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REVIEW ARTICLE

Overall equipment effectiveness as a metric for assessing operational losses in wind farms: a critical review of literature

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ABSTRACT

To become more competitive, less dependent on financial support and more attractive for investors, wind energy needs to reduce its final cost of energy. According to Levelized Cost of Energy, there are two ways to achieve this goal, by reducing costs or increasing production. Overall Equipment Effectiveness (OEE) is a widely used metric in manufacturing systems, supporting operators to enhance productivity by reducing operational losses. Therefore, this study aims to perform a qualitative literature review of the main operational losses following the OEE metric, namely availability, performance and quality, adjusting it to wind energy systems. Introduction of this metric can be a valuable tool towards an integrated indicator linking production and losses, allowing comparison between assets deployed in different settings.

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Overall equipment effectiveness; wind energy; availability; performance

1. Introduction

With several political and financial incentives during the last years, wind power has sustainably increased its contribution to the national energy mix, covering 15% of European electricity demand in 2019 (WindEurope 2020) and aiming to achieve around 30% in 2030 (Nghiem and Pineda 2017). However, for wind energy to become more independent of incentives and attract more investors, it still has some challenges to overcome, such as reducing the cost of electricity and increasing its performance, towards maximising profitability throughout its service life.

A very common metric to calculate the cost of electricity is through Levelized Cost of Energy (LCoE). LCoE should be thought as the ratio between the total production and total costs during its lifespan, considering financial costs, time value of the money, and some profits to investors. The total cost of implementation is known as Capital Expenditure (CAPEX), while during the operational lifetime, there are Operation and maintenance (O&M) and management costs, also known as Operational Expenditure (OPEX) (Kolios et al. 2019). At the same time, it is during this period that the benefits are achieved through the electricity produced and sold. Finally, after the nominal service life period and a potential service life extension, Decommissioning Expenditure will take place and relevant costs should be considered (Jadali et al. 2021). Figure 1 summarises all these costs and benefits. It is important to mention that some returns might come from the disposal of materials and equipment after decommissioning, and, for that reason, the disposal is represented in blue and denoted by a question mark. Studies show that recycling can cover up to 20% of offshore decommissioning costs (Topham et al. 2019).

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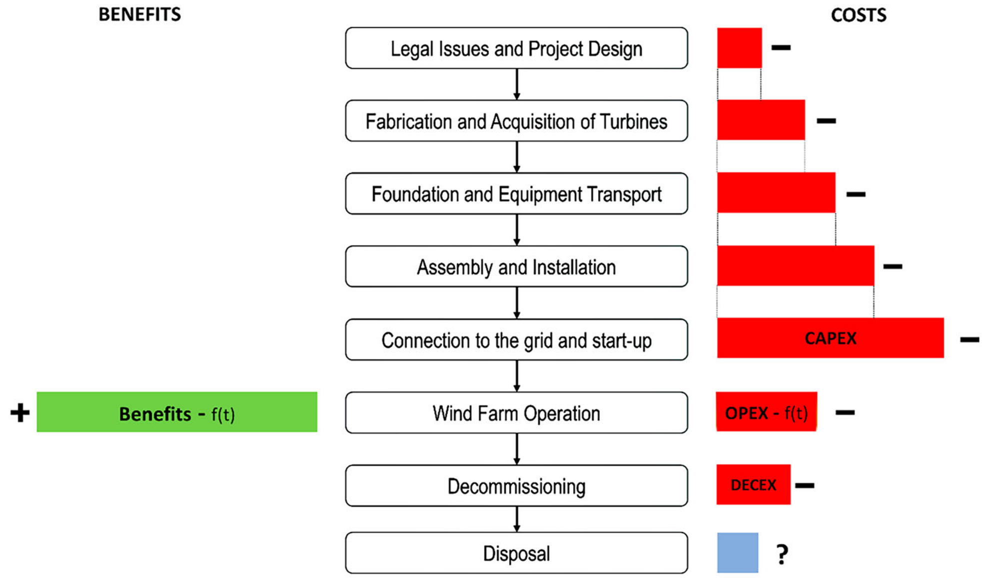

Figure 1. Costs of wind turbine lifespan – adapted from Sathler (2013).

Even though one might consider that reducing the CAPEX value might be an adequate approach to reduce the total life cycle cost of a wind power project, it can be a rather simplistic solution. As shown in the first scenario of Figure 2, a poor implementation choice can affect the whole operational performance, increasing the total cost. Therefore, a balance between all costs must be considered during the project design, since over-reducing implementation costs can affect future operational costs and even result in higher total costs than before, as presented in the second scenario of Figure 2.

Towards reducing LCoE, there are mainly two approaches to be followed: increasing production or reducing the total costs. Traditionally, after installation, connection to the grid and commissioning, operators assume that the project aims to produce as much electricity as possible at the lowest possible costs. More modern wind farms operate following more sophisticated KPIs (Key Performance Indicators), such as the maximisation of profitability, because after a certain point production of more electricity may come at an additional cost, which may not be justified by the additional benefit. Usually, OPEX costs vary between 20% and 35% of the total costs depending on the age

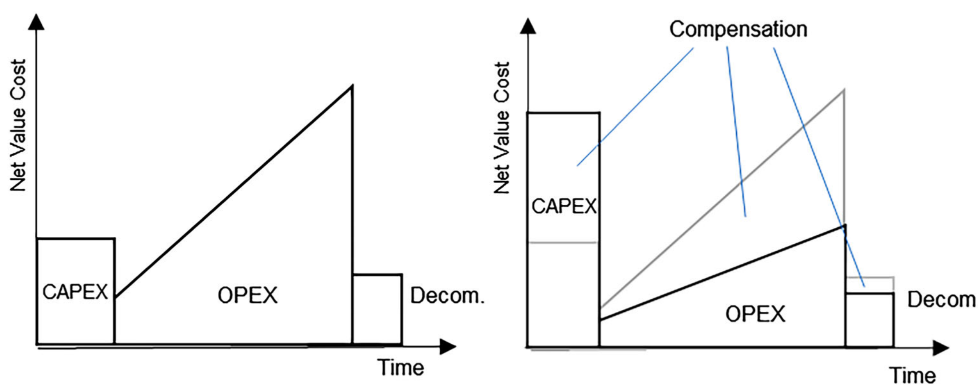

Figure 2. Comparison of two life cycle cost scenarios – Source: Adapted from Sakurai (1997).

