A Comparison of Multi-Objective Optimisation of Two Wind Turbine Controller Designs

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1. Abstract
This paper presents a comparison between two pitch controllers for a 10MW wind turbine, a baseline using PI and a state-space model, where each controller's parameters have been chosen using Bayesian optimization. Four objectives are simultaneously examined: energy output; pitch action; blade load; and tower load. First, it is shown that, for both controllers, using parameters selected from the obtained Pareto fronts achieves higher energy production with less energy consumption of pitch activities and with less load in blade and tower, compared with settings chosen by an expert. Second, in this robust comparison of the capabilities of both controllers, the increased degrees of freedom and reduced simplification in the more advanced controller are seen to have greater potential to improve each of the objectives.

2. Introduction
A wind turbine is a highly integrated system consisting of a substantial number of components, such as blades, tower, drive-train, and nacelle. The design process must balance the capital cost of these components with their expected lifetime operational cost (due to structural reliability) and energy output. Controller design is one of the main procedures to balance loads with power output, thereby maximizing the payback on a given structural turbine design. Advanced wind turbine control algorithms, such as H_2, LQG, H_∞ and the state-space model, are required to further reduce the cost of energy. However, in conventional empirical design, the basic criteria needed to guarantee optimal control design for these methods are not met, due to the non-linear system, non-linear objective functions and stochastic inflow conditions.

Setting the parameters to maximize the performance of a given controller design is therefore a difficult task, however this is traditionally performed using empirical design methods. The use of advanced machine learning algorithms, such as Bayesian optimization, has already shown potential for improving the performance of a controller from the traditional empirically-tuned approach [1]. Bayesian optimization can intrinsically deal with the non-linear system, the non-linear objective functions and uncertainty in the inflow conditions.

The multi-objective optimization framework presented in this paper enables an efficient way to find the Pareto front. In other words, the trade-offs and ultimate potential of a controller for each of the objectives can be quickly explored. This offers an opportunity to find the best parameters for advanced controllers, benefitting the wind energy industry.

3. Research Objectives

The main goal of this research is twofold:

(i) To investigate the benefit of using a multi-objective optimization than empirical method for tuning a wind turbine controller.

(ii) To investigate the benefit of using a more advanced state-space model wind turbine controller compared to a baseline wind turbine controller in a multi-objective design using Bayesian optimization.

4. Methodology

4.1. Multi-objective Bayesian optimization

Bayesian Optimisation [2] is a method for global optimisation, from the family of meta-heuristic (black box) optimisation algorithms. A probabilistic surrogate model for the real objective is built using a Gaussian Process and then optimally sampled, using an acquisition function such as Expected Improvement. This method is particularly appropriate for minimising the number of required evaluations of a time-expensive and noisy process.

Optimising for multiple objectives has been achieved through several methods, depending on the optimisation algorithm, with the intention to find a widely-spread set of solutions which form the global "Pareto Front" [3]. This set contains only mutually non-dominating solutions (where better performance on one objective can only be achieved through worse performance on at least one other objective). Many metrics to assess the success of such an algorithm have been proposed, and indeed no single metric captures all user requirements: in terms of spread and optimality of solutions, and speed of discovery. However, the hypervolume (also referred to as the hypervolume indicator)—defined as the area contained between the discovered Pareto Front and some reference nadir point—is commonly used as an excellent determinant of the effectiveness of a multi-objective optimisation algorithm.

In multi-objective Bayesian Optimisation, a new acquisition function is usually defined, which determines the next sampling point by calculating the Expected Hypervolume Improvement once this point is added to the current set of solutions [4]. However, in this work we instead apply an infill criterion, in order to enable the application of standard, faster acquisition functions. The chosen infill criterion (called Extended Hypervolume Improvement) is based on the contribution of each solution to the currently-achieved hypervolume [5].

4.2. Baseline PI controller

The first controller to be analysed is a structured PI controller maintaining the rotor speed, combined with a separate loop to reduce tower motion. The controller uses separate estimators for drive train and tower motion and filters to filter out 3p and 6p harmonics in both the PI and tower motion controller. A lead-lag filter is also included to adjust the phase at the first tower resonance frequency. The tower motion controller itself is essentially a gain applied to the tower top velocity and fed back as a pitch angle.

