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When and How to Repower Energy Systems? a Four Strategies-Based Decision Model

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Abstract

Repowering systems is a long-lasting managerial endeavor where decision-makers face maintenance and optimization problems. The decision time to repower an energy system is one of the most important matters in this field. Also, in the real-world, each component of the system has different versions available in the market, so choosing the best version of components can be one of the valuable and practical issues in repowering a system. Therefore, decision-makers need optimal repowering policies in order to generate the optimal combination of system's components as well as the optimal time to repower this system with respect to important concerns such as cost, availability and safety issues. This paper provides a first-step decision-making model based on four independent repowering strategies for energy systems. A case study from offshore wind turbine system is presented afterwards to demonstrate the effectiveness of the presented policies. This decision support tool deals with the optimal repowering time and the best combination of components based on cost, availability, and safety constraints.

Keywords: energy systems, repowering, age replacement, optimization, maintenance, wind turbine.

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1. INTRODUCTION

Energy is essential for the development of our world, including renewable energy. Wind energy is one of the most promising renewable energy sources in Europe. In those countries where wind energy has an increased potential in energy mixes, efforts have been made to develop offshore wind energy [1]. Eurostats, for instance, agreed to say that most of the EU countries are on course to achieve the 2020 renewable energy targets [2, 3], which is reaching 20% of energy consumption from renewable sources. Such performance should be reached despite the challenging sanitary and economic environments [4]. However, it is also agreed that this cannot be achieved without a high reliability performance of these technologies. Thus, efforts have been made through these last decades to achieve high technological performances of renewable power plants. Among these renewable sources, wind energy reliability was the centre of many studies. For instance, Tavner et al. [5], Spinato et al. [6] and Faulstich et al. [7] performed several studies about onshore and offshore wind turbines and their subassemblies' failure rates. Since the environmental factors are more crucial in offshore wind energy, several studies focused on the reliability analysis of offshore wind turbines. For example, Faulstich et al. in [7] analyzed the downtime of offshore wind turbines and how it affects its deployment. Van Bussel and Zaaijer in [8] studied the reliability, availability and maintenance aspects of large-scale offshore wind turbines. Negra et al. in [9] presented a list of factors that influence offshore wind turbines generation. Other studies focused on reliability analysis of wind turbine sub-assemblies in offshore environment [10, 11, 12].

Afterwards, economic constraints of wind turbines' deployment were studied to assess the optimal investment in wind energy, including the so-called finding the optimal topology of wind turbines, which means finding the optimal number of wind turbines to be set up in a wind farm taking into account environmental, technological and economic constraints [13, 14].

Besides, when investigating with wind turbines' topology optimization, one also deals with the optimal time to replace the system. Replacement of wind turbines

31 (and their subsystems) is generally one of the three scenarios characterized by
32 the end-of-life management of the power plant [15]: i.e., if the replacement is
33 due to a need to dismantle the system, we talk about general end-of-life of power
34 facilities. Another scenario is the lifetime extension of components in the system.
35 However, when the replacement of an energy system is decided with an aim to
36 upgrade the system performance under several project's constraints, we talk
37 about repowering [16]. Hence, wind farm managers may decide to upgrade
38 partially some components of the wind farm (electrical components, blades,
39 ...) or upgrade the wind farm completely including the replacement of wind
40 turbines and their foundations. In the first case, we talk about partial repowering,
41 whereas the full repowering covers the second case [17], which will be handled
42 in this paper. However, the major issues stated by the literature; when dealing
43 with repowering; are the economic constraints [15, 18, 19]. But in such projects,
44 environmental, legal and technological constraints should also be handled [20].
45 Thus, the objective of this paper is to provide a decision support tool for energy
46 systems subject to repowering. The model provides the optimal time to repower
47 the system as well as the best topology of the repowered system under economic,
48 technological and warranty constraints.

49 This paper is structured as follows. Section 2 investigates the state-of-the-art of
50 repowering and life extension decision support tools. It also defines the research
51 gap. The methodology subsection formulates the problem stated. The optimiza-
52 tion section defines the mathematical models for optimal repowering time and
53 optimal topology of the system (the best combination of components). Different
54 types and configurations of systems were studied in section 4. Afterwards, an
55 example of offshore wind turbine subsystems is presented in section 5. We
56 conclude the paper with general remarks and an appendix explaining in depth
57 the cost and availability functions used in this paper.

58 **2. Literature review & methodology**

59 *2.1. Literature review: repowering actions in decision models*

60 The current state-of-arts of repowering energy systems in general and wind
61 turbines specifically are relatively poor compared to the general state-of-art of
62 improving technological, cost, and environmental performances of energy systems
63 and wind turbines. Nevertheless, authors focused on six main parameters when
64 dealing with decision models of systems subject to repowering. These parameters
65 are in general: "time; cost; availability and reliability; social; best topology;
66 safety and warranty constraints".

67 For instance, Ziegler et al. in [21] proposed a decision-making model in order
68 to optimize the switching time from lifetime extension to repowering of wind
69 turbines. Bezbradica et al. in [22] introduced a multi-criteria decision analysis
70 for repowering wind turbines based on several criteria such as technical, social
71 or economic ones. The objective of that paper was to investigate which of the
72 proposed scenario is adapted to the stakeholder goals. However, they did not
73 investigate all technical parameters such as the optimal repowering time nor
74 the optimal topology to adopt. Piel et al. in [23] provided a GIS (geographic
75 information system) decision based model to assess the feasibility of repowering
76 the German wind fleet. Other authors from the literature also investigated
77 repowering based decision models as well as decision support tools that assess
78 lifetime extension of systems. The main chosen parameters in the literature are
79 listed in Table 1.

Table 1: Parameters of repowering based decision models presented in the literature. Literature was extended to repowering, replacement and decommissioning based decision support tools for offshore and onshore systems.

Reference	Parameters						
	Time	Cost	Reliability / availability	Social / legal	Safety / warranty	Topology	Environmental
[24]	x	x	x	x			
[22]		x	x	x			x
[23]		x	x			x	
[25]		x					
[26]		x		x			
[27]	x	x					
[28]		x	x	x		x	x
[29]		x	x		x		
[30]	x	x					
[31]		x	x	x			
[32]		x					
[33]		x		x			x
[34]		x		x			
[16]		x	x			x	
[35]			x			x	
[36]		x	x	x			
[37]				x			x
[38]	x	x					
[39]		x	x			x	
[40]		x	x				
[41]	x	x	x				
This paper	x	x	x		x	x	

80 As seen in this table, repowering or replacement based decision support
81 tools are mostly cost oriented. This is generally due to the fact that decision
82 support tools involve ad-hoc assessment of costs of each available strategy [42].
83 Afterward, the technical criteria (reliability, availability, performance...) come in
84 the second order when choosing the most important parameter to be included in
85 the decision support tool.