of the project, its location, and whether it is onshore or offshore (Rajgor 2012; Ioannou, Angus, and Brennan 2018a; Ioannou, Angus, and Brennan 2020). The operational period is very important because it is during this period that the project performance is more critical for the success of the entire project and subsequently the potential of an extended service life can be anticipated or postponed. This decision is made based on the decrease in profitability, reliability and performance (Luengo and Kolios 2015). It has been reported that in some situations, O&M costs can increase around 253% over a 20-year turbine lifespan (Rajgor 2012), making it impractical to sustain operation.

Other industries and technologies have followed the same steps towards qualification, commercialisation and cost optimisation. First, early adopters benefit from financial support in order to become commercially viable and improve towards further development. Later, they involve in a mature level, where competition forces a continuous improvement culture. In this scenario, managers start focusing on improving all aspects of the process to improve their productivity, quality and costs. For instance, Boyd et al. (2000) and Apostolos et al. (2013) discuss and relate productivity with energy consumption efficiency. Stavropoulos et al. (2020) used machine learning to improve quality diagnosis in laser welding and Papacharalampopoulos et al. (2020) used neural networks and image recognition to improve defect detection in solar reflectors. To understand the real benefit of these solutions, reliable metrics and tools are necessary to help managers to track their overall productivity.

Among these multiple tools and approaches available, the concept of Overall Equipment Effectiveness (OEE), which focus on improving equipment productivity by reducing the main operational losses in the system, can become particularly useful towards technology optimisation. This tool is sufficiently versatile and can be adapted to different scenarios due to its simplicity and efficiency to support decisions and a continuous improvement culture. To this end, the aim of this paper is to identify in the literature the multiple sources of losses in wind power assets and classify them following the three main elements of OEE, that is, availability, performance, and quality. The results have the potential to become the basis of the adaptation of this metric in wind energy.

The rest of the paper is organised as follows. The OEE tool is explained in detail and the review strategy is defined in Section 2. Findings from the review and the identification of the main operational losses are presented in Section 3, while Section 4 discusses the outcomes and analysis of the literature review. Finally, Section 5 presents conclusions drawn based on the bibliographical review and some recommendations for future research works.

2. Method

2.1. Overall equipment efficiency concept

In the early 1970s, the Japan Union of Scientists and Engineers has developed a maintenance strategy called Total Productive Maintenance (TPM), where the goal was to achieve maximum performance in its production considering all phases related to the production. In order to check its efficiency, a metric called Overall Equipment Effectiveness (OEE) was introduced, where all possible causes of losses and the main six losses are identified and classified into three main elements, namely availability (A), performance (B) and quality (C), as shown in Figure 3.

Any change in the process can influence one or more elements. For that reason, OEE became an important productivity tool, since it considers the overall result and efficiency, helping to identify where losses are more frequent, and hence targeting improvement interventions. The OEE index is obtained through the multiplication of the three elements, and it represents the overall performance of the equipment. This index is considered an important metric to help asset managers and operators to make decisions, increasing the productivity of the equipment or process.

$$\text{OEE} = \text{Availability (A)} \times \text{Performance (B)} \times \text{Quality (C)}.$$

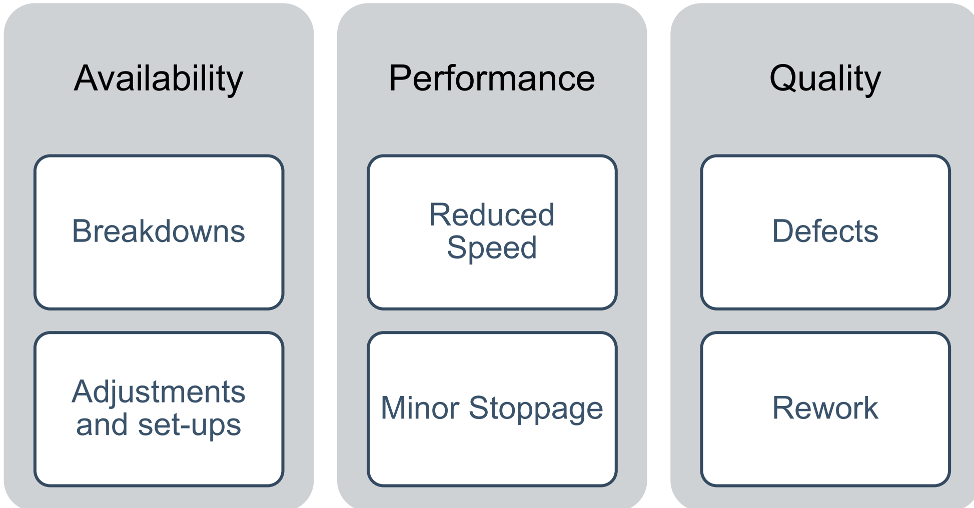

Figure 3. Six main losses.

2.1.1. Availability

Availability is calculated considering the planned operating time discounted by the period that the equipment is not available to operate, known as downtime (Scheu et al. 2017). There are two main types of losses in the availability category which can cause downtime, as shown in Figure 3. The first accounts for breakdowns, which are generally related to maintenance or failures and the time spent to fix the interruption cause. The second type accounts for adjustments and set-ups, where we refer to pauses in production which are not related to breakdowns. Relevant examples include planned maintenance interventions and adjusting the equipment for new products. Even though some losses are expected, it is important to quantify them and understand their influence on key output indicators, in order to identify areas of improvement in the process. The basic formula to calculate operational availability is:

$$A = \frac{\text{Planned Operating Time-Downtime}}{\text{Planned operating time}}$$

It should be noted that in practice different formulas are adopted for different types of availability, such as inherent, time-based, revenue-based, etc., so it is important to ensure that the right metric is adopted.

