldsymbol{P}, \boldsymbol{R}} C \\ &\text{s.t.} \\ &C = \sum_{t=1}^{T} \left(\alpha \sum_{i=1}^{N} s_{i,t} P_{i,t} + \beta R_t + \Delta P_t^{\tau+1} \Big/ (\phi U_t)^{\tau} \right) \\ &\sum_{i=1}^{N} s_{i,t} P_{i,t} + R_t + \Delta P_t = U_t \\ &\overline{p}_{i,t} = f\left(p_{i,1}, \ldots, p_{i,T-t}, v_i, \omega_i, \theta_i \right), \ \overline{p}_{i,t} \le P_{rated} \\ &\frac{1}{T} \sum_{t=1}^{T} \frac{\Delta P_t}{U_t} \le 1 - \zeta \\ &0 \le P_{i,t} \le \min\left\{ d_{i,t} \overline{p}_{i,t}, P_{rated} \right\} \\ &0 \le R_t \le \psi U_t, \Delta P_t \ge 0 \end{aligned} \quad (15)$$

Denote the model (15) considering different uncertainty sets, $\tilde{U}_1$ and $\tilde{U}_2$, as M1 and M2. Through previous settings, we can infer that the solution of M1 is more conservative than M2.

Data-driven wind farm operational optimization

Two-level heuristic search

Problem simplification

$$C^* := \max_{\boldsymbol{u}} \min_{\boldsymbol{x}} F(\boldsymbol{x}, \boldsymbol{u}) \quad \text{s.t.} \, g_m(\boldsymbol{x}, \boldsymbol{u}) \geq 0, m = 1, \ldots, M \;\Rightarrow\; C^* := \min_{\boldsymbol{x}} F(\boldsymbol{x}, \boldsymbol{u}_j) \quad \text{s.t.} \, g_m(\boldsymbol{x}, \boldsymbol{u}_j) \geq 0, m = 1, \ldots, M \tag{17}$$

PSO + Barrier Method

In the PSO, the j-th particle of the swarm is denoted as a D-dimensional vector, $X_j = (x_{j1}, x_{j2}, \ldots, x_{jD})^{\mathrm{T}}$, which is the case of the set $\tilde{U}$ in the proposed method. The velocity of the j-th particle indicating its displacement is described by $V_j = (v_{j1}, v_{j2}, \ldots, v_{jD})^{\mathrm{T}}$. The best previously visited position of the j-th particle is denoted as $Y_j = (y_{j1}, y_{j2}, \ldots, y_{jD})^{\mathrm{T}}$. Define g as the index of the best particle in the swarm and let n denote the iteration number. The swarm is manipulated based on (18).

$$\begin{aligned} v_{jd}^{n+1} &= w v_{jd}^{n} + c_1 r_1^n \left(y_{jd}^n - x_{jd}^n \right) + c_2 r_2^n \left(y_{gd}^n - x_{jd}^n \right) \\ x_{jd}^{n+1} &= x_{jd}^n + v_{jd}^{n+1} \end{aligned} \tag{18}$$

where $d = 1,2, \ldots, D$, $j = 1,2, \ldots, J$, and J is the size of the swarm. Variable w is the inertia weight, c_1 and c_2 are positive constants, as well as r_1 and r_2 are random numbers in the range [0, 1].

In this work, the logarithmic barrier function is introduced and problem (17) is converted to (19).

$$\min_{\boldsymbol{x}} qF(\boldsymbol{x}, \boldsymbol{u}_j) - \sum_{m=1}^{M} \log(g_m(\boldsymbol{x}, \boldsymbol{u}_j)) \tag{19}$$

where q is a large number. The iterative process of the barrier method is described by following steps:

Step 1:	Start at $q = q^{(0)} > 0$, and solve the problem(19) by using the Newton's method to produce $\boldsymbol{x}^{(0)} = \boldsymbol{x}^*(q)$.
Step 2:	Repeat following steps for $k = 1, 2, 3, \ldots, K_{\max}$
Step 2.1:	Solve the barrier problem(19) at $q = q^{(k)}$ by using the Newton's method initialized at $\boldsymbol{x}^{(k-1)}$ to produce $\boldsymbol{x}^{(k)} = \boldsymbol{x}^*(q)$;
Step 2.2:	Update $q^{(k+1)} = \mu q$ where μ, $\mu > 1$, is the barrier parameter;