86 In general, due to the rising interest in repowering, replacement, and decom-
87 missioning with an upgrade aim in offshore or onshore systems. It is generally
88 agreed that the selected parameters for the decision support model should be
89 economic, technological, social, legal, environmental and should finally cover
90 safety concerns. This was highlighted in the short literature review presented in

91 Table 1 and resumed by Martins et al. in [42] for oil and gas energy systems.
92 Thus, the contribution of this paper to the literature is the introduction of the
93 time parameter to the top chosen parameters in a repowering based decision-
94 support tool. This parameter is crucial due to its importance in project man-
95 agement and during the decision making process. An asset's owner should be
96 able to know at any time what would be the next life cycle step of his project:
97 enhance the performance for life extension of the existing project, keep existing
98 assets of the project until failure or until reaching critical safety concerns or
99 repowering the old project [41].

100 Besides the time parameter, economic, technological, safety, and topology con-
101 cerns were included in this decision-support tool. At this step, stakeholders and
102 environmental parameters were not included in this first step decision support
103 tool and should be investigated further in the future.

104 Thus, to the best of authors' knowledge, no study on a decision making model
105 that bounds optimal repowering time, technical, safety and economic concerns
106 of energy systems has been published. Also, in the real-world, each component
107 of the system has different versions available in the market, so choosing the best
108 version of components (also known as best topology) can be one of the valuable
109 and practical issues in repowering the system. As far as we know, there is no
110 study on this concern with respect to cost, availability, and safety constraint for
111 a system.

112 Thus, we aim in this paper to complement previous studies made in this field
113 and provide the following contributions:

- 114 • Find the optimal repowering topology to upgrade the energy system under
115 performance, safety and cost constraints.
- 116 • Find the optimal repowering time to upgrade the system under the previous
117 constraints.
- 118 • Provide a decision-making tool based on four full independent repowering
119 strategies.

120 In this paper, four different strategies of repowering systems are presented. These
121 strategies are independent but are tested under the same cost, warranty and
122 performance constraints. Costs are an important criterion for a decision-maker,
123 the cost function is going to be minimized in the first strategy by considering a
124 lower bound for the availability and safety constraints. In the second strategy,
125 the availability of the system will be maximized by considering the limited
126 budget and a fixed safety constraint. In the third and fourth strategies, two
127 joint functions of cost and availability functions will be optimized under safety
128 constraints. To do so, mathematical models are provided next for series, parallel
129 as well as for series-parallel systems.

130 2.2. Methodology

131 Let's study a system of n components. Each component within this system
132 has various versions with different lifetimes and costs' versions available in
133 the market. The lifetime for the j -th version of i -th component (denoted
134 as $j^{(i)}$ -component) is $X_j^{(i)}$, where $j = 1, 2, \dots, v_i$, and v_i is the number of
135 versions available in the market for the i -th component, and $i = 1, 2, \dots, n$. The
136 density and the distribution functions for the $j^{(i)}$ -component are $f_j^{(i)}(\cdot)$ and
137 $F_j^{(i)}(\cdot)$, respectively. Suppose that the k_i -th version of the i -th component ($k_i^{(i)}$ -
138 component) is selected, then the lifetime of the original system can be denoted by
139 $\phi(X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)})$, where $\phi(\cdot, \dots, \cdot)$ is the structure function. Thus, for series
140 system; $\phi(X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)}) = \min\{X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)}\}$, and for parallel
141 system; $\phi(X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)}) = \max\{X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)}\}$. Afterwards, a
142 policy similar to the age replacement one is applied in this model. Replacement
143 policy is one of the most common policies when maintaining a system. In such
144 policy, the system undergoes a replacement at failure or at age T , whatever
145 occurs first. Several authors from the state of art assessed the optimal age
146 replacement based strategies, see [43, 44, 45, 46]. In this work, the system is being
147 repowered either at a constant time T ($T > 0$), or at $\phi(X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)})$,
148 whichever occurs first. Moreover, repowering at age $\phi(X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)})$ is
149 called non-planned repowering and repowering at age T is denoted planned

150 repowering. Thus, the system's lifetime is $X_T = \min\{T, \phi(X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)})\}$.
 151 For a parallel system we have $X_T = \min\{T, \max\{X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)}\}\}$, and for
 152 a series system $X_T = \min\{T, \min\{X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)}\}\}$.

One of the main goals of this paper is to find the optimal value for repowering time T by considering four objective functions under the selected constraints. Also, the safety constraint should be considered. This constraint is implemented by bounding the probability that there is not any unplanned repowering in the interval $[0, z]$, where $z > 0$ is a constant. If the bound is denoted by p_0 , this constraint means that with $100p_0\%$ confidence, the system has not any unplanned repowering from 0 up to z units time (a unit time can be in years, months, days, ..., depending on the data). This constraint is expressed as following.

$$L(T, z) \equiv (\bar{F}_{X_T}(T))^m \bar{F}_{X_T}(z - mT) > p_0, \quad (1)$$

153 with $\bar{F}_{X_T}(t)$ is the reliability function of X_T , $m = \lceil \frac{z}{T} \rceil$ and $0 < p_0 < 1$ and $[x]$
 154 shows the integer part of x . This constraint shows that there is no non-planned
 155 failure from the installation of the system until z units time with the confidence
 156 of at least $100p_0\%$. In practice, this safety constraint is generally linked with
 157 warranty issues.

In maintenance theory, there are some important metrics such as cost, safety and performance. In this paper, the long-term cost function, availability function and safety constraint are considered. The long-run average cost (expected cost in a cycle per expected lifetime of the system of a cycle) is widely used in the literature and was introduced by [47]. For examples, see [48, 49].