2.1.2. Performance

Losses related to performance can be the most challenging ones to identify since they are considered through instances where the equipment is performing outside the specification limits set (Salameh and Jaber 2000). This type of loss can be related to reduced speed, meaning that for any reason a part of the equipment is running with lower performance, which can be caused by damage, a not-well-lubricated bearing or lack of alignment, for instance. Another reason for performance losses is minor stoppages, where faults cannot be measured, but production performance is affected. An example is when in a cycle for any reason a motor is taking one second more to start due to a mechanical or electric fault, which is not easy to be recognised by operators. However, it can become a significant loss when accumulated throughout every operational cycle. A performance rate control can warn operators when something is wrong and needs to be investigated. Performance is calculated over planned operating time minus downtime, so the availability loss is not considered twice:

$$B = \frac{\text{Standard production rate} \times \text{Parts produced}}{\text{Planned operating time-Downtime}}$$

2.1.3. Quality

Finally, quality is related to the final product as a result of a process or operation of equipment. Any producing process should ensure that the final product meets the end user's or the client's requirements. The first type of loss in this factor accounts for defects, that is, when the product is out of specification, and it should be discarded. The second element is rework, when minor defects are identified and extra work is required in order to recover the product. According to the OEE concept, this is also considered as a loss because the time and the resources spent to fix it could be used to produce a new product or they can reduce the operational life of the process. The formula to calculate quality only considers products that were produced during the period assessed:

$$C = \frac{\text{Units produced} - \text{Defective units}}{\text{Units produced}}$$

2.2. Review activity

To identify the operational losses, before categorising them, an extended literature review was performed. The focus was on papers published from 2010 onwards that had key words or expressions such as 'operational losses', 'quality losses', 'production losses', and 'performance losses', together with 'wind energy' or 'wind power', in their titles and/or abstract. Then, a careful reading was performed to check if important information could be retrieved and if the paper was really related to wind power and operational losses. Section 2.3 presents the criteria used to classify and collate the identified losses considering OEE elements stated in Section 2.1. Also, the papers were divided into five groups as follows. 'Investigation' refers to papers that assess the operational losses and discusses the topic, through reviews, numerical models, trends, or data analysis. 'Decision Support' refers to when a framework or a new methodology is created or adapted, which resolves important information that could help operators to minimise losses. 'Controllers' refer to the development of a controller to reduce losses, find optimal point, or change the premises and settings of traditional controllers. 'Machine Learning' refers to papers which use any machine learning technique to perform predictions or find correlations among inputs and outputs. And, finally, 'Others' refer to solutions that are not listed before, including technical changes or the addition of components or gadgets in the system.

2.3. Classification criteria

As demonstrated in Section 2.1, the OEE metric focuses on identifying, classifying, and quantifying operational losses. To adapt it to wind farm projects, some considerations need to be taken into account. The flowchart shown in Figure 4 illustrates the assumptions considered in this paper to classify the losses found in literature and what the authors believe would be a suitable approach to adapt the tool for wind energy assets. It is important to notice that the decision element in the flowchart started with the preposition 'from' because each index is considered from the result of the previous one, avoiding losses being accounted twice during the process analysis.

Another important observation in the flowchart is related to the final result. Although the decision question was included in the flowchart, it is very unlikely that no losses are registered in an industry or application. This could be achieved in a short-term period, but considering

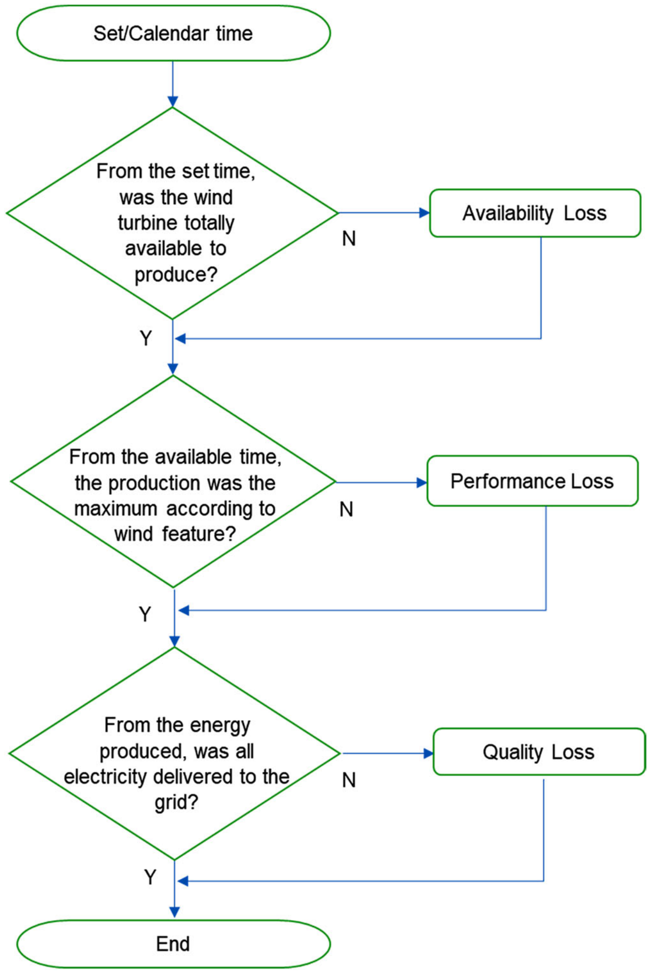

Figure 4. Flow chart losses in wind power according to OEE tool.

long-term periods, losses are expected and considered in all projects. For instance, an OEE of 85% is considered world-class benchmark (Stamatis 2017), representing that, even in reliable projects, there are losses. The following subsections detail the losses and how the scientific community has been aiming to minimise them, especially in the operational perspective. Also, it is important to mention that OEE results cannot be fully compared between deployments. Even turbines from the same company may not have the same OEE, as the equipment productivity relies not only in operational system, but also on the management commitment, involvement of the team, maintenance efficiency, wind farm location, deployment environment and other particularities that any project faces.

