

Optimization and control of offshore wind farms with energy storage systems

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Abstract: This paper studies the optimal control strategies of hybrid renewable energy systems, focusing on offshore wind farms with energy storage systems (ESS), considering challenges of economic costs, operational reliability, and environmental impacts. Wind energy is widely exploited as a promising renewable energy source worldwide. The development of offshore wind farms (OWF) is emerging to utilize wind energy on a large scale, but face more complicated operational conditions and higher costs. A systematic methodology is proposed to optimize the costs of an OWF with ESS based on a framework that extends from the supervisory level dispatch strategies to individual pitch control for load reduction and fatigue mitigation. This holistic approach is able to improve the efficiency and economic performance of a wind farm through overall system optimization, while explicitly operating each wind turbine using a formally designed control framework leading to an extension of their service lifespan. This work provides novel solutions of wind energy and storage components deployment and has strong application potential.

Keywords: offshore wind farm; energy storage; economics; optimization; control.

1. INTRODUCTION

Wind energy is one of the most promising clean and renewable energy sources with a total 2-6 TW equivalent amount of globally extractable wind power that can satisfy current global electricity consumption which is around 2.3 TW (Armaroli and Balzani, 2007; IEA, 2016). Although fossil fuels are supplying the majority of energy demand worldwide, it is desired to continuously develop and deploy environmentally friendly and socially sustainable alternative energy technologies (Dresselhaus and Thomas, 2001). Offshore wind resources are abundant and consistent in many regions to provide reliable energy production (Perveen, Kishor and Mohanty, 2014).

Although there exist advantages of offshore wind energy conversion systems compared with onshore generation, such as higher wind speed, more flexible locations and less concerns around turbine noise, the difficulties in installation and maintenance cannot be overlooked (Snyder and Kaiser, 2009). In spite of the wide implementation of renewable resources, the discrete generation and inherent uncertainty in renewable resources also cause an issue. Currently the construction and operation costs of offshore wind farms are considerably higher than their onshore counterparts (Timilsina, Cornelis van Kooten and Narbel, 2013; Heuberger *et al.*, 2016). The time-varying electricity on-grid pricing also requires more comprehensive scheduling to lower the energy cost (Wang, El-Farra and Palazoglu, 2016). It is desired to have an integrated multi-scale approach that generates operational plans to optimize the state of each wind turbine and evaluate the overall wind farm performance in real-time. Another operation issue is caused by the structural loads experienced by wind turbines that are becoming more obvious as their size increases and shortening the working life of wind turbines (Bossanyi,

2003). As a solution, individual pitch controllers of wind turbine can act to mitigate the vibrations and resulting loads on its main flexible components such as blades, tower, and drive shaft (Namik and Stol, 2010).

Moreover, the inherent intermittency and large fluctuations of wind power caused by uncertain weather conditions need to be managed to prevent jeopardizing the stability of the electricity grids. The integration of an energy storage system (ESS) with the offshore wind farms is a convenient and feasible solution to overcome this drawback (Wang, Palazoglu and El-Farra, 2015). Furthermore, although wind energy conversion systems serve as a clean technology, there still exist many environmental issues that cannot be overlooked, where the key environmental concerns include noise, visual impacts, electromagnetic interference, and negative impact on wildlife, especially birds and bats (Gill, 2005; Tabassum *et al.*, 2014). Regardless of the extensive cost and operation analysis of OWF, it lacks a systematic architecture to link the system analysis and control structures, leading to direct industrial applications.

In this paper, an innovative framework of proactive offshore wind farm design and operation is presented, which can also be applied to other hybrid renewable energy systems. The detailed wind turbine dynamic model and environmental conditions, especially wind speed information, are used to obtain the optimal trajectory, while returning performance indicators and full system updates. The methodology of economic model predictive control (EMPC) is applied by incorporating a general cost function to reflect and further optimize the system economics (Ellis, Durand and Christofides, 2014). While most work focus on the control strategies of a single component, we aim to emphasize both the whole wind farm's operation through economic modelling and optimization of life-cycle costs

including installation, operations, and maintenance, and the individual control systems for wind turbines. We will first discuss the overall system design and operation methodology of supervisory level wind farm modelling and optimization in Section 2. Individual pitch control strategies combined with wind turbine aerodynamic and structural model is then described in Section 3. In Section 4, a brief case study is presented within real-world environment. Conclusions along with future work are given in Section 5.