For the proposed model, the long-run average cost as a cost function is given by equation (2).

$$Cost(T) = \frac{c_F + (c_T - c_F)\bar{F}_{X_T}(T)}{\int_0^T \bar{F}_{X_T}(t)dt}, \quad (2)$$

where c_F is the cost of repowering at $\phi(X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)})$ and c_T is the cost at age T . The objective here is to minimize (2) and find T_{cost}^* so that $Cost(T)$ needs to be minimized at $T = T_{cost}^*$. By using the results of [47] and [50], the following remark is presented.

Remark:

Suppose the hazard function of a system is denoted by $r_{X_T}(t) = \frac{f_{X_T}(t)}{\bar{F}_{X_T}(t)}$. Then the optimal T_{cost}^* to minimize $Cost(T)$ satisfies

$$r_{X_T}(T) \int_0^T \bar{F}_{X_T}(t) dt + \bar{F}_{X_T}(T) = \frac{c_F}{c_F - c_T}. \quad (3)$$

158 If it is assumed further that $r_{X_T}(t)$ is increasing, it will lead to the increase of
159 the left side of (3), and an optimum solution exists, and perhaps infinite. If
160 there is no solution to (3), then the optimal policy is "replacement only when
161 failure occurs". Finally, a unique and finite solution to equation (3) exists if the
162 function $r_{X_T}(t)$ is both continuous and strictly increasing to infinity.

163 When dealing with performance metrics, the availability function is also an
164 important index. The availability of a system is well defined in the state of art
165 and is defined in some ways: interval availability, pointwise availability, multiple
166 cycle availability, limiting interval availability [51, 52]. We thus consider in this
167 paper the limiting interval availability, $Ava = \frac{MTTF}{MTTF+MTTR}$, where $MTTF$ is
168 the mean time to failure and $MTTR$ is the mean time to replace the system.
169 The $MTTF$ and $MTTR$ can be calculated as following

$$MTTF = E(X_T) = \int_0^T \bar{F}_{X_T}(t) dt,$$
$$MTTR = \mu_F F_{X_T}(T) + \mu_T \bar{F}_{X_T}(T).$$

170 Thus, the limiting interval availability for the proposed model can be written as

$$Ava(T) = \frac{\int_0^T \bar{F}_{X_T}(t) dt}{\int_0^T \bar{F}_{X_T}(t) dt + \mu_F + (\mu_T - \mu_F) \bar{F}_{X_T}(T)}, \quad (4)$$

171 where μ_F and μ_T are the expected times' lengths to set up the new system in
172 non-planned repowering as well as in planned repowering, respectively. Thus, one
173 wants to maximize (4) and finds T_{ava}^* such that $Ava(T)$ needs to be maximized
174 at $T = T_{ava}^*$. The optimal solution can also be generated theoretically in the
175 same manner as T_{cost}^* (mentioned in the remark). In this paper, four strategies

176 are presented in the following in order to find the optimal topology as well as
 177 the optimal time for repowering a system.

178 3. Optimization

179 The optimization framework for the proposed model developed is presented
 180 in this section. In the following subsections, the decision making model based on
 181 four strategies is presented. Each strategy provides the optimal repowering time
 182 as well as the best topology for the system. The best/optimal topology provides
 183 the optimal combination of components that respects cost, availability and
 184 safety constraints. The decision-maker should decide which of these strategies is
 185 appropriate based on the situation. Afterwards, a comparison between the four
 186 strategies is presented within the case study section.

187 3.1. Optimal repowering time

188 The optimal time needed to repower the system for each combination of
 189 components is explained in this section, whereas the methodology for finding
 190 the best combination of components is presented in the next section.

191 **Strategy 1)** In this strategy, the cost function is minimized by considering
 192 two constraints: The availability of the system is more than a desired level (A^*)
 193 and there is no non-planned repowering for z units time with at least $100p_0\%$
 194 confidence. Therefore

$$\text{minimize } Cost(T) = \frac{c_F + (c_T - c_F)\bar{F}_{X_T}(T)}{\int_0^T \bar{F}_{X_T}(t)dt}, \quad (5)$$

subject to

$$Ava(T) = \frac{\int_0^T \bar{F}_{X_T}(t)dt}{\int_0^T \bar{F}_{X_T}(t)dt + \mu_F + (\mu_T - \mu_F)\bar{F}_{X_T}(T)} > A^*, \quad (6)$$

$$P(T, z) = (\bar{F}_{X_T}(T))^m \bar{F}_{X_T}(z - mT) > p_0, \quad (7)$$

195 where $0 < A^* < 1$ is the desired level for availability of the system, $m = \lceil \frac{z}{T} \rceil$
 196 and $0 < p_0 < 1$. The case $A^* = 0$ shows that the cost function is only considered

197 in optimization and the availability function is not taken into account. As a
 198 result, if the cost function is more important for the decision-maker and also
 199 there is a minimum availability target to reach, then the decision-maker should
 200 select Strategy 1.

201 **Strategy 2)** In this strategy, the availability function is maximized by
 202 considering two constraints: The cost of the system is less than the desired
 203 level (C^*) and there is no non-planned repowering for z units time with at least
 204 $100p_0\%$ confidence. Therefore

$$\text{maximize } Ava(T) = \frac{\int_0^T \bar{F}_{X_T}(t)dt}{\int_0^T \bar{F}_{X_T}(t)dt + \mu_F + (\mu_T - \mu_F)\bar{F}_{X_T}(T)}, \quad (8)$$

subject to

$$Cost(T) = \frac{c_F + (c_T - c_F)\bar{F}_{X_T}(T)}{\int_0^T \bar{F}_{X_T}(t)dt} < C^*, \quad (9)$$

$$P(T, z) = (\bar{F}_{X_T}(T))^m \bar{F}_{X_T}(z - mT) > p_0, \quad (10)$$

205 where $C^* > 0$ is the desired level for the cost of the system, $m = \lceil \frac{z}{T} \rceil$ and
 206 $0 < p_0 < 1$. The case $C^* = \infty$ shows that the availability function is only
 207 considered in optimization and the cost function is not taken into account. As a
 208 result, if the availability of the system is more important for decision-maker and
 209 there is also a limited budget, then the decision-maker should select Strategy 2.