3. Literature review

3.1. Availability losses

The first aspect to be considered is the set time contemplated in the OEE calculations. In the wind energy industry, turbines are designed to operate all year round, so considering the entire calendar period as a set time base is realistic. The first source of downtime mentioned in OEE is breakdowns.

This item is related to any time that the turbine is not available to produce due to unexpected downtimes, such as failures and corrective maintenance. Reliability Centred Maintenance (Fischer, Besnard, and Bertling 2012), Fault Tree Analysis (Kang, Sun, and Guedes Soares 2019), Failure Mode Effect Analysis (Luengo and Kolios 2015; Scheu et al. 2019; Li, Teixeira, and Guedes Soares 2020), reliability-based methods (Leimeister and Kolios 2018) and studies about failure rates (Faulstich, Hanh, and Tavner 2011; Tavner et al. 2013), such as RAM analysis, are examples of methodologies aiming to reduce availability losses and increase reliability and lifespan of the wind turbine and its components.

The second downtime factor mentioned in OEE refers to adjustment and set-ups. Differently from the traditional manufacture industry, wind turbines do not need to change worn out tools or adjust their process for new products. Therefore, the only 'expected downtime' for wind turbines is preventive maintenance. Many papers that cover availability discuss both downtime cases, corrective and preventive maintenance, which makes hard to separate them efficiently. However, some papers focus on suggesting strategies to improve preventive maintenance schedule (Li et al. 2016; Yürüşen et al. 2020; Zheng, Zhou, and Zhang 2020), including the use of machine learning to better predict wind conditions (Yin et al. 2020), which could be used to affect less the wind energy output (Duchesne et al. 2020).

Offshore deployments have a particular approach. While onshore wind farms can achieve around 98% of availability (Hahn and Jung 2006), offshore wind farms present a lower pattern achieving around 92% (Ioannou, Angus, and Brennan 2018a, 2018b). Besides the distance to the shore and the need of vessels, also considering safety constraints, accessing the turbine is only possible in appropriate climate conditions. Therefore, the cost may be increased affected by this dependency, since some maintenance or changing of components needs to be done in advance, in the appropriated time, instead of the best and more effective time, underutilising some of the components' remaining life (Yang 2016). A logistic maintenance review for offshore operations is presented in (Shafiee 2015) and a maintenance cost reduction review for offshore farms in Tusar and Sarker (2021).

Table 1 presents the main causes of losses by the availability of wind turbine. The second column gives some examples of the losses causes, and the third column includes studies in which losses were assessed or quantified, suggested solutions, or compared different approaches. The category of the papers, as mentioned in Section 2.2, is also included in Table 1.

3.2. Performance losses

Differently from the traditional manufacturing industry, wind turbines have different performance rates to be assessed, since the production output depends directly on the wind features, especially wind speed and density. Therefore, before discussing about the losses, the standard rate needs to be commented. The most usual way to assess wind production is through the wind power curve, which defines the production according to the wind speed, normally tested in a lab and later confirmed in a Power Curve Test, according to IEC 61400-12 standard and some local regulations (Asgarpour 2016). Some researchers have proposed more accurate power curve considerations including other factors such as wind direction (Pandit, Infield, and Kolios 2019; Yan, Pan, and Archer 2019; Pandit, Infield, and Kolios 2020), turbulence (Saint-Drenan et al. 2020) or air density (Pandit, Infield, and Carroll 2019) and controllers (Pandit, Infield, and Kolios 2020).

Even though these approaches are good for a better production prediction, according to OEE, this can hide some opportunities for improvement. To illustrate this, one common problem related to wind direction is the wake effect. Although wake effect losses are expected, some researchers have proposed solutions to minimise them during the operational phase, such as intentional misalignment of yaw controller (van Dijk et al. 2017; Kanev 2020) or changing individual controllers to farm controller (Park and Law 2016; Ciri, Rotea, and Leonardi 2017). In other words, although

Table 1. Main cause of losses by availability of wind power.

Losses	Example	Related papers	Investigation	Decision support	Controllers	Machine learning	Others
Breakdowns	Failures Corrective maintenance	FMEA – Luengo and Kolios (2015), Li, Teixeira, and Guedes Soares (2020), Scheu et al. (2019), Li, Huang, and Guedes Soares (2022), Lopez and Kolios (2022)	X	X		X	
		Reliability and failure rate analysis – Faulstich, Hanh, and Tavner (2011), Tavner et al. (2013), Bhardwaj, Teixeira, and Guedes Soares (2019), Leimeister and Kolios (2018), Santelo et al. (2021), Fischer, Besnard, and Bertling (2012)	X	X			
		Fault tree analysis on floating offshore turbine – Kang, Sun, and Guedes Soares (2019)	X				
		Fault predictions/detection – Helbing and Ritter (2018), Chen et al. (2019), Lin, Liu, and Collu (2020), Zhang et al. (2018), Koltsidopoulos Papatzimos, Thies, and Dawood (2019), Martin, Mailhes, and Laval (2021), Han et al. (2022), McMorland et al. (2022)		X		X	
		Uncertainties in O&M models – Ioannou, Angus, and Brennan (2019), Yang et al. (2020)	X				
		Human impact on maintenance – Mentes and Turan (2019)	X				
		Fatigue and failures related to weather – Gözcü and Stolpe (2020), Stewart and Lackner (2014), Horn, Krokstad, and Leira (2019), Reder, Yürüşen, and Melero (2018), Fæster et al. (2021), Gao, Sweetman, and Tang (2022), Zheng and Chen (2022)	X	X		X	X
Preventive maintenance	Preventive maintenance	Maintenance cost review for offshore Tusar and Sarker (2021), Nguyen, Chou, and Yu (2022)	X				
	Inspections	Method for better maintenance scheduling – Nguyen and Chou (2018), Duchesne et al. (2020), Zhong et al. (2019), Shafiee (2015), Nguyen and Chou (2019), Yürüşen et al. (2020), Li et al. (2016), Zheng, Zhou, and Zhang (2020), Sa'ad, Nyoungue, and Hajej (2022), O'Neil et al. (2023), Pandit, Kolios, and Infield (2020)		X		X	
		CBM – Li, Teixeira, and Guedes Soares (2020), Baboli et al. (2020)	X	X		X	
		Reliability monitoring – Martin, Mailhes, and Laval (2021), Lin, Liu, and Collu (2020), Zhang et al. (2018), Izquierdo et al. (2020), Yin et al. (2020)		X		X	