2. SYSTEM DESIGN AND OPERATION

A wind farm with ESS is to be deployed as an integrated system. We first show the whole system design combining wind energy conversion and energy storage systems. An economic optimization, also taking operational and environmental issues into account, at the supervisory level for the whole wind farm with predictive functionality and model updates is proposed correspondingly.

2.1 Modelling of system

The hierarchical framework for whole farm optimization and individual turbine control proposed in this paper is depicted in Figure 1. The time dependent operational setpoints for power generation are obtained from the receding horizon prediction and optimization, which are further sent to the local controllers to ensure that each wind turbine in the farm reaches the desired state.

The integration of an ESS with the offshore wind farms is a convenient and feasible solution to overcome this drawback. Energy storage technologies have the potential to provide many benefits in the electrical power grid, which can be divided into three categories: uninterruptible power supply (UPS) and power quality, transmission and distribution (T&D) grid support and load shifting, and bulk power management (Nordling *et al.*, 2016). Despite the wide range of energy storage technologies, no single technology can offer all the application requirements of the power grid. Therefore, a suitable energy storage technology needs to be matched with the specific application scenario. Figure 2 shows the comparison between energy storage applications and technologies, based on the criteria of power and time requirement, and maturity. Pumped hydro storage (PHS) is the most mature energy storage technology for wind power management while compressed air energy storage (CAES) and battery energy storage (BES) are also mature technologies with great potential and large market share, which can be applied at OWF.

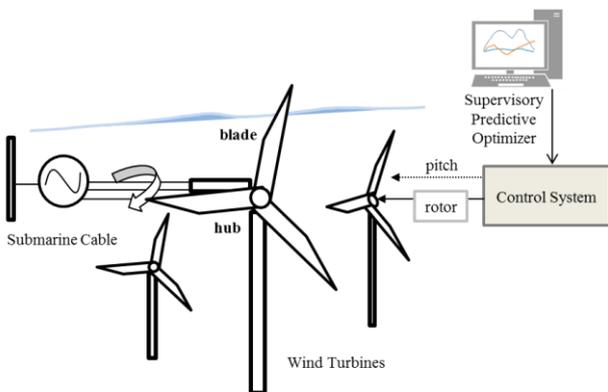


Fig. 1. Overall diagram of the wind turbines in OWF.

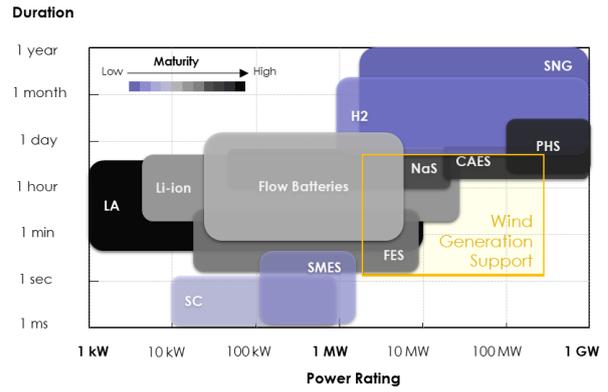


Fig. 2. Comparison of energy storage technologies.

2.2 Optimization at supervisory level

For the optimization problem at the supervisory level, the objective function incorporates the evaluation of revenue collected from selling electricity, the incentives or subsidies given for wind energy penetration, the operational costs of power generation and the environmental impacts mainly related to noise and ecological issues such as bird deaths.