The parameters that are to be optimised are the Kp and Ki of the rotor speed controller, the phase of the tower lead-lag filter and the gain of the tower motion controller.

4.3. State-space model controller

The second controller is a newly developed scheduled state-feedback controller [6]. In this controller the states of the wind turbine and the local wind are estimated using a single extended Kalman Filter. Compared to the baseline controller, the advantage is that a more detailed wind model is used, which includes a filter to estimate the current mean wind speed, the rotor effective turbulence, and the dynamic inflow. Furthermore, both the rotor speed and tower top

acceleration signals can now be used to update the complete state estimate, whereas they were independently used in the baseline controller. The estimated states are:

(i) rotor speed
(ii) generator speed
(iii) main shaft torsion
(iv) tower top displacement
(v) tower top velocity
(vi) mean undisturbed wind speed
(vii) turbulent wind component
(viii) rotor effective induction

The state feedback controller uses scheduled gains, based on LQR controllers for linearisations of a non-linear model at different points. An additional state (the integral of the difference between the measured and desired rotor speed) is added to these states to achieve good set-point control. However, this means that these gains are only optimal for a very specific set of circumstances and for the quadratic cost function used in the design of the LQR gains.

The optimisation acts on the 8 relative gains applied in the state feedback. That is, once the scheduled gains are calculated they are further multiplied with a factor determined by the optimisation. This allows the optimiser to change the relative weighting of the gains for each state, and the overall gain of the controller.

4.4. Objectives

The objectives are all configured to require minimisation: the load of tower and blade, pitch effort and energy loss. They are represented by the damage equivalent load of tower bottom fore-aft bending moment (DEL_{tbm}), blade root flap-wise bending moment (DEL_{brm}), pitch load duty cycle($E_{\text{load duty cycle}}$) and power loss compared to the rated power, respectively.

The pitch load duty cycle is defined by

$$E_{\text{load duty cycle}} = \frac{1}{t_1 - t_0} \int_{t_0}^{t_1} \left| \dot{\theta} \cdot M_{brm} \right| dt. \tag{1}$$

where $\dot{\theta}$ and M_{brm} are the pitch rate and the blade root flap-wise bending moment, respectively.

The energy loss is the difference between the mean value of the produced energy of a 10-minute simulation (P_{mean}) and the rated power (P_{rated}), it is given by

$$\text{Energy loss} = P_{\text{rated}} - P_{\text{mean}}. \tag{2}$$

4.5. Simulation settings

The Bayesian optimisation framework is set up using the GPyOpt library developed by the University of Sheffield [7] and extended using the hypervolume calculation algorithm from DEAP [8]. Initial experimental design is created using the PyDOE library.

The 10 MW wind turbine model developed in the AVATAR project [9] is chosen to apply both the baseline controller and the state-space model controller. The evaluations run fatigue load case DLC 1.2 NTM [10] at wind speeds of 17m/s, 18m/s and 19m/s. In order to minimize the sensitivity of the optimization to the turbulence, two different seeds are chosen for each of the wind speeds.

The design space for the baseline controller is given in Table 1. The design space for the eight gains relating to the eight states of the state-space model controller is [0.1, 5.0].

Table 1: The design space of the baseline controller.

Design variables	phase	gain	Ki	Kp
Lower bounds	$-\pi/4$	-0.1	-0.2	-0.7
Upper bounds	$\pi/4$	-0.004	-0.008	-0.02

5. Results

Fig. 1 compares the 4-dimensional Pareto front from the Bayesian optimization for the baseline controller and the state-space model controller, represented by the red and green symbols respectively. The parameters selected by the conventional empirical design is provided, and a selected result from the pareto front of Bayesian optimisation for each controller is marked for further analysis below. As can be seen from the figures, for both the controllers Bayesian optimisation has identified various settings which dominate the empirical design.