Data-driven wind turbine condition monitoring

Data-driven wind turbine condition monitoring

- Condition monitoring based on SCADA data

- Condition monitoring based on image data

Data-driven wind turbine condition monitoring

Data-driven wind turbine condition monitoring

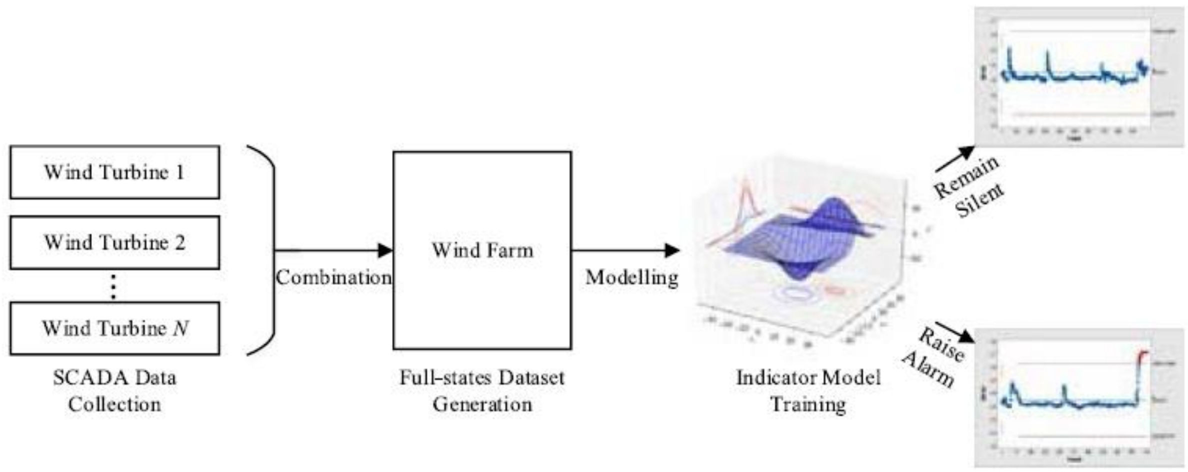


Fig. 3. Blade breakage monitoring framework.

Step 1. Generate a training dataset: Collect SCADA data of all wind turbines in the wind farm and incorporate SCADA data of normal wind turbines into one dataset.

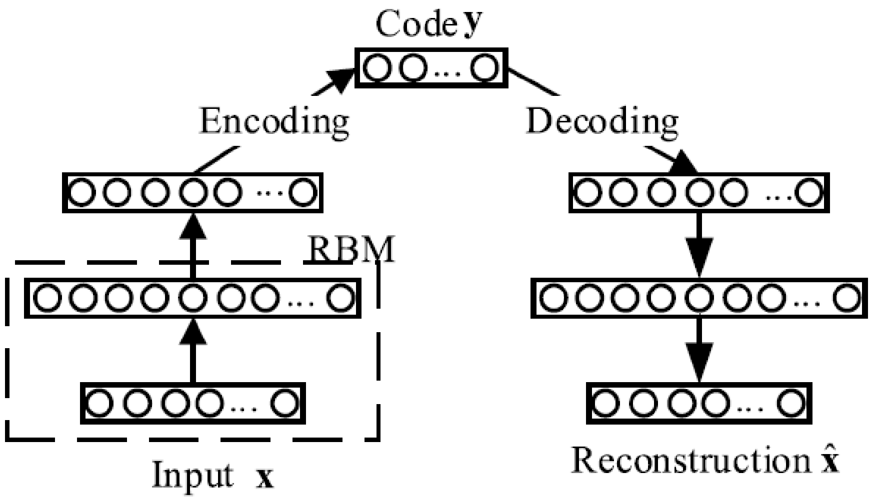
Step 2. Build a DA model: Apply all SCADA parameters to develop the DA model based on the training dataset.

Step 3. Compute REs: Compute the RE of wind turbine i, $i = 1, 2, \ldots, N$, via the DA model. Wind turbines with impending blade breakages will have larger REs.

Step 4. Develop the EWMA control chart: Based on REs, a EWMA control chart is applied to estimate the upper and lower limits. If the RE of the wind turbine i exceeds the control limit, an alarm of the impending blade breakages will be activated.