We address the shortcomings of the levelized cost of energy (LCOE) by proposing an alternative metric, the unit system cost (USC), which evaluates the life-cycle costs of unit electricity generated from off-shore wind farm at the present value, which is defined as Equation (1):

$$USC_i = \frac{CAPEX_i + \sum_{t=0}^T OPEX_{i,t} / (1+r)^t + Env_{i,t} / A_{i,r} + Retire_{i,t} / (1+r)^T}{Ele_i / A_{i,r}} \quad (1)$$

where i represents wind turbine $1, 2, 3 \dots N$, $CAPEX$ is the capital expenditure, $OPEX$ includes operations and maintenance (O&M) cost, Env is the annual environmental cost, $Retire$ denotes the retirement or decommissioning cost and Ele is the electricity produced (kWh), A is present value to annuity, r is the interest rate, and t is each year over the total lifetime T . The key performance indicators adopted in this case are several cost terms summarized by the USC and revenue from selling electricity. A receding horizon optimization approach as in Equation (2) is adopted so that the system can forecast future conditions and return the power reference $P_{i,ref}$ based on the environmental variables and wind turbine parameters.

$$\min_{P_{i,ref} \in S(\tau_j)} \sum_{j=0}^{j=m} f(P_{i,ref}(\tau_j))$$

s.t. $i = 1, 2, 3 \dots, N$ number of wind turbines

$j = 1, 2, 3 \dots, m$ number of time interval

with duration τ

$$f(P_{i,ref}(\tau_j)) = USC(\tau_j) \times P_{i,ref}(\tau_j) + C_{ess} \times \Delta P_{i,ess}(\tau_j) - Revenue(\tau_j)$$

$$P_{i,min}(\tau_j) \leq P_{i,ref}(\tau_j) \leq \min_{\tau} \{P_{i,max}(\tau_j)\}$$

$$\Delta P_{i,ess}(\tau_j) = P_{i,ess}(\tau_j) - P_{i,ess}(\tau_{j-1})$$

$$\Delta P_{i,ess}(\tau_j) \leq P_{i,ref}(\tau_j) - P_{i,grid}(\tau_j)$$

$$0 \leq P_{i,ess}(\tau_j) \leq P_{i,max,ess}$$

$$P_{i,min}(\tau_j) \leq P_{i,grid}(\tau_j) \leq P_{i,max,grid}(\tau_j)$$

$$\begin{aligned} P_{i,ref}(\tau_j) - P_{i,ref}(\tau_{j-1}) &\leq dP_{i,max} \\ P_{i,ess}(\tau_j) - P_{i,ess}(\tau_{j-1}) &\leq dP_{ess} \end{aligned} \quad (2)$$

The simplified evaluation of instantaneous revenue is the real-time, on-grid price multiplied by instantaneous real power generation expressed as Equation (3):

$$Revenue(\tau_j) = c_{grid}(\tau_j) \times P_{i,grid}(\tau_j) \times CF \quad (3)$$

For application in real-time operation, the cost terms, power trajectory and constraints are discretized to cascade each hour over the considered time horizon. C_{ess} is the levelized cost for energy storage and $\Delta P_{i,ess}$ is the electricity that goes in or out of the energy storage system during time interval τ . $P_{i,ref}$ at each time step τ_j is constrained by both minimal $P_{i,min}(\tau_j)$ and maximal limits $P_{i,max}(\tau_j)$ which are not fixed values but vary according to environmental conditions. $P_{i,ess}(\tau_j)$ and $P_{i,ess}(\tau_{j-1})$, constrained by the minimum capacity of the energy storage system, which is set to 0, and maximum capacity $P_{i,max,ess}$, are the state of charge of the energy storage system at time τ_j and τ_{j-1} . $P_{i,grid}$ is the amount of electricity transmitting through the grid while $P_{i,max,grid}$ is the maximum capacity for grid transmission in real-time. $dP_{i,max}$ and $dP_{i,ess}$ are the maximum allowed ramping rates for electricity generation and storage components that meet the continuity requirement of the functions. $c_{grid}(\tau_j)$ is the real-time feed-in rate to sell electricity to the grid. The capacity factor CF is a measure of power output of a wind turbine or farm, compared with the maximum possible output as a proportion, which will penalize the total electricity generation capacity when calculating the revenue. The generated electricity can be sold back to the grid at various tariffs set by regulations and contracts.

3. LOCAL PITCH CONTROL

The power trajectories for each type of wind turbine are returned by the hourly based real-time optimization discussed above over a 24-hour day. With these power commands sent to the local controllers for load tracking, wind turbine systems are operated to track the time-varying set-points instead of a constant steady-state and deal with uncertainties in wind conditions at the same time. By manipulating the parameters such as electronic torque and pitch angle of each blade, the control system of wind turbines not only tracks the desired power output, but also functions to reduce loads on blades and tower as much as possible for extending their service life.