Table 2 compares, for the baseline controller, the empirical selected setting and a selected setting from the Pareto Front obtained using Bayesian optimization. This demonstrates a slight increase in power production even with 23.8% less pitch effort, 0.8% less blade load and 3.8% less tower load.

Table 2: Comparison of baseline controller performance when using empirical settings and a selected parameter set from the Pareto front obtained by Bayesian optimization.

controller	energy loss [%]	$E_{\text{load duty cycle}}$[W]	DEL_{brm} [Nm]	DEL_{tbm} [Nm]
empirical optimum	+0.040	7446543.3	12204085.1	9701539.5
selected dataset	+0.028	5672976.9	12102237.5	9330078.7
difference [%]	-0.012	-23.8	-0.8	-3.8

Fig. 2 compares the time series results of the baseline controller using the empirical selected setting and the selected setting set from the Pareto front of the Bayesian optimization. In addition to the higher mean power production (already shown in table 2), Fig. 2 demonstrates that the fluctuation in generator power is significantly reduced when using the selected Pareto-optimal settings. It can also be seen that the peaks of the fluctuation in blade and tower bending moment is reduced. It is noted that the peaks in pitch rate are, however, higher. The combined effect of the changes in pitch rate and blade root bending moment is reduced pitch load duty cycle.

Table 3 compares, for the state-space model controller, the empirical selected parameters and a selected setting from the Pareto front obtained using Bayesian optimization. This demonstrates a significant increase in energy production (2.9%, relative to rated power) with 20.3% less pitch effort, 0.5% less blade load and 8.1% less tower loads.

Fig. 3 compares the time series results of the state-space model controller using the empirical selected parameters and the selected setting set from the Pareto front of the Bayesian optimization. Consistent with table 3, it can be seen in Fig. 3 that the peaks of the fluctuation pitch rate, blade and tower bending moment are reduced using the Pareto-optimal parameters. The power production is higher than rated power, which is driven by the optimization objective on reducing power loss. However, this may need to be restricted in the real design in the future.

Table 4 compares, for the baseline and state-space model controllers, the selected settings from the Pareto fronts obtained using Bayesian optimization. It shows that the state-space