Data-driven wind turbine condition monitoring

Stacked denoising autoencoder for deriving health indicator



Data-driven wind turbine condition monitoring

EWMA chart for monitoring

The EWMA, q_t, is computed as (20).

$$q_t = \lambda RE_t + (1-\lambda) q_{t-1} \tag{20}$$

where t is the time index, $\lambda \in (0, 1]$ is a weight of historical RE considered in constructing the EWMA, and q_0 is the mean of REs for the monitored wind turbine during a specific period. The λ is arbitrarily set to 0.2 in this study based on the recommendation from [34].

The mean and variance of q_t are next calculated according to (21).

$$\mu_{q_t} = \mu_{\mathrm{RE}}, \sigma_{q_t}^2 = \frac{\sigma_{\mathrm{RE}}^2}{n_{\mathrm{s}}}\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right] \tag{21}$$

where μ_{RE} is the mean of REs for all wind turbines within the same wind farm, σ_{RE} is the standard deviation of REs, and n_s is the sample size.

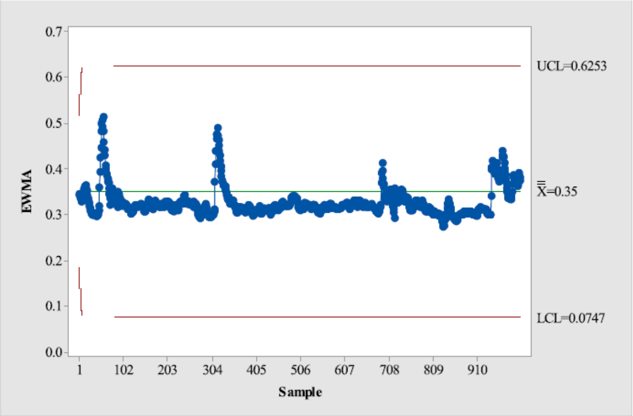
The upper and lower control limits of the EWMA chart in (22) and (23) are functions of t.

$$UCL(t) = \mu_{\mathrm{RE}} + L\sigma_{\mathrm{RE}}\sqrt{\frac{\lambda[1-(1-\lambda)^{2t}]}{(2-\lambda)n_{\mathrm{s}}}} \tag{22}$$

$$LCL(t) = \mu_{\mathrm{RE}} - L\sigma_{\mathrm{RE}}\sqrt{\frac{\lambda[1-(1-\lambda)^{2t}]}{(2-\lambda)n_{\mathrm{s}}}} \tag{23}$$

where L is usually set to 3 [35].

Data-driven wind turbine condition monitoring



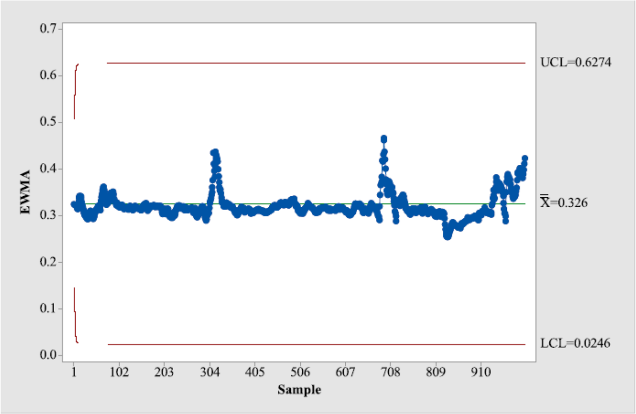
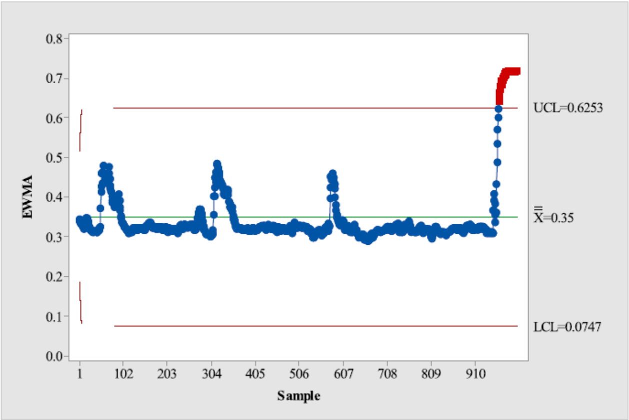
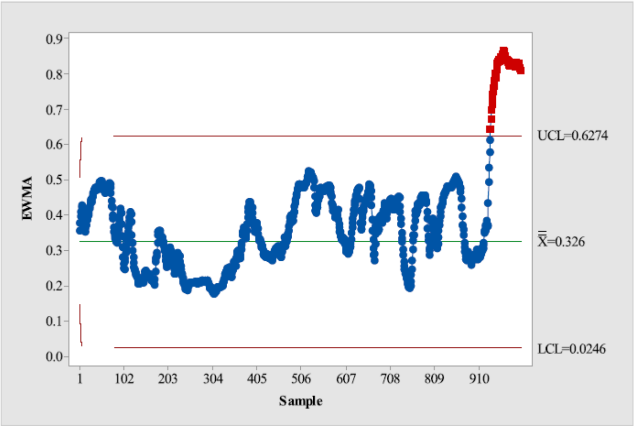