A basic wind energy conversion model is used for a preliminary estimation of potential output power of the wind turbine. Figure 3 shows a typical curve of the relationship between the output power and wind velocity. The control objectives for each region are clearly different. In Region 1 before the cut-in wind speed (normally 3-5 m/s), the wind is used to accelerate the rotor to get ready for start-up although the generator has zero torque and no power is generated. Region 2, which is between the cut-in speed and the rated or nominal wind speed (normally 11-16 m/s), is a control region aimed at optimizing power capture, where the maximum output power follows the relationship in Equation (4):

$$P_t = \frac{1}{2} C_p(\lambda) \rho A v_w^3 \quad (4)$$

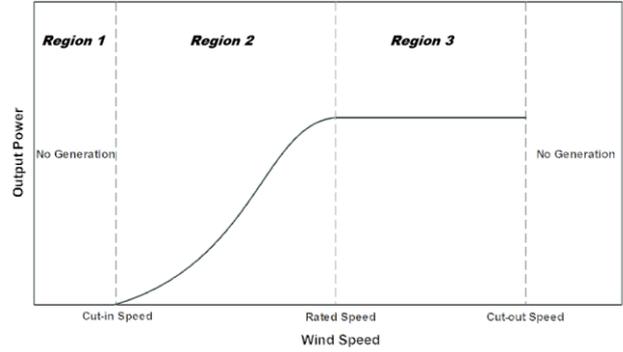


Fig. 3. Relationship between power output and wind speed.

where ρ is the air density, A is the area swept by the rotor blades, v_w is the wind velocity and C_p is the power coefficient which is a function of the tip speed ratio λ . In Region 3, the generator power is held at a constant rated power so that the generator torque is inversely proportional to the filtered generator speed because load mitigation becomes an additional main goal besides power control to prevent damage to the generator and the corresponding power electronic devices caused by the more complex wind conditions in this region. If the wind speed is even higher than the wind turbine's cut-out speed (normally 17-30 m/s), the system is stopped to protect its components.

Therefore, the local control system mainly focuses on Region 2 and 3 where power is generated. A benchmark framework combining torque control in Region 2 and proportional-integral (PI) based individual pitch control in Region 3 is proposed at the local layer. To achieve constant power control, the full-span rotor-collective blade-pitch-angle commands are computed using gain-scheduled PI controllers (Plants, 2009). The multi-blade coordinate transformation (MBC) is applied to wind turbines to realize a rotating-frame to nonrotating-frame transformation of coordinates, and individual pitch control adopted for fatigue load mitigation. The open source code FAST as introduced in Section 1 is used to model the three-bladed, horizontal-axis wind turbines, with 24 degrees-of-freedom to describe the turbine dynamics. The advantage of incorporating both rigid and flexible parts modeling (e.g., blade, shaft and tower) makes it ideal to test variable-speed operation and control, with efficient computational time for real-time applications.

The load transformation yields M_{tilt} and M_{yaw} as the two main axes for the tilt and yaw loads from three blade root-bending moments M_1 to M_3 . The blade coordinates given the rotor coordinates are evaluated using Equation (5) below:

$$\begin{bmatrix} M_{tilt} \\ M_{yaw} \end{bmatrix} = \frac{1}{3} \begin{bmatrix} \cos(\omega t) & \cos(\omega t + \frac{2\pi}{3}) & \cos(\omega t + \frac{4\pi}{3}) \\ \sin(\omega t) & \sin(\omega t + \frac{2\pi}{3}) & \sin(\omega t + \frac{4\pi}{3}) \end{bmatrix} \times \begin{bmatrix} M_1 \\ M_2 \\ M_3 \end{bmatrix} \quad (5)$$

where ω is the angular velocity in rad/s, and t is time in s.