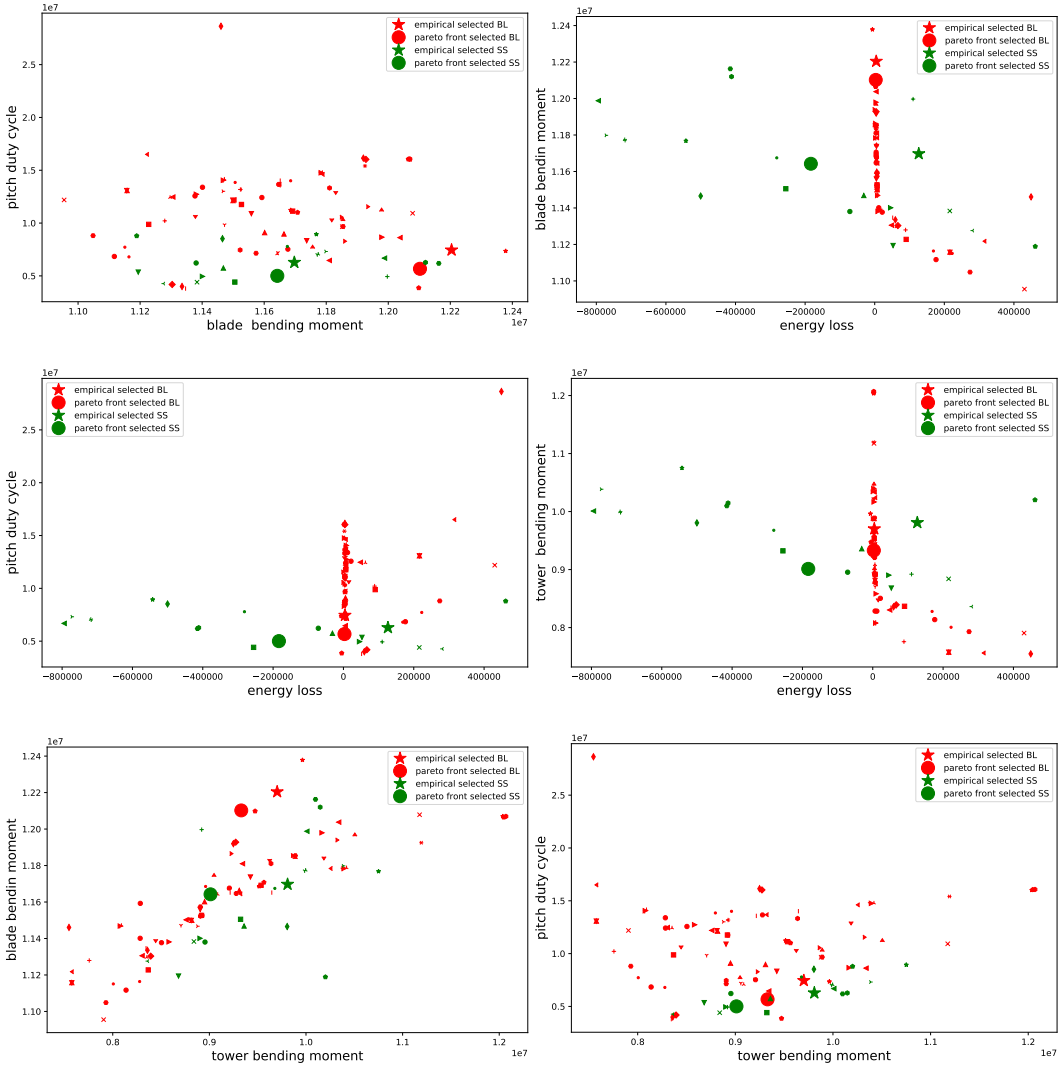

Figure 1: Pareto frontier of the baseline controller (red symbols) and the state-space controller (green symbols) obtained by Bayesian optimization.

Table 3: Comparison of the state-space model controller performance when using empirical settings and a selected parameter set from the Pareto front obtained by Bayesian optimization.

controller	energy loss [%]	$E_{\text{load duty cycle}}$[W]	DEL_{brm}[Nm]	DEL_{tbm} [Nm]
empirical optimum	+1.19	6276514.3	11697187.4	9809253.8
selected dataset	-1.72	5004054.9	11642295.2	9011701.3
difference [%]	-2.9	-20.3	-0.5	-8.1

model controller can achieve 1.75% higher energy, with 11.8% less pitch effort, 3.8% lower blade loads and 3.4% less tower loads.

Fig. 4 compares the time series results of the baseline controller and the state-space model controller using the selected Pareto-optimal parameter sets. As discussed previously, the mean power production of the state-space controller is not restricted to the rated power. This results