210 **Strategy 3)** In this strategy, a joint function $AC(T)$ composed of cost and
 211 availability functions is maximized. In [53] was introduced a similar parameter
 212 based on combined availability and cost functions, as $AC(T) = \frac{Ava(T)}{Cost(T)}$. In fact,
 213 this criterion shows the system's availability per unit of cost. We also consider
 214 in this strategy an additional safety constraint. Therefore

$$\text{maximize } AC(T) = \frac{Ava(T)}{Cost(T)}, \quad (11)$$

subject to

$$P(T, z) = (\bar{F}_{X_T}(T))^m \bar{F}_{X_T}(z - mT) > p_0, \quad (12)$$

215 where $m = \lceil \frac{z}{T} \rceil$ and $0 < p_0 < 1$. Thus, if the availability and the cost of the

216 system are both important for decision-maker, then Strategy 3 is an appropriate
 217 selection.

218 **Strategy 4)** This strategy considers min-norm methods. Lin [54] presented
 219 min-norm methods for optimization in multi-objective problems. The general
 220 description based on the concept of least distance and weighted Holder norms
 221 can be described as following

$$\underline{\text{minimize}} \quad L(x) = \left\{ \sum_i (w_i |J_i(x) - G_i(x)|)^p \right\}^{1/p}$$

222 where G_i is the goal (the target value or demand level) for objective i and w_i
 223 a positive weight on objective i ; p is a positive integer (1, 2, ...). None of the
 224 weights implemented here are null, since if any objective gets a zero weight, it is
 225 substantially outweighed and should have been excluded. The practitioners are
 226 free to choose any value for the parameter p depending on the running problem.
 227 The case of $p = \infty$, when p is infinite, is also reformulated using the Tchebycheff
 228 (or max-) norm and is described as:

$$\underline{\text{minimize}} \quad L(x) = \max_i (w_i |J_i(x) - G_i(x)|).$$

229 This paper presents two objective functions; cost and availability functions. In
 230 view of the range, these two functions are different and thus are rescaled by
 231 dividing these functions by the optimal solutions. Therefore, for the fourth
 232 strategy in case of $p = \infty$

$$\underline{\text{minimize}} \quad L(T) = \max \left\{ w_1 \frac{Cost(T) - \min Cost(T)}{\min Cost(T)}, (1 - w_1) \frac{\max Ava(T) - Ava(T)}{\max Ava(T)} \right\} \quad (13)$$

subject to

$$P(T, z) = (\bar{F}_{X_T}(T))^m \bar{F}_{X_T}(z - mT) > p_0, \quad (14)$$

233 where $0 \leq w_1 \leq 1$ is the weight for cost function and $1 - w_1$ is the weight for
 234 availability function. It is worth mentioning that availability is reported within

235 [0,1], and the proposed cost function is supposed to handle all Capex and Opex
 236 expenditures and thus there is no limit for this function so it is within [0, ∞].
 237 Accordingly, to make a balance between two objective functions by integrating
 238 them into a unified objective function, we changed the scales of both objective
 239 functions into [0,1].

240 The value $w_1 = 0$ shows that the cost function is only considered, whereas
 241 $w = 1$ shows the case when only the availability function is considered. Therefore,
 242 if the availability and the cost of the system are important for decision-maker
 243 but with specific weights, then Strategy 4 is a suitable selection.

244 3.2. Optimal combinations

245 This paper considers a system that is composed of n components and each of
 246 the components has various versions with different lifetimes and system's engineer
 247 wants to select the optimal combination of components. Suppose the number of
 248 versions for the i -th component is v_i , therefore the number of combinations is

$$NoC = \prod_{i=1}^n v_i.$$

In this section, the aim is to find the best combination between NoC combinations.
 For each combination based on four strategies that are presented in section 3.1, an
 optimal time for repowering the system is calculated, therefore for s -th strategy
 we have:

$$T^{(s),1}, T^{(s),2}, \dots, T^{(s),NoC},$$

249 where $s = 1, 2, 3, 4$, and $T^{(s),i}$ is the optimal repowering time for the i -th
 250 combination based on the s -th strategy. At this step, the best combination for
 251 each strategy is assessed. For each strategy, the best combination is selected as
 252 follows:

253 **Strategy 1)** The b -th combination is the best combination if:

$$Cost(T^{(1),b}) < Cost(T^{(1),i}), \quad \forall i \in \{1, 2, \dots, NoC\}.$$

254 **Strategy 2)** The b -th combination is the best combination if:

$$Ava(T^{(2),b}) > Ava(T^{(2),i}), \quad \forall i \in \{1, 2, \dots, NoC\}.$$

255 **Strategy 3)** The b -th combination is the best combination if:

$$AC(T^{(3),b}) > AC(T^{(3),i}), \quad \forall i \in \{1, 2, \dots, NoC\}.$$

256 **Strategy 4)** Finding the best combination in this strategy depends on w_1 ,

257 so that

258 • For $0 < w_1 < 1$, the b -th combination is the best combination if:

$$L(T^{(4),b}) < L(T^{(4),i}), \quad \forall i \in \{1, 2, \dots, NoC\}.$$

259 • For $w_1 = 0$, the b -th combination is the best combination if:

$$Ava(T^{(4),b}) > Ava(T^{(4),i}), \quad \forall i \in \{1, 2, \dots, NoC\}.$$

260 • For $w_1 = 1$, the b -th combination is the best combination if:

$$Cost(T^{(4),b}) < Cost(T^{(4),i}), \quad \forall i \in \{1, 2, \dots, NoC\}.$$

261 4. Types of systems

262 In this work, three types of systems are considered; parallel, series and
263 series-parallel systems and the cost and availability functions are described.

264 4.1. Parallel system

265 The lifetime of the parallel system by considering $k_i^{(i)}$ -component, is $X_T =$
266 $\min\{T, \max\{X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)}\}\}$. For $T \geq t$, the distribution function of X_T
267 is given by $F_{X_T}(t) = \prod_{i=1}^n F_{k_i}^{(i)}(t)$. The cost function defined in equation (2) can
268 be rewritten as follows

$$Cost(T) = \frac{c_T + (c_F - c_T) \prod_{i=1}^n F_{k_i}^{(i)}(T)}{T - \int_0^T \prod_{i=1}^n F_{k_i}^{(i)}(t) dt}, \quad (15)$$