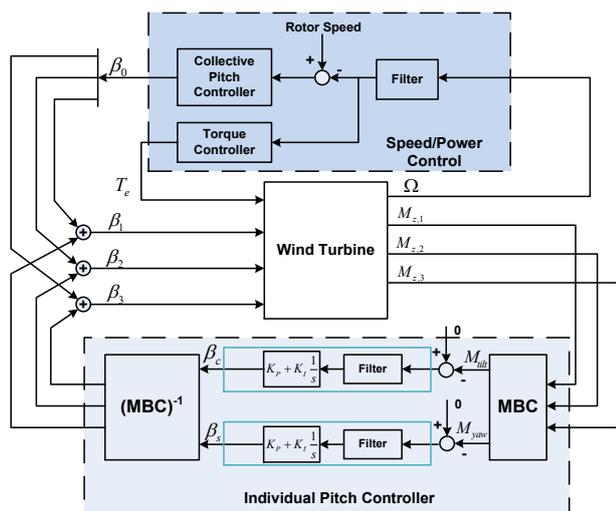


Figure 4. Local control system framework.

The local control structure is illustrated in Figure 4. The maximum power point tracking (MPPT) torque controller and standard collective pitch controller are adopted to manipulate rotor speed and thereafter regulate power output in Regions 2 and 3, respectively. Moreover, individual pitch controllers are applied when the wind speed exceeds the boundary of Regions 2 and 3 to mitigate loads.

To demonstrate the effects of local control systems that can track power set-points and reduce fatigue loads at the same time, a follow-up life-load analysis is conducted and the updated lifespan is returned to the initial operational optimization as a feedback loop. There has been a great deal of research on analyzing wind turbine fatigue using both theoretical and empirical methodologies (Ragan and Manuel, 2007). We use a basic relationship between the damage equivalent loads (DEL) and use life expectancy of wind turbines. The DEL is a common standard in industrial application to evaluate the fatigue load on mechanical components (Buhl, 2008), which is obtained from simulation and described by an empirical relation for the trend of changes in use life with respect to the fatigue loads carried. Similar to the stress-life diagram (S-N Diagram) widely applied in high-cycle fatigue situations, a power law equation is adopted to describe the relationship between the wind turbine service life and fatigue loads as given in Equation (6) (Veldkamp, 2006):

$$L_{i,t} = L_{i,0} \sum_{k=1}^3 \left(\frac{M_{k,t}}{M_{k,rated}} \right)^{\frac{1}{m_k}} / 3 \quad (6)$$

Here k stands for blade 1, 2, 3, and M indicates moments.

The lifespan is estimated from data profiles of fatigue loads on wind turbine blades, shafts and tower. As there are no evident relationships between the expected life time and fatigue loads on each component of a wind turbine, a Monte Carlo simulation can be used to adjust the relationship between average lifespans from load data.

4. CASE STUDY

In this demonstrative case study, we study a typical grid-connected offshore wind farm that can consist of about 15 and as many as 150 turbines.

The investigated offshore wind farm is constructed with two types of wind turbines of 5 MW and 1.5 MW rated power, respectively. A turbine with 5 MW nameplate capacity (e.g., Repower 5M or AREVA Multibrid M5000) calls for capital investment around USD 7.43 million, while a 1.5 MW utility scale wind turbine (e.g., GE 1.5sle) costs around USD 3.34 million. The key parameters to describe these wind turbines are listed in Table 3. Using the market price of 5MW and 1.5MW wind turbines as a benchmark, the scaling correlation exponent m is estimated to be -0.337.

Table 3. Main parameters of the 5 MW and 1.5 MW wind turbines

Parameter	WT 1	WT 2
Rated rotor speed	12.1 rpm	20 rpm
Cut-in wind speed	3 m/s	3 m/s
Blade length	63 m	35 m
Rated power	5 MW	1.5 MW
Cut-off wind speed	25 m/s	25 m/s
Tower height	87.6 m	82.39m
Rated wind speed	11.2 m/s	12 m/s

Data series that mimic the real-time and hourly weather forecasting of temperature and wind speed adapted from observatory information in the near sea of Rhode Island are used and adjusted to fill data gap (Liu *et al.*, 2013; Musial, 2016). The wind speed series over a day, which is shown in Figure 5, is used for both the whole wind farm optimization and wind turbine control.