some wind features cannot be controlled, considering it in the best performance rate can skew the results and do not incentivise operators to find ways to minimise them in case of a high impact.

Some additional observations need to be discussed about the standard rate. Although there is no rigid rule and these concepts can be adapted by operators following their own necessity, the standard time needs to be as simple as possible to minimise human errors and misinterpretations. Also, differently from other performance metrics, OEE focuses on being as close as possible to the best performance. Therefore, instead of using average production, standard rate should be the best rate and the goal of operators becomes minimising the gap between best performance and actual production. As a rule of thumb, if the actual performance frequently exceeds 100%, the standard time is underestimated, and if the actual performance is not even close to the standard rate or never has been, even for a short time, the standard time is overestimated.

With respect to performance losses, two main causes were pointed out: reduced speed and minor stoppages. As mentioned in Section 2.1.2, the performance index considers losses that cannot be measured as easily as availability, so comparing production output at the same conditions could be the best way to identify reduced speed and minor stoppages, including faults and failures in the system that does not send alerts to operators. Since wind turbines are complex equipment and are exposed to hard and uncontrolled environments, the performance losses can be caused by several factors. Some of these are related to the equipment itself, while others are related to the environment.

Even though climate features are not controlled by the operator, they need to be considered to better understand the performance behaviour. Some papers relate differences in performance due to seasonal conditions or periods of the day (Tian et al. 2020), humidity (Danook, Jassim, and Hussein 2019), turbulence (Bardal and Sætran 2017), and other papers are looking for a way to minimise losses due to rain (Arastoopour and Cohan 2017) and icing (Yirtici, Ozgen, and Tuncer 2019; Dong et al. 2020; Stoyanov and Nixon 2020), even using machine learning (Chen et al. 2019). For offshore wind farms, some additional issues can be considered in this category, such as wave impact due to misalignment of the turbine (Stewart and Lackner 2014; Horn, Krokstad, and Leira 2019) and platform motion that can affect the performance of other controllers (Namik and Stol 2010; Wen et al. 2018; Fang et al. 2020; Karimian Aliabadi and Rasekh 2020; Li et al. 2020).

The ones related to the system can be influenced by the condition of other components. Usually, the increase in temperature, vibration, or abnormal effort can affect productivity. Thus, these can be considered examples of reduced speed caused by damaged bearing (Chang et al. 2020), lack of lubrication, wear outs in components or even ageing (Hamilton et al. 2020). For instance, Reder, Yürüşen, and Melero (2018) indicate a performance decrease before failures. Another important loss that is usually neglected is the time spent to start the generation of energy. Every time the turbine is shut down, due to safety reasons, maintenance, or lack of wind, the equipment spends time to gain inertia, start rotation and generate electricity. Thus, a more efficient 'starting up' time can directly affect the production rates throughout the year. In some situations, the time needed to achieve the operational rotation can be affected by wind speed, as demonstrated in (Wright and Wood 2004), which tested this in small-scale wind turbines. However, some innovative solutions have been proposed to deal with this problem, such as engaging a motor to increase production range and reduce loss due to starting up (Fan and Zhu 2019).

Finally, another cause of losses that were not mentioned before is controllers' systems (which include sensors and actuators). They could be related to reduced speed or minor stoppages due to malfunctioning or faults. However, in this paper, controllers were considered separately because some researchers focused on improving production by changing controller`s models, settings and/or premises. Besides reducing wake effects, as mentioned in the second paragraph of this section, yaw systems can be used to increase production (Kragh and Hansen 2015; Kress, Chokani, and Abhari 2015; Yesilbudak, Sagiroglu, and Colak 2015; Dai et al. 2018; Dai et al. 2021). The same stands true for other controllers, such as pitch control (Jiang, Karimirad, and Moan 2014; Zamzoum et al. 2020), stall (Mohammadi, Fadaeinedjad, and Naji 2018), and other PI controllers (Mirzaei, Tibaldi, and Hansen 2016). Artificial Neural Networks, Machine Learning and new algorithms to control or find optimum sensor placement are studied as well (Lee et al. 2013; Dahbi, Nait-Said, and Nait-Said 2016; Dou et al. 2020; Kanev 2020).

To summarise, it is important to keep OEE calculation as simple as possible, so using maximum performance in a certain range of wind speed can be appropriate as a start. Obviously, this does not indicate to the operator the reason for the loss, but it shows that something is not functioning well and, depending on the level of the loss, the operator can decide if some action needs to be prioritised. Table 2 gathers the main losses identified and papers related. Some losses can be classified by different criteria, but the most important is to have a reliable and simple index that does not account for the same loss twice.

3.3. Quality losses

Quality is the most challenging factor to assess associated with wind energy production. It is hard to calculate and classify all losses that occur after the electricity is produced by the generator. However, since the aim of this paper is to keep OEE implementation as simple as possible, all losses between generator and the grid are considered as quality losses. Different from the traditional manufacturing industry, the final result of the production process is not a physical product. Therefore, rework can be eliminated as a loss from wind energy, since it is impossible to 'resent' electricity to any part of the process to be 'fixed'.