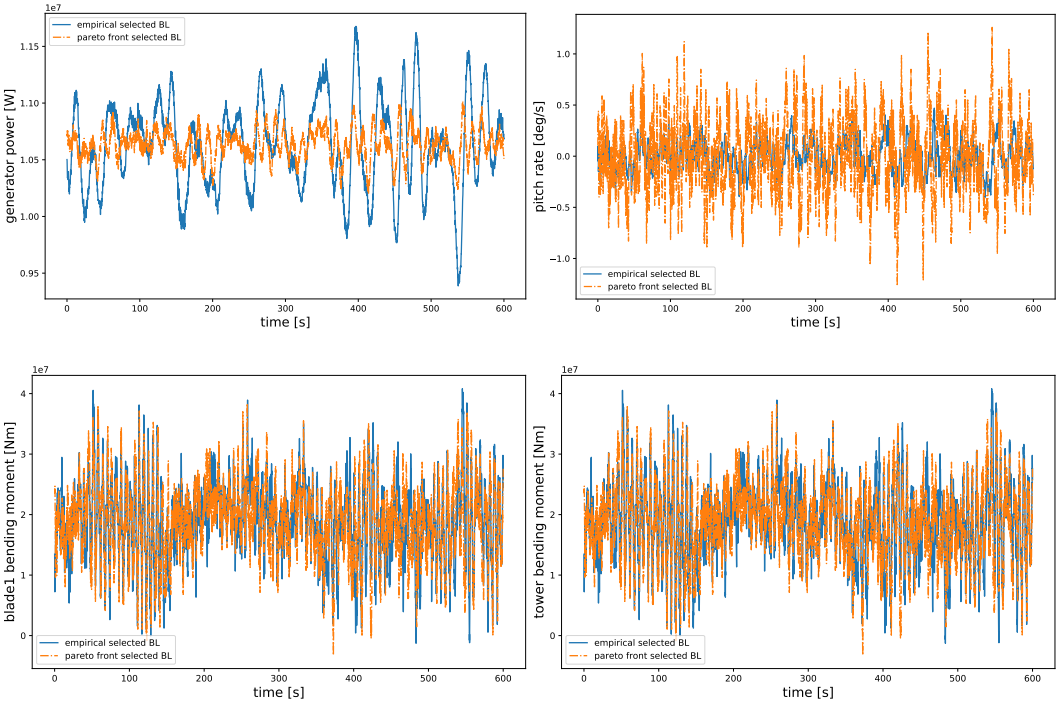

Figure 2: Time series comparison of baseline controller performance when using empirical settings and selected Pareto-optimal settings.

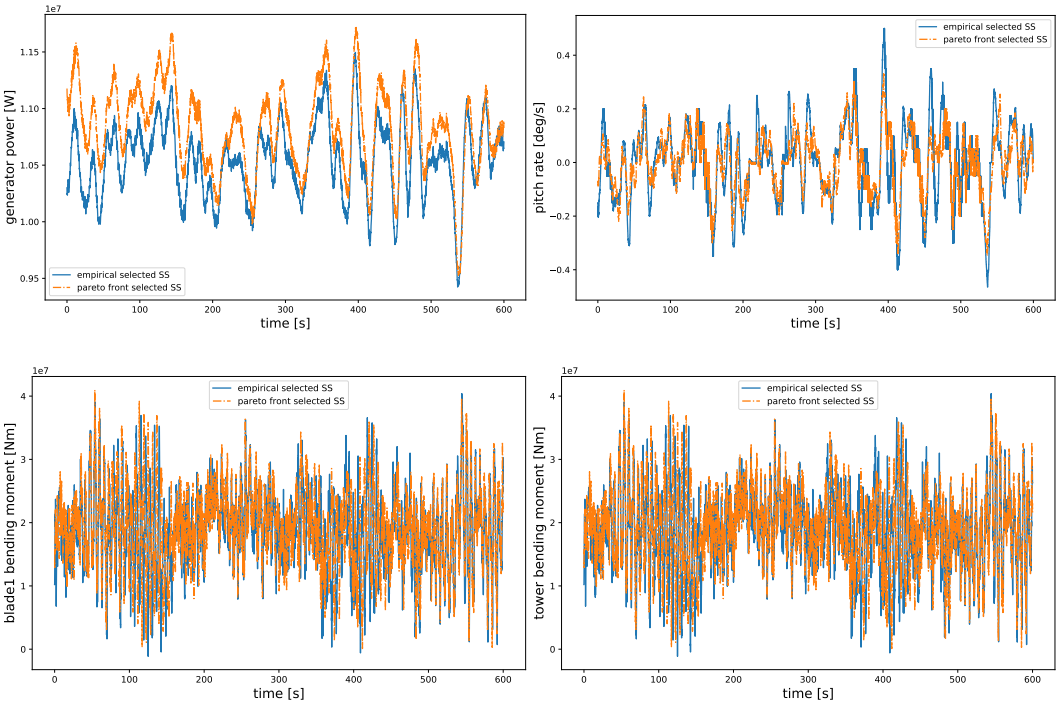

Figure 3: Time series comparison of state-space model controller performance when using empirical settings and selected Pareto-optimal settings.