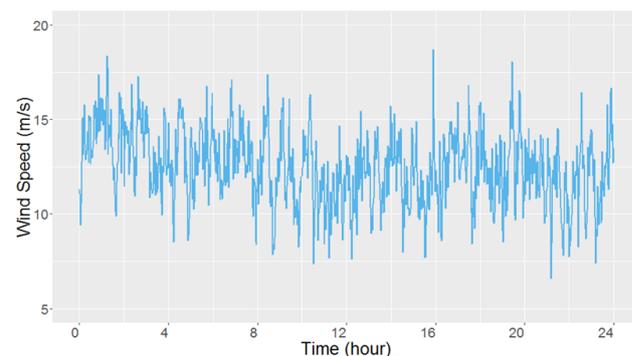


Figure 5. Wind speed series over a 24-hour period.

4.1 Wind farm operation

The grid-connected wind farm with no energy storage system is studied for an initial evaluation. We first use the metric of long-term USC as the minimization target together with the energy storage costs and grid selling revenue to schedule the wind farm operation. All the capital expenditure, operation and maintenance costs, as well as life-cycle environmental costs are taken into account and translated into a present value through Equation (1). In this case study, assuming the annual operation and maintenance costs account for 3% of the total capital investment, and no fuel costs are incurred for power generation, the LCOE can be calculated relating to CAPEX and decommissioning costs. The feed-in-tariff scheme used in the scenario is time-varying and corresponds to typical price schemes employed by utility companies for peak, normal and off-peak hours.

The most economical operation plans for each wind turbine and the energy storage system are demonstrated in Figure 6. This is a typical scenario when the on-grid price is always sufficient to guarantee the profitability of wind generation, and the real-time operation with maximal power output is favourable thereafter.

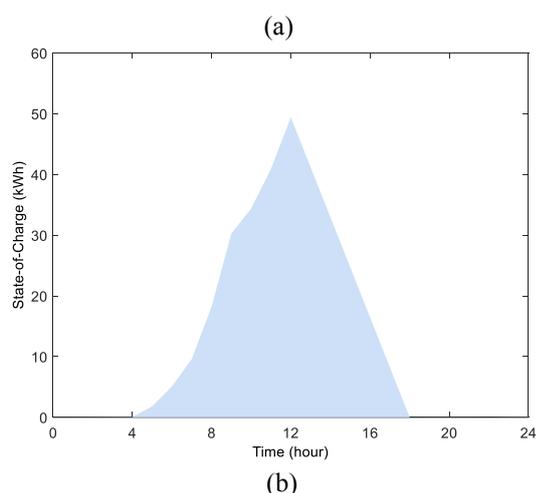
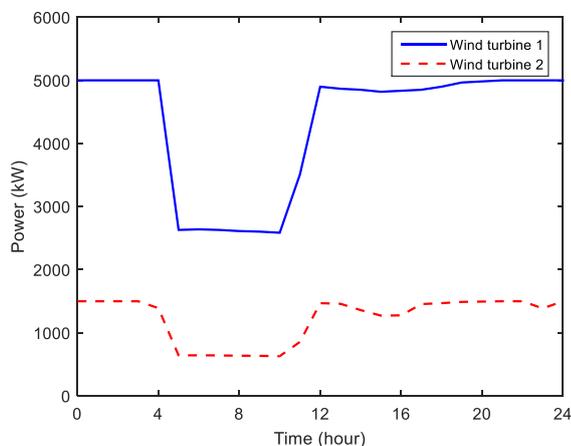


Figure 6. Power and energy trajectory from overall wind farm optimization over 24 hours: (a) two types of wind turbines; (b) energy storage system.

The results are reasonable as the system tends to drive both type of wind turbines to be operated at the maximum possible power output when the real-time selling price exceeds costs induced. However, in other scenarios, if the subsidies are not sufficient to incentivize the energy producers, or the demand is low during off-peak hours, the wind farm may desire a lower power output to obtain the cost-effective generation, and therefore there exists an operational compromise to curtail partial power output through the control strategy.

4.2 Wind turbine control

To prove the effectiveness of control strategies applied to an individual wind turbine, the operationally profitable conditions are tested under which each turbine is required to operate at the maximum power constrained by wind speed and states. This corresponds to the scenario when offshore wind becomes economically efficient, or only

operating costs are considered leading generation at maximum capacity a preferred strategy. Figure 7 first illustrates the real-time power output from the 5 MW wind turbine that follows the supervisory power trajectory denoted by the blue line in Figure 6(a). Despite the initial oscillations in power generation caused by the control system transients, the real-time operation is able to deliver the desired output.