As mentioned in Section 2.1.3, defects refer to when the outcome does not achieve the client's requirements. In the wind industry, the client can be considered the grid, so quality in this paper refers to grid requirements. Due to the intermittent and uncontrolled input, wind power suffers from several variances and fluctuations. Some of the problems related are flickers, harmonic variance, impedance, resonance and frequency fluctuation. It is out of scope of this paper to discuss each of these problems, but it is important to mention that they can vary according to each grid's characteristics or country regulations. Further grid problems related to quality, including local issues in different countries, are discussed in the relevant literature (Rona and Güler 2015; Archer et al. 2017; Nobela, Bansal, and Justo 2019; Đaković et al. 2020).

Some of the quality problems are related to the efficiency of intermediate equipment or design solutions (Margaris et al. 2011; Sáiz-Marín et al. 2015; Li, Yu, and Xu 2018; Sowa, Domínguez-García, and Gomis-Bellmunt 2019). However, some researchers are studying ways to minimise them with operational approaches, such as control frequency (Prasad, Purwar, and Kishor 2019) or harmonics (Zamzoum et al. 2020) through pitch angle, and flickers and voltage fluctuation through yaw and stall control (Mohammadi, Fadaeinedjad, and Naji 2018).

Another problem related to the grid which could affect the quality index is the grid availability. As mentioned before, the input in wind energy cannot be controlled, so if the grid cannot receive the electricity, the generation is disconnected and this becomes an important loss. This can happen due to safety reasons, which include ramps, unstable electricity, grid faults or by lack of demand. Some operational measurements can reduce these losses as well. To minimise ramps, a paper suggests new controller approaches (Martín-Martínez et al. 2013), while other works identify safety problems and relate them to other variables (Jiang, Karimirad, and Moan 2014; Beza and Bongiorno 2019; Luo, Shi, and Wang 2020), which could be strategic for operators knowing when instability is more likely to occur. Curtailment issues have become a widely discussed topic (Mc Garrigle, Deane, and Leahy 2013; Jorgensen, Mai, and Brinkman 2017), with some proposed solutions related to better production predictions (Wang et al. 2018; Probst 2020), expand grid capacity (Nycander et al. 2020) or strategically increase demand during high production (Davison-Kernan et al. 2019).

Finally, the last problem related to quality elements is due to transmission. This includes basically cabling and intermediary equipment. The transmission system is designed in the project phase and some technical losses are assumed, but it can be difficult to modify it after implementation. However, monitoring transmission losses can indicate when abnormal behaviour or wear outs occur in cables (Jin et al. 2019; Pérez-Rúa, Das, and Cutululis 2019; Rentschler, Adam, and

Table 2. Main cause of losses by performance in wind power (*Not fully responsibility of operators **Only offshore deployments).

Losses	Example	Related papers	Investigation	Decision support	Controllers	Machine learning	Others
Climate conditions*	Wind features: Turbulence Direction Air density Rain Humidity Season High temperature Period of the day Waves**	Power curve models (important to define standard rate) and output prediction – Archer et al. (2017), Yu et al. (2020), Paiva, Veiga Rodrigues, and Palma (2014), Sathler et al. (2020), Saint-Drenan et al. (2020), Shen and Ritter (2016), Yan, Pan, and Archer (2019), Pandit, Infield, and Carroll (2019), Sathler and Kolios (2022)	X	X		X	
		Investigation of the impact of climate and wind conditions:					
		Turbulence – Bardal and Sætran (2017)	X				
		Air density – Pandit, Infield, and Kolios (2020)				X	
		Rain – Arastoopour and Cohan (2017)	X				
		Humidity – Danook, Jassim, and Hussein (2019)	X				
		Period of the day – Tian et al. (2020)	X				
		Seasons – Simão et al. (2017)	X	X			
		Direction – Argyle and Watson (2017)	X	X		X	
		Waves – Li et al. (2020), Horn, Krokstad, and Leira (2019), Fang et al. (2020)	X				
Reduced Speed	Ageing Blades Factures/Erosion Icing Dust Wake effects Low speed of components Start-up	Losses due to ageing – Dai et al. (2018), Hamilton et al. (2020), Staffell and Green (2014), Liu and Zhang (2022)	X				
		Losses due to fractures/erosion – Chen (2018), Sareen, Sapre, and Selig (2014)	X				
		Icing losses detection and estimation – Chen et al. (2019), Dong et al. (2020), Stoyanov and Nixon (2020), Yirtici, Ozgen, and Tuncer (2019), Scher and Molinder (2019), Swenson et al. (2022)	X		X	X	
		Investigation on wake effects – Ciri, Rotea, and Leonardi (2017), Kheirabadi and Nagamune (2019), El-Asha, Zhan, and Iungo (2017), Argyle and Watson (2017), Pryor, Barthelmie, and Shepherd (2021), Chang et al. (2022)	X	X			
		Reduce wake effects – van Dijk et al. (2017), Park and Law (2016), Frederik et al. (2020), Fleming et al. (2014), Kanev (2020), Howland, Lele, and Dabiri (2019), Lee et al. (2013), Dou et al. (2020), Shu, Song, and Joo (2022)		X	X		
		Losses due to impact of wave loads – Stewart and Lackner (2014), Li et al. (2020), Karimian Aliabadi and Rasekh (2020)		X	X		X
		Improving performance – Astolfi et al. (2015), Pieralli, Ritter, and Odening (2015), Karakasis et al. (2018)	X		X		
		Balance between load and output – Liao et al. (2020)			X		
		Reduce cut in and minimise losses – Fan and Zhu (2019)					X
Minor stoppage	Small failures (don`t stop production) Defects	Identifying malfunctioning – Archer et al. (2017), Chang et al. (2020), Astolfi et al. (2015), Liao et al. (2020), Al-Khayat et al. (2021)	X	X		X	
		Fault-tolerant identification – Shahbazi, Poure, and Saadate (2018)		X			
Controllers	Misinterpretation of signals Faults Controller`s setting	Yaw controller – Dou et al. (2020), Dai et al. (2021), Dai et al. (2018), Kragh and Hansen (2015), Yesilbudak, Sagiroglu, and Colak (2015), Kress, Chokani, and Abhari (2015)	X		X	X	
		Stall controller Mohammadi, Fadaeinedjad, and Naji (2018)			X		
		Pitch controller – Namik and Stol (2010), Jiang, Karimirad, and Moan (2014), Lee et al. (2013), Zamzoum et al. (2020), Dahbi, Nait-Said, and Nait-Said (2016)	X		X		
		PI controller – Mirzaei, Tibaldi, and Hansen (2016)			X		