Fig. 10. The EWMA chart of turbine No. 3 in Anhui (July 26th to August 2rd, 2015).

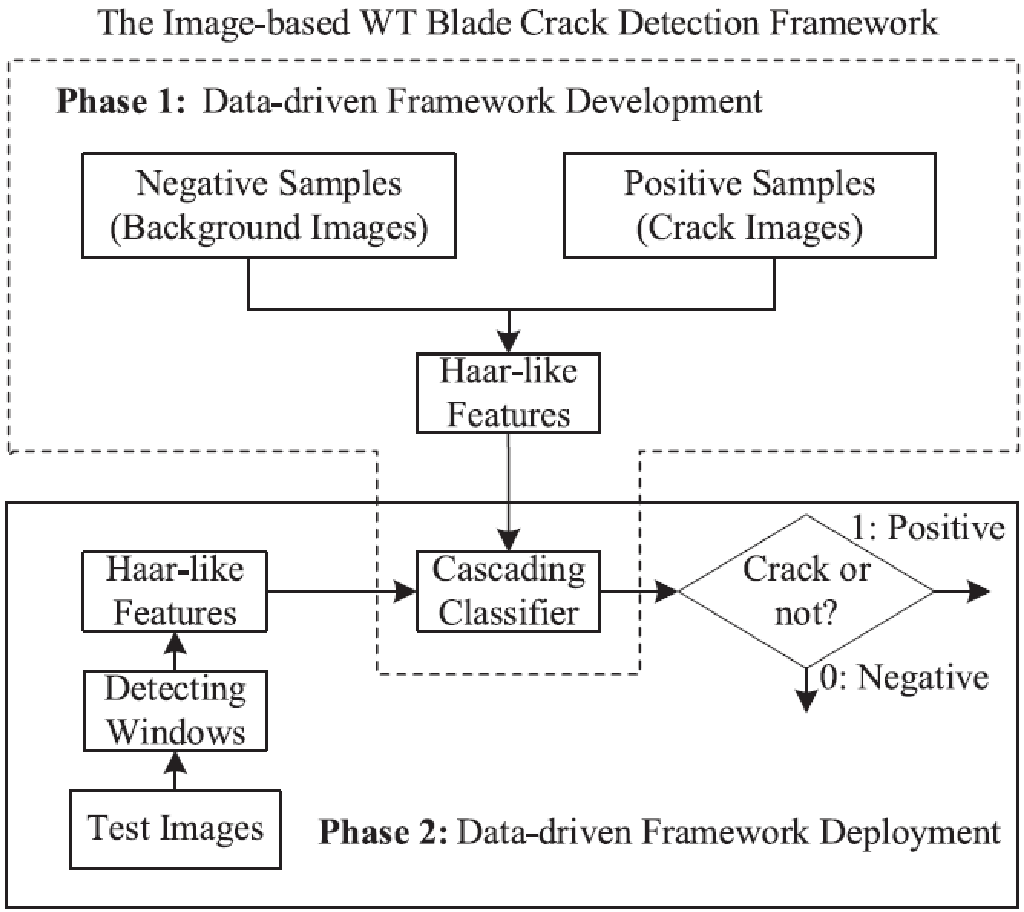
Fig. 12. The EWMA chart of turbine No. 15 in Shandong (May 6th tc May 13th, 2014).