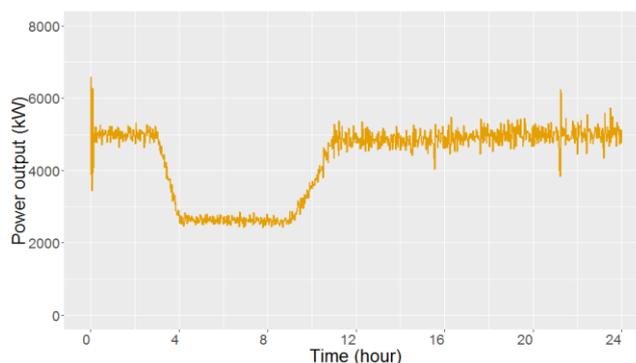


Figure 7. Real-time power output from 5 MW wind turbine.

The damage equivalent loads on different dimensions and components including tilt, yaw, tower and each blade are also calculated to evaluate fatigue load level and service life of wind turbines on an hourly basis using the real-time load variations obtained from FAST wind turbine simulation tools. These quantitative criteria along with local control systems are analyzed to evaluate how performance of wind farm operation influences real-time scheduling through a feedback loop. The benchmark load data under rated conditions are listed in Table 4. The expected lifetime corresponding to rated environmental conditions is the default 25-year service life for common wind turbines.

Table 4. Loads on wind turbines under rated condition

Loads/ kN m	Tilt	Yaw	Tower	M1	M2	M3
WT 1 (5 MW)	785	472	4,840	4,850	4,830	4,920
WT 2 (1.5 MW)	132	72.2	924	760	765	752

Using the basic set of economics and load information obtained from Equations (1)-(3), the unit cost of energy generated from the 5MW wind turbine is 0.116 USD/kWh. With the load control methods applied, the expected life increases to 27.4 years and the unit cost is reduced to 0.113 USD/kWh. While for the 1.5 MW turbine, the levelized unit cost of energy reduces from 0.160 USD/kWh to 0.158 USD/kWh, with life expectancy increased for 25 years to 26.5 year.

The offshore operation may face extreme environmental conditions that could compromise the functioning of the sensor network. In this case, a decoupled control framework would have advantages over a fully centralized control strategy in regulating the whole wind farm operation. The controllers at the local level are designed with their default trajectory in case the communication with the supervisory level is disrupted. Hence if part of the controller network stops working, it will not influence the other normally

operated turbines. The power controllers and individual pitch controllers are also operated independently so that one failure does not sacrifice performance or cause maintenance costs on the other. In a simplified case, the default trajectory for local wind turbines can be defined initially as constant or the maximum power output under current wind conditions, so that a disconnection to the supervisory level does not stop operation of the whole wind farm.

5. CONCLUSIONS AND FUTURE WORK

This paper introduced a proactive methodology that combines supervisory optimization over the whole wind farm and individual control strategies for modern utility-scale wind turbines for the development of offshore wind farm with energy storage systems. We introduced a holistic approach that relies on developing whole wind farm modelling and optimization techniques as well as wind turbine aerodynamic and structural models and associated control strategies. It is demonstrated how the proposed methodology is applied to an offshore wind farm constituted by multiple wind turbines in real wind environments and various scenarios of costs and incentive schemes with details. The simulation results show that the adopted control strategy is able to further reduce unbalanced loads acting on the rotor with reduced computational efforts, making it suitable for real-time implementation. This work also serves as a feasible solution for avoiding the wasted offshore energy that cannot be connected to the grid.

Based on this preliminary study, a lot of future work still remains to be explored. It should be noted that some parameters such as the turbine service life and equivalent monetary impacts used in the current simulation are by estimation, which can be further improved through data mining techniques when applied in an actual scenario. An explicit evaluation of other indirect economic or environmental impact categories of offshore wind farms and their integration into the whole wind farm optimization would be useful elements for future study. The application of the developed framework to other hybrid renewable energy systems is also in plan.

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