Chainho 2019), or when intermediary equipment lose their effectiveness throughout the time. Also, the quality of the electricity produced can cause losses during transmission, as pointed in (Bantras et al. 2012). This information can guide some decisions made by operators, since the increase in the losses could justify some more extreme interventions. Table 3 outlines the main quality losses identified in a wind farm.

4. Discussion

Quantifying losses has proven to be an efficient method to identify clear gaps and lead to improvement priority decisions in equipment and systems. Even though wind power has many aspects that are not in the control of operators, researchers have presented interesting and promising approaches towards minimising the losses and improve the production and performance during operational periods. This shows that wind power has still many opportunities for improvement.

To keep OEE as a simple index, some assumptions were made. Firstly, differently from most manufacturing applications, wind power has uncontrolled inputs, so climate features were considered an extra performance loss. In addition, controllers were assessed separately due to the number of factors that they can influence. Finally, about quality, all losses between generator and grid were included, from grid requirements to distribution. For that reason, the six main losses of an equipment can be extended to nine in wind energy assets, as shown in Figure 5. It is important to mention that some losses could be classified into different items, but, for efficiency of the tool, the focus did not consider the same loss twice, following a linear reasoning.

While several papers focus on investigating and assessing the losses, some of them propose solutions focusing on minimising or identifying failures and losses. Typical possible solutions discussed in these references identified during the review activity could be summarised as follows:

- Understanding lifespan, failure rates and behaviour of the turbine and components,
- Machine Learning to identify causalities,
- Increasing performance and minimising losses through controllers' settings (considering the whole farm instead of individual turbines to reduce wake effects),
- More accurate wind regime prediction, especially short-term, for decision-making, including maintenance scheduling and avoidance of curtailment,
- Controllers' settings and the use of energy storage to minimise losses due to fluctuations that can also affect transmission system and grid availability.

From the solutions proposed, most could be implemented during the operational phase, which indicates that regardless of the project design or if the wind farm has already started its operation, developers and operators could still improve their productivity. In addition, some other manufacturing tools could be used to reduce losses. As an example, according to Ioannou, Angus, and Brennan (2019), when a failure occurs in an offshore turbine, on average 22% of time is spent for the actual repair activity, while the rest is due to organisation, waiting for suitable weather and spare parts management. The papers identified in the review investigated how to reduce logistic time and scheduling; however, they are not suggesting solutions to reduce the repair time itself. So, tools such as the Single-Minute Exchange to Die (SMED), in which changeover during maintenance could be reduced drastically, could also be very beneficial to wind power installations. To identify the need of further tools, OEE is pivotal to quantify and identify these gaps, according to a TPM strategy.

As mentioned before, OEE can be used in many situations, such as for comparing before and after changings in the process (Azizi 2015), simulating which scenario has the potential for achieving better results (Caterino et al. 2020) or encouraging the continuous improvement culture (Andersson and Bellgran 2015). The main advantages of using OEE are first, its simplicity and, secondly, the overall analysis, with all possible operational losses included in one single index. To

Table 3. Main causes of losses by quality in wind power (*Not fully the responsibility of operators).

Losses	Example	Related papers	Investigation	Decision support	Controllers	Machine learning	Others
Out of requirements	Frequency voltage harmonics flickers converters` fault	Fluctuations in output – Al kez et al. (2020), Benzohra et al. (2020), Margaris et al. (2011), Mahela et al. (2020)	X				
		Loses due frequency – Datta, Shi, and Kalam (2019), Prasad, Purwar, and Kishor (2019), Wang, Wang, and Liu (2020)			X		X
		Flickers – Al kez et al. (2020), Mohammadi, Fadaeinedjad, and Naji (2018)	X				
		Losses in quality due to wave misalignments – Li et al. (2020), Wen et al. (2018)	X				
		Harmonics – Zamzoum et al. (2020), Bantras et al. (2012)	X		X		
		Voltage fluctuation – Mohammadi, Fadaeinedjad, and Naji (2018), Sáiz-Marín et al. (2015), Sáiz-Marín, Lobato, and Egido (2018), Ge et al. (2016)	X		X		
		Losses due to power flow controller and converter`s fault – Sridhar and Kumar (2019), Yoo et al. (2019), Liang et al. (2022)			X		
Grid availability*	Curtailment inertia security grid faults ramps	Estimation and investigation of curtailment in different countries – Davison-Kernan et al. (2019), Jorgensen, Mai, and Brinkman (2017), Mc Garrigle, Deane, and Leahy (2013), Nycander et al. (2020)	X				X
		Proposed method to reduce curtailment – Probst (2020), Mora, Spelling, and Van Der Weijde (2019), Zhang et al. (2018), Soroudi, Rabiee, and Keane (2017), Wang et al. (2018)	X		X		X
		Reducing/Monitoring ramps – Zhang et al. (2014), Kiviluoma et al. (2016), Martín-Martínez et al. (2013)	X				
		Hybrid system to reduce curtailment and instability – Wimalaratna et al. (2022), Al-Ghussain et al. (2023), Kealy (2023)	X				
		Instability in grid, reduce inertia – Basu, Staino, and Basu (2014), Luo, Shi, and Wang (2020), Zhang et al. (2020), Đaković et al. (2020), Nobela, Bansal, and Justo (2019), Rona and Güler (2015), Beza and Bongiorno (2019), Jiang, Karimirad, and Moan (2014), Simão et al. (2017), Tharakan and Panigrahi (2017), Yang et al. (2022)	X	X	X	X	
Transmission	Cabling impedance controllers equipment intermediaries	Lifespan and efficiency of cables – Bantras et al. (2012), Pérez-Rúa, Das, and Cutululis (2019), Rentschler, Adam, and Chainho (2019), Jin et al. (2019)	X	X			
		Reducing transmission losses – Almeida et al. (2020), Li, Yu, and Xu (2018), Wang et al. (2019), Gustavsen and Mo (2017), Cullinane et al. (2022), Jiang, Li, and Liu (2022)		X	X		X
		Losses in grid due to wind penetration – Makhloufi, Koussa, and Pillai (2017), Sultana et al. (2016), Da Rosa et al. (2016)	X	X			
		Impact of impedance and harmonic resonance – Sowa, Domínguez-García, and Gomis-Bellmunt (2019), Beza and Bongiorno (2019)	X				