Table 4: Performance comparison of the state-space model controller and the baseline controller using selected parameter sets from the Pareto fronts obtained by Bayesian optimization.

controller	energy loss [%]	$E_{\text{load duty cycle}}$[W]	DEL_{brm}[Nm]	DEL_{tbm} [Nm]
baseline	+0.028	5672976.9	12102237.5	9330078.7
state-space	-1.72	5004054.9	11642295.2	9011701.3
difference [%]	-1.75	-11.8	-3.8	-3.4

in higher mean power being generated, which may be not desired in reality. While the controller designer should perhaps choose a different solution from the Pareto front, the optimisation objective could also be shaped to target solutions where excessive power generation does not occur. As seen from top left figure in Fig. 4, the fluctuation of power production should be also taken into account in a future study. Consistent with table 4, the fluctuation in pitch rate of the state-space controller is significantly reduced. This also holds for the blade and tower bending moments.

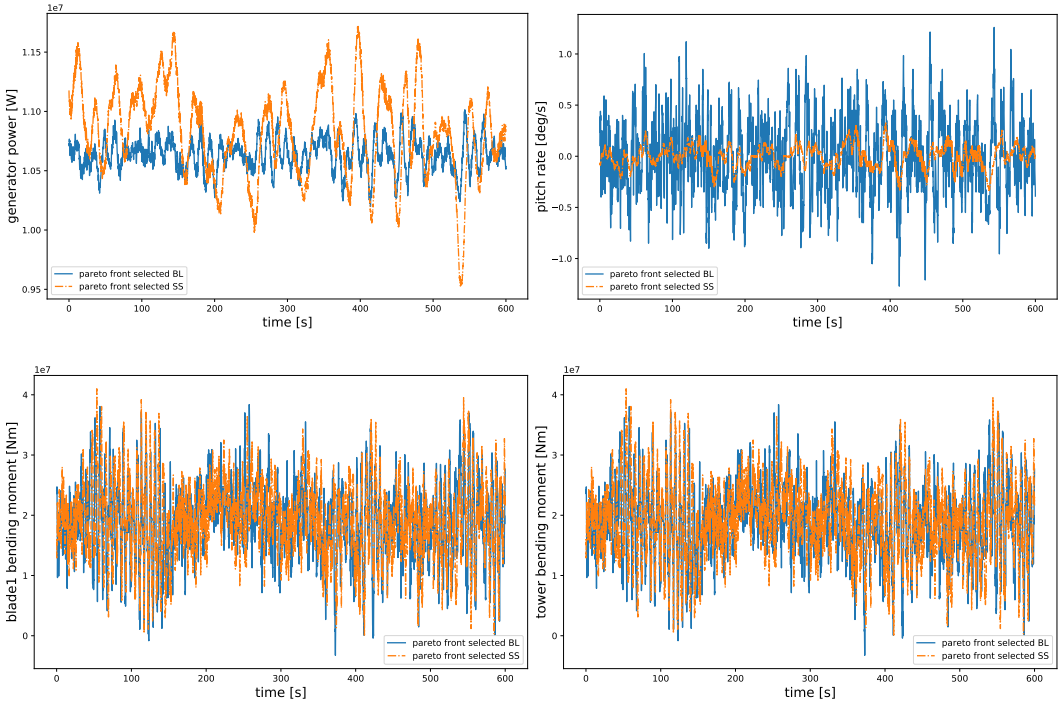

Figure 4: Time series comparison of the baseline and state-space model controller performance, when using the selected Pareto-optimal settings.

6. Conclusions

This paper compares a baseline controller and a state-space model controller for the AVATAR 10 MW wind turbine model, through applying multi-objective Bayesian optimization to tune their parameters. This results in a Pareto-optimal set of settings choices, which the controller designer can choose from, trading-off performance on different objectives. Comparison of a selected parameter set from the Pareto front for both controllers has demonstrated the improvements

possible over traditional empirically-chosen parameter settings, improving power production while reducing the consumption of pitch activity and the loads in blades and tower. Direct and meaningful comparison (due to the application of Bayesian optimisation) between the two different controllers has also shown that the more advanced state-space controller provides most improvement in the power production, while reducing the consumption of pitch activity and loads in blades and tower.