269 and upon (4), the availability of a parallel system (availability function of T) is

$$Ava(T) = \frac{T - \int_0^T \prod_{i=1}^n F_{k_i}^{(i)}(t) dt}{T - \int_0^T \prod_{i=1}^n F_{k_i}^{(i)}(t) dt + \mu_T + (\mu_F - \mu_T) \prod_{i=1}^n F_{k_i}^{(i)}(T)},$$

and for the safety constraint

$$P(T, z) = (1 - \prod_{i=1}^n F_{k_i}^{(i)}(T))^m (1 - \prod_{i=1}^n F_{k_i}^{(i)}(z - mT)) > p_0.$$

270 4.2. Series system

The **series**-system's **lifetime** considering the $k_i^{(i)}$ -component is $X_T = \min\{T, \min\{X_{k_1}^{(1)}, X_{k_2}^{(2)}, \dots, X_{k_n}^{(n)}\}\}$. For $T \geq t$, the reliability function of X_T is $\bar{F}_{X_T}(t) = \prod_{i=1}^n \bar{F}_{k_i}^{(i)}(t)$. Using equation (15), the **cost function** for series system is

$$Cost(T) = \frac{c_F + (c_T - c_F) \prod_{i=1}^n \bar{F}_{k_i}^{(i)}(T)}{\int_0^T \prod_{i=1}^n \bar{F}_{k_i}^{(i)}(t) dt},$$

271 and from equation (4), the availability of the system (**availability function of T**)
272 is

$$Ava(T) = \frac{\int_0^T \prod_{i=1}^n \bar{F}_{k_i}^{(i)}(t) dt}{\int_0^T \prod_{i=1}^n \bar{F}_{k_i}^{(i)}(t) dt + \mu_F + (\mu_T - \mu_F) \prod_{i=1}^n \bar{F}_{k_i}^{(i)}(T)}.$$

As for the safety constraint

$$P(T, z) = \prod_{i=1}^n (\bar{F}_{k_i}^{(i)}(T))^m \bar{F}_{k_i}^{(i)}(z - mT) > p_0.$$

273 4.3. Series-Parallel system

274 In the field of system **dependability**, a typical series-parallel system **is com-**
275 **posed** of multiple subsystems in series, **and each of them are in parallel**. As
276 mentioned in [55], **series-parallel systems are a large type** of multi-component
277 systems **and can describe concisely** the basic features of **any** complex system.
278 **Let's suppose there are** three subsystems **that are** in series. **Each** subsystem
279 **is formed** by parallel components. **Besides**, the lifetime of the k_i -th version of
280 the i -th component in the **1st** subsystem is $X_{k_i}^{(i)}$ with a distribution functions
281 $F_{X_{k_i}^{(i)}}^{(i)}(\cdot)$, for $i = \{1, 2, \dots, d_1\}$. **In** the second subsystem, $Y_{k_i}^{(i)}$ **is the lifetime**

282 of its components with a distribution functions $F_{Y_{k_i}}^{(i)}(\cdot)$, for $i = \{1, 2, \dots, d_2\}$.
 283 In the third subsystem, $Z_{k_i}^{(i)}$ is the lifetime of correspond components with a
 284 distribution function $F_{Z_{k_i}}^{(i)}(\cdot)$, for $i = \{1, 2, \dots, d_3\}$, where d_1, d_2 , and d_3 are the
 285 number of components in the first, second and third subsystems, respectively.
 286 Therefore

$$X_T = \min\{T, \max_{1 \leq i \leq d_1} X_{k_i}^{(i)}, \max_{1 \leq i \leq d_2} Y_{k_i}^{(i)}, \max_{1 \leq i \leq d_3} Z_{k_i}^{(i)}\}.$$

287 for $T \geq t$, one have

$$\bar{F}_{X_T}(t) = (1 - \prod_{i=1}^{d_1} F_{X_{k_i}}^{(i)}(t))(1 - \prod_{i=1}^{d_2} F_{Y_{k_i}}^{(i)}(t))(1 - \prod_{i=1}^{d_3} F_{Z_{k_i}}^{(i)}(t)) \quad (16)$$

288 The mean time to repower the system can be expressed as

$$E(X_T) = \int_0^T (1 - \prod_{i=1}^{d_1} F_{X_{k_i}}^{(i)}(t))(1 - \prod_{i=1}^{d_2} F_{Y_{k_i}}^{(i)}(t))(1 - \prod_{i=1}^{d_3} F_{Z_{k_i}}^{(i)}(t))dt. \quad (17)$$

289 By substituting (16) and (17) in equation (2), the expected cost rate was
 290 generated and was presented in (G.1). The *MTTR* for the proposed policy is

$$MTTR = \mu_F + (\mu_T - \mu_F)(1 - \prod_{i=1}^{d_1} F_{X_{k_i}}^{(i)}(T))(1 - \prod_{i=1}^{d_2} F_{Y_{k_i}}^{(i)}(T))(1 - \prod_{i=1}^{d_3} F_{Z_{k_i}}^{(i)}(T)), \quad (18)$$

291 and the *MTTF* for the proposed policy is

$$MTTF = \int_0^T (1 - \prod_{i=1}^{d_1} F_{X_{k_i}}^{(i)}(t))(1 - \prod_{i=1}^{d_2} F_{Y_{k_i}}^{(i)}(t))(1 - \prod_{i=1}^{d_3} F_{Z_{k_i}}^{(i)}(t))dt, \quad (19)$$

292 Upon substituting (18) and (19) into equation (4), the series-parallel system's
 293 availability considered as a function of T is obtained which is given in (G.2).
 294 The terms in (G.1) and (G.2) are supposed to ease the numerical computation
 295 of such metrics as it will be presented in the following example.

296 **5. Case study**

297 We retake the example of a geared wind-turbine (WT) considered as a series-
298 parallel system presented in [56, 20]. In this paper, was provided an aggregate
299 of four series-parallel sub-systems from the offshore WT is studied and showed
in Fig. 1.