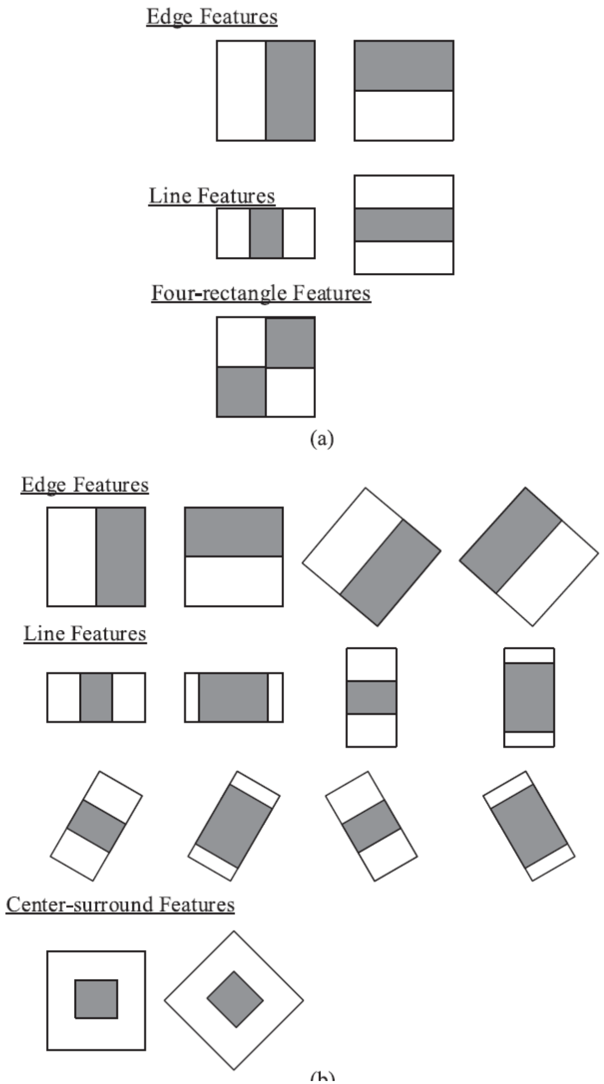
Data-driven wind turbine condition monitoring

Image data based studies



Data-driven wind turbine condition monitoring

Haar-like features



Data-driven wind turbine condition monitoring

Cascading classifier

+

Sliding window

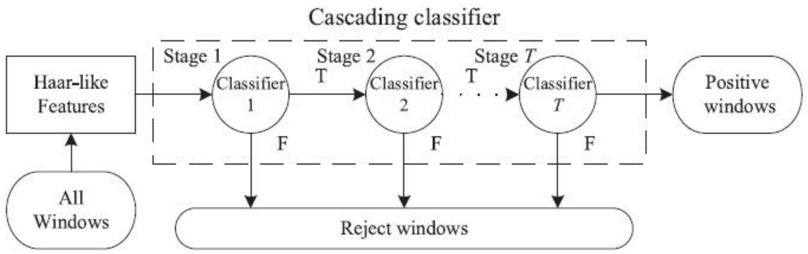


Fig. 4. Cascading classifier.

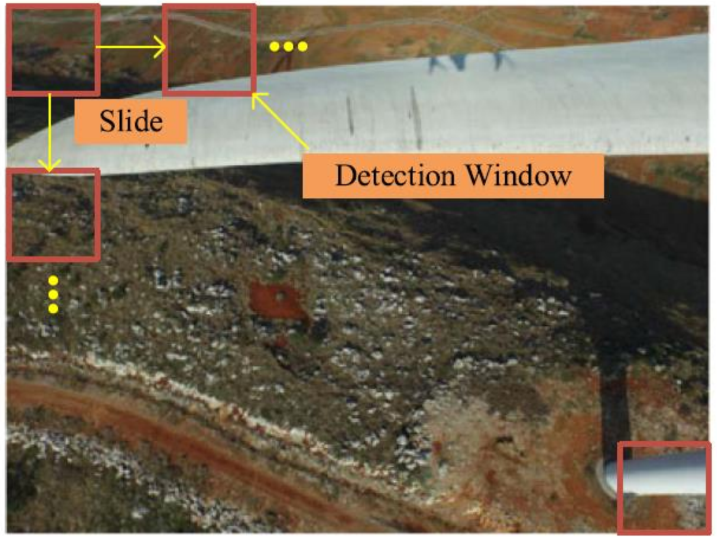


Fig. 5. Schematic diagram of the sliding window method. A window scans the whole image with a predefined sliding scale and the cascading classifier is applied to determine labels of its every move, positive and negative.

Data-driven wind turbine condition monitoring