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Appendix
Fig. 5 further presents the four objectives of the baseline controller and the state-space model controller for all the evaluated parameter sets. It further shows that to which extend each of the objectives can be reduced is determined by the applied controller.

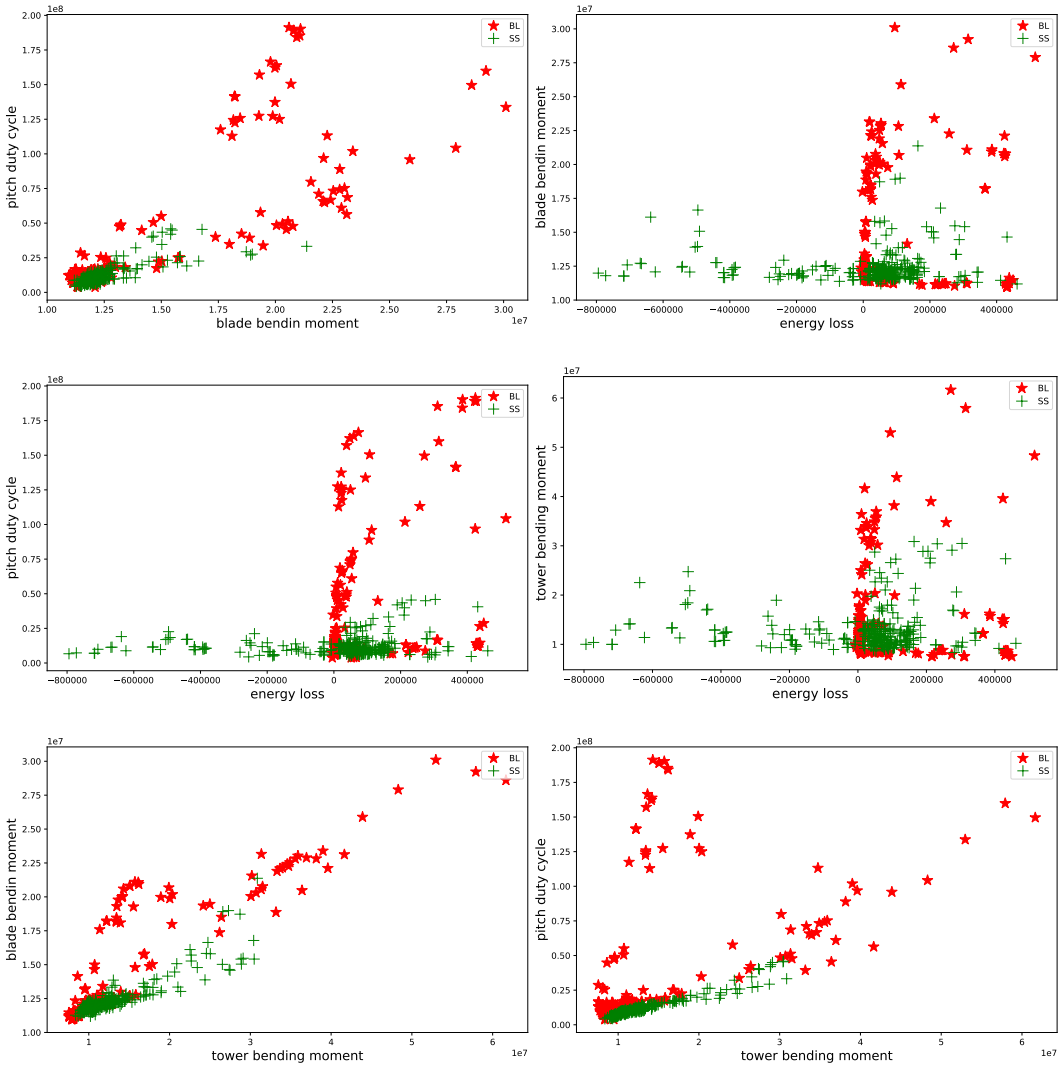

Figure 5: Performance of the wind turbine of the baseline controller and the state-space controller for all the evaluated parameter sets.