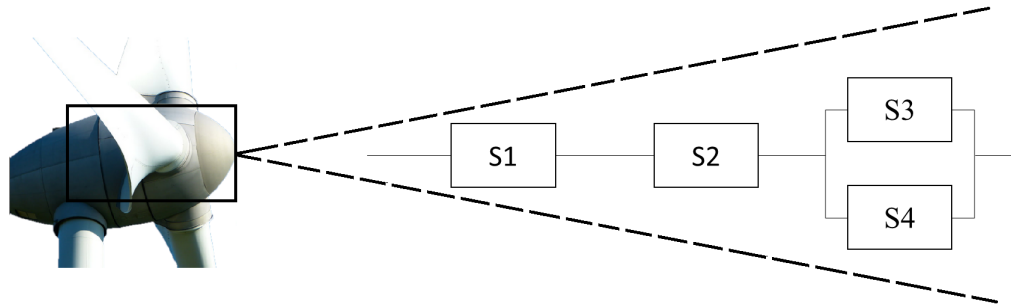


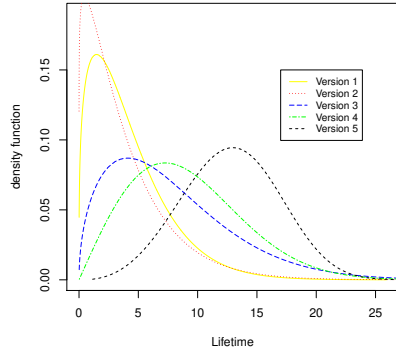
Figure 1: Configuration of the studied system.

300

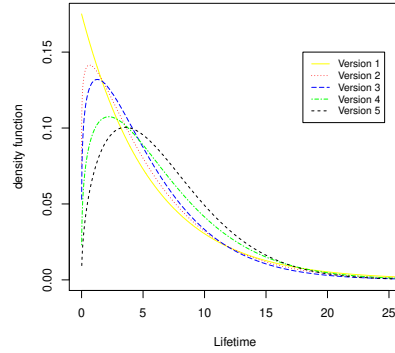
301 This case study is configured by four major components $\{S_1, S_2, S_3, S_4\}$. These
302 components have various versions (variants) available in the market. These
303 versions can be catalogued based on their cost and reliability parameters. Besides,
304 as seen in Table 2, versions can be classified by their failure rate, reliability and
305 cost of planned & non-planned repowering. Then, the decision-maker should
306 select a version of each component to compose its system, thus $NoC = 5^4$.

307 Figure 2(a) shows the probability density functions of the different available
308 versions of component S1. Figures 2(b-d) are also for S2, S3, and S4 components'
309 versions available in the market. Figure 2(a) depicts that Version 5 of component
310 S1 has a noticeable difference in mean lifetime when compared with other versions
311 of the same component. It is then a good candidate to be among the optimal
312 combination. The same statement is not expressed for the other components'
313 versions based on Figures 2(b-d).

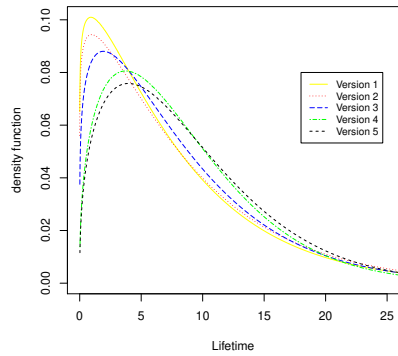
314 The main problem in such cases is finding the best or optimal combination
315 (topology) of components and the optimal repowering time for such system.



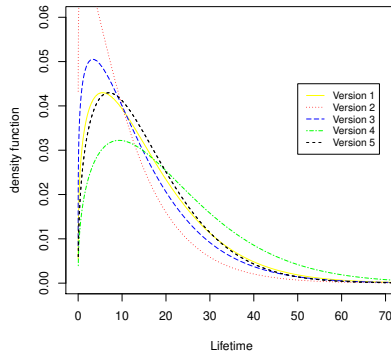
(a) Lifetime distribution for each version of component S1.



(b) Lifetime distribution for each version of component S2.



(c) Lifetime distribution for each version of component S3.



(d) Lifetime distribution for each version of component S4.

Figure 2: Lifetime distribution of each version of components S1, S2, S3, and S4.

316 The optimal time to repower should be calculated taking into account four
 317 strategies presented in Section 3.1, and the best combination of components
 318 should be optimized by considering the suitable strategy. The studied system is
 319 a series-parallel system so the equations (16)-(19), (G.3) and (G.4) are used in
 320 optimization.

321 According to Figure 1, the system is composed of three subsystems such as

Table 2: Example data (the units are: λ (year), c_T (€), μ_F (hours), c_F (€), μ_T (hours)).

components	Data parameters	versions				
		Ver1	Ver2	Ver3	Ver4	Ver5
S1	β	1.3	1.1	1.5	2	3.5
	λ	4.57	4.00	8.57	10.27	14.27
	c_T	24000	20000	18000	25000	30000
	μ_T	12	12	12	12	12
	c_F	68400	64400	62400	69400	74400
	μ_F	36	36	36	36	36
S2	β	1	1.1	1.2	1.3	1.5
	λ	5.71	5.71	5.71	6.85	7.42
	c_T	30000	32000	31200	32000	32500
	μ_T	52	52	52	52	52
	c_F	36000	38000	37200	38000	38500
	μ_F	76	76	76	76	76
S3	β	1.1	1.1	1.2	1.4	1.4
	λ	8.00	8.56	8.56	9.13	9.70
	c_T	1100	1200	1200	1200	1300
	μ_T	6	6	6	6	6
	c_F	37100	37200	37200	37200	37300
	μ_F	30	30	30	30	30
S4	β	1.3	1.1	1.2	1.4	1.4
	λ	17.12	11.42	14.93	22.83	17.12
	c_T	34000	30000	36000	45000	45000
	μ_T	60	60	60	60	60
	c_F	288400	284400	290400	299400	299400
	μ_F	108	108	108	108	108

322 $d_1 = 1$, $d_2 = 1$ and $d_3 = 2$ (The 1st subsystem is composed of (S1), the 2nd
323 subsystem of component (S2), and the latter has both components (S3, S4)).