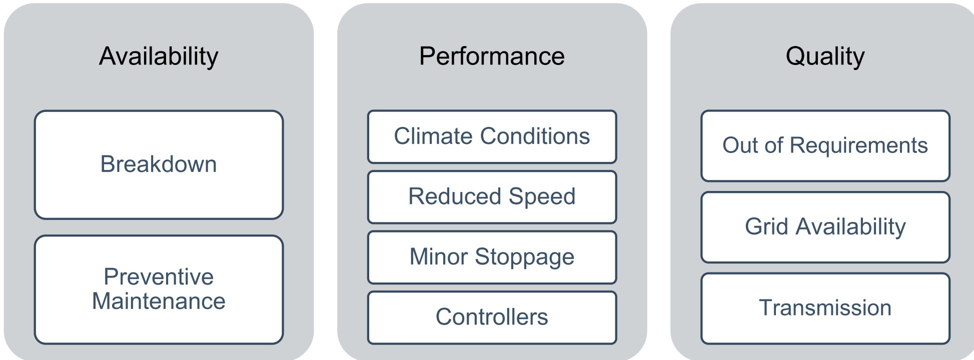

Figure 5. Main operational losses in wind power.

exemplify this last advantage, back in Section 3.2, one of the solutions found to reduce wake losses is through the yaw control system. Nonetheless, some researchers used the same yaw system to increase quality performance by reducing ramps. These are two different outcomes to be managed by the same actuator, where one can affect the other. There is a study which suggests an optimum point for these two losses (van Dijk et al. 2017), however, it is not clear if these interventions can also affect availability. With that in mind, OEE seems to be a great solution to find overall improvements.

Another important observation about decision-making through OEE is that it can, and should, be related to the financial perspective. Even though it is out of scope of this paper, any improvement suggested should find a balance between increased production and extra costs, since the final objective is to reduce LCoE, keeping equipment reliability and power quality high. Some papers, indeed, have proposed new equipment, gadgets, or more intrusive solutions, however, most of those presented in this review focused on changing control principles or using algorithms such as machine learning to find a better performance scenario, which probably does not require significant investments. Focusing on machine learning, due to computational developments, improved processors, and a large and confident amount of data, including real-time data, the use of artificial intelligence and algorithms brought a huge variety of possibilities in different areas of study. Related to wind power losses, this tool proved to be an efficient method to find solutions to improve performance and reduce losses in all the three categories defined in OEE, finding optimal settings or improving predictions. Additionally, some studies present mixed algorithms, statistics and machine learning within the OEE simulation (Heng et al. 2019).

To sum up, another three possible advantages of using OEE can be identified as follows. First, finding the actual OEE and tracking when the best rate was achieved can help operators and researchers to better understand the equipment. Second, the OEE tool considers that any equipment is unique, which means that the tool is conceptually tailored for each turbine particularity and wind farm location. Finally, some components reduce their performance before breakdown (Reder, Yürüşen, and Melero 2018), so monitoring OEE has a potential preventive application, by detecting problems that could potentially affect performance, but do not trigger any fault signals, warning operators for upcoming failures.

5. Conclusion

Wind energy has developed so far at an accelerated rate initially relying on subsidies or financial incentives. However, to become more attractive to investors and more independent, the final cost of energy needs to become more competitive. The most common way to define total cost is through LCoE, which can be obtained through the division of total costs and total production during the assets' entire lifespan. Using LCoE as a reference, there are two approaches to reduce the final price: reducing costs or increasing its production.

Other industries have developed different tools to assess and increase production, achieving the best performance from their equipment. One of these tools, largely used in the manufacturing industry, is OEE, which focuses on minimising all possible operational losses in the process. To assess the best alternative, a simple index is created gathering all losses, through which the best rate implies better equipment effectiveness. The aim of this paper was to perform and report a literature review to identify the main losses in wind turbine deployments and to adapt the OEE tool to wind energy assets.

Different from manufacturing industries, wind energy has different causes of losses. Therefore, an extension of the main losses causes was proposed as shown in Figure 5, following the assumptions contained in the flowchart in Figure 4. In addition, some of the benefits of using OEE were discussed in Section 4, including the main aspect, a global assessment of operational losses. Since one decision can affect others, having all causes of losses in one index is a valuable tool for comparison and decision-making.

For future work, it is proposed to quantify losses and estimate OEE from different farms using the consideration of this review, in order to assess and confirm the benefits of this metric, and check if any adjustments are needed. Since wind energy is surrounded by uncertainties, a stochastic approach might be more suitable than deterministic for the quantitative analysis. Another important task is to relate OEE values with cost analysis.

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