324 Besides, each component has 5 versions in the market.
 325 The lifetimes of the i -th versions for components S1 and S2 are X_i and Y_i . They
 326 follow a Weibull distributions with parameters (λ_i, β_i) , (λ'_i, β'_i) , respectively.
 327 Also, the lifetimes of the i -th versions of S3 and S4 subsystems are $Z_i^{(1)}$ and $Z_i^{(2)}$.
 328 They follow a Weibull distributions with parameters $(\lambda''_{i,1}, \beta''_{i,1})$, and $(\lambda''_{i,2}, \beta''_{i,2})$,
 329 respectively, where $i = 1, 2, \dots, 5$.
 330 For $t < T$, and by considering the i -th version for each component

$$\bar{F}_{X_T}(t) = e^{-\left(\frac{t}{\lambda_i}\right)^{\beta_i} - \left(\frac{t}{\lambda'_i}\right)^{\beta'_i}} \left\{ 1 - \prod_{j=1}^2 \left(1 - e^{-\left(\frac{t}{\lambda''_{i,j}}\right)^{\beta''_{i,j}}} \right) \right\},$$

331 and

$$E(X_T) = \int_0^T e^{-\left(\frac{t}{\lambda_i}\right)^{\beta_i} - \left(\frac{t}{\lambda'_i}\right)^{\beta'_i}} \left\{ 1 - \prod_{j=1}^2 \left(1 - e^{-\left(\frac{t}{\lambda''_{i,j}}\right)^{\beta''_{i,j}}} \right) \right\} dt.$$

332 Then, cost and availability functions can be determined and are presented in (G.3)
 333 and (G.4), respectively. To show the obtained results, components' parameters
 334 in Table 2 are used. In this table, each version of the four components is fully
 335 characterized by: Weibull distribution with parameters $(\beta, \lambda$ in years), costs
 336 of planned and un-planned repower (c_T and c_F in €), and respectively time to
 337 planned and un-planned repower (μ_F and μ_T in hours).

338 Thus, the aim is to generate the optimal time to repower each combination
 339 (topology) of components' versions, then the best topology based on the four
 340 strategies is selected accordingly.

341 The "DEoptim" package in R is used in order to obtain the numerical results.
 342 In this package, the Differential Evolution (DE) algorithm is implemented
 343 for global optimization of a real-valued function of a real-valued parameter
 344 vector as described in [57]. DE is a search heuristic introduced by [58]. Its
 345 noticeable performance as a global optimization method on continuous numerical
 346 minimization problems has been extensively studied and explored; see [59]. DE
 347 belongs is a genetic algorithm which uses biology-inspired operations of crossover,

348 mutation, and selection of a population so that it minimizes the objective
 349 function over the course of successive generations (see [60]). Same as the rest of
 350 evolutionary algorithms, DE solves optimization problems using the evolution of a
 351 population of candidate solutions using operators such as alteration and selection.
 352 DE also uses floating-point encoding instead of bit-string encoding of population
 353 members. Arithmetic operations are also used instead of logical operations in
 354 mutation. This heuristic is particularly well-suited for global optimum search
 355 of a real-valued function of real-valued parameters. Besides, it does not require
 356 constraints on the function to be either continuous or differentiable.

357 The main results for numerical computations are presented in Table 3. The
 358 parameters for safety constraints (p_0, z) are determined by the decision-maker.
 359 If we consider $z = 4$ years and $p_0 = 0.6$. Then the decision-maker would like
 360 that the system does not have any unplanned repowering from 0 up to 4 years
 361 with at least 60% confidence.

Table 3: Results for case study.

	Best combination $\{S1,S2,S3,S4\}$	T^*	$Cost(T^*)$	$Ava(T^*)$	$P(T^*, z)$
Strategy 1	$\{5,5,5,4\}$	5.73	56213.04	0.9955	0.7199
Strategy 2	$\{5,5,5,4\}$	7.77	58000	0.9958	0.7199
Strategy 3	$\{5,5,5,1\}$	4.88	55743.86	0.9951	0.7063
Strategy 4 ($w_1=0$)	$\{5,5,5,4\}$	10.18	61256.78	0.9958	0.7199
Strategy 4 ($w_1=0.1$)	$\{5,2,2,4\}$	7.69	69609.56	0.9951	0.6147
Strategy 4 ($w_1=0.5$)	$\{5,2,2,4\}$	7.25	69509.44	0.9950	0.6147
Strategy 4 ($w_1=0.75$)	$\{5,2,2,4\}$	7.13	69497.4	0.9950	0.6147
Strategy 4 ($w_1=0.95$)	$\{5,2,2,4\}$	7.05	69493.22	0.9950	0.6147
Strategy 4 ($w_1=1$)	$\{5,5,5,1\}$	4.87	55743.68	0.9951	0.7063

- 362 • Strategy 1: the cost function is minimized subject to a threshold level
 363 for the availability function (0.9955) and safety constraints. The level for
 364 availability can be selected by the decision-maker. By using equations

365 (5)-(7), $\{5, 5, 5, 4\}$ is the best combination of components. The optimal
 366 time is $T^* = 5.73$ (years) and the minimum cost function is 56213.04
 367 (euros). The availability of the system in this situation is 0.9955 and
 368 the probability of non-planned repowering for not occurring in the time
 369 interval $[0, 4]$ is 0.7199. Therefore we must select version "5" of components
 370 $\{S1, S2, S3\}$ and version "4" of component 'S4'. If the system don't fail
 371 before time $T = 5.73$, then a planned repowering strategy is to be done at
 372 time $T = 5.73$ so that the cost function subject to the constraints can be
 373 minimized. Also, with 71.99% confidence, the system will not have any
 374 unplanned repowering from 0 up to 4 years. Figure 3 shows cost function
 375 for the best combination of this strategy. This figure also shows feasible
 376 region by considering the mentioned constraints.

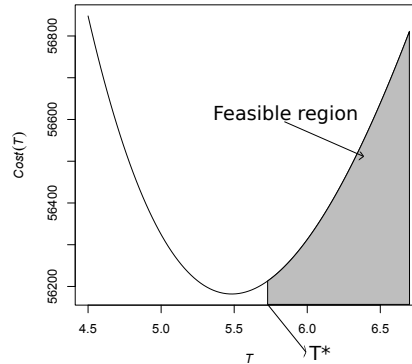


Figure 3: Best topology selected from strategy 1- $\{5,5,5,4\}$.

- 377 • Strategy 2: the availability function is maximized under a threshold level
 378 for the cost function (58000 €) and safety constraints. By using equations
 379 (8)-(10), $\{5, 5, 5, 4\}$ is the best combination of components. The optimal
 380 time is $T^* = 7.77$ (years) and the maximum availability function is 0.9958,
 381 the cost of the system in this situation is 58000 and the probability of
 382 non-planned repowering for not occurring in the time interval $[0, 4]$ is
 383 0.7199. Therefore we must select version "5" of components $\{S1, S2, S3\}$
 384 and the 4th version of component 'S4', and if the system don't fail before

385 time $T = 7.77$, a planned repowering is to be done at time $T = 7.77$
 386 so that we can maximize the availability of the system subject to the
 387 described constraints. Figure 4 shows the availability function for the
 388 optimal combination for this strategy. This figure also shows feasible
 389 region by considering the mentioned constraints.

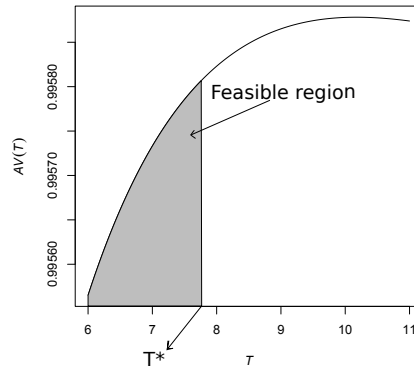


Figure 4: Best topology selected from strategy 2- $\{5,5,5,4\}$.

390 • Strategy 3: the $AC(T)$ function is maximized subject to safety constraints.
 391 By using equations (13) and (14), $\{5, 5, 5, 1\}$ is the best combination of
 392 sub-systems. The optimal time is $T^* = 4.88$ (years), the maximum $AC(T)$
 393 function is $1.78e - 05$, the availability and cost functions of the system
 394 in this situation are 55743.86 and 0.9951, respectively. The probability
 395 of non-planned repowering for not occurring in the time interval $[0, 4]$ is
 396 0.7063. Therefore we must select version "5" of components $\{S1, S2, S3\}$
 397 and the 1st version of component 'S4', and if the system don't fail before
 398 time $T = 4.88$, the planned repowering is to be done at $T = 4.88$ in order
 399 to respect the strategy constraints. Therefore we must select version "5"
 400 of components $\{S1, S2, S3\}$ and the version "4" of component 'S4', and if
 401 the system don't fail before time $T = 4.88$, the planned repowering should
 402 be made at $T=4.88$ in order to maximize $AC(T)$ function. Also, with an
 403 70.63% confidence, the system will not have any unplanned repowering
 404 from 0 up to 4 years. Figure 5 shows AC function for the best combination

405 for this strategy. This figure also shows feasible region by considering the
 406 mentioned constraint.

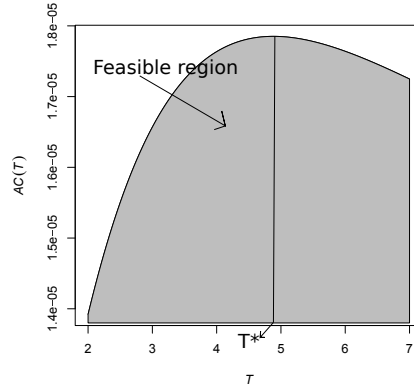


Figure 5: Best topology selected from strategy 3- $\{5,5,5,1\}$.

407 • Strategy 4, $L(T)$ function is minimized subject to safety constraints. Ac-
 408 cording to the value of w_1 , different optimal repowering times and best
 409 combinations of components can be provided. Thus:

- 410 – if $w_1 = 0$: the best combination of the components to be chosen is
 411 the 5-th version of the three first components and the 4-th version of
 412 the last component ($\{5,5,5,4\}$), also $T^* = 10.18$.
- 413 – if $w_1 = 1$: the best topology to be picked is the topology ($\{5,5,5,1\}$),
 414 also $T^* = 4.87$.
- 415 – if $0 < w_1 < 1$: the best combination is $\{5,2,2,4\}$. Besides, a sensitivity
 416 study was performed to assess the influence of w_1 on the optimal
 417 time to repower. Thus, as presented in Table 3, T^* decreases as w_1
 418 increases, so when the weight of the cost function decreases (the weight
 419 of availability function increases, $1 - w_1$), the planned repowering time
 420 is higher and the cost function at optimal repowering time decreases.
 421 However, no changes are noticed for availability and probability of
 422 non-planned repowering parameters. Figure 6 shows $L(T)$ function
 423 with $w_1 = 0.5$ for the best combination for this strategy. This figure

424

also shows feasible region under the considered constraint.

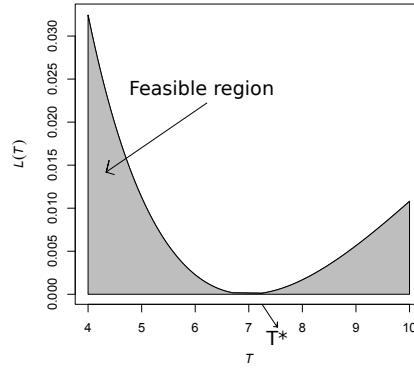


Figure 6: Best topology selected from strategy 4 with $w = 0.5\text{-}\{5,2,2,4\}$.

425

Figures 7 and 8 are drawn for comparison purposes between the presented strategies. They show the optimal cost and availability for each strategy, respectively.

426

427

Figure 7 illustrates how the optimal cost is significantly affected by the strategies.

428

For example, the minimum and the maximum costs are 55743.68 and 69609.56, which are respectively caused by the same strategy 4 with $w_1 = 1$ and $w_1 = 0.1$.

429

430

Moreover, based on Figure 8, it can be seen that although changing the strategy

431

has no significant effect on optimal availability (minimum is 0.9950 and maximum

432

is 0.9958), Strategies 2 and 4 with $w_1 = 0$ do have maximum availability.

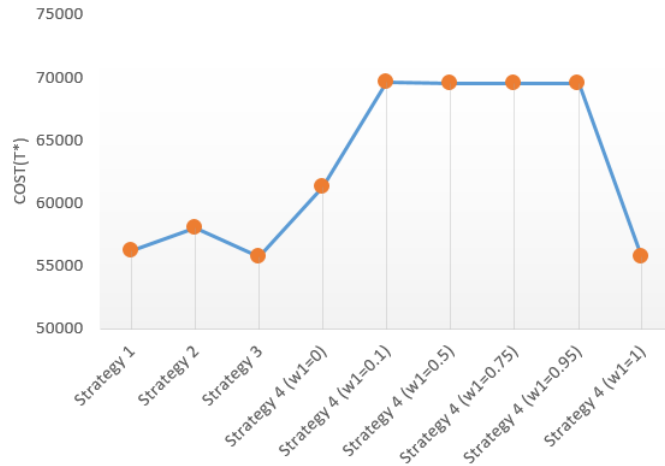


Figure 7: Optimal cost for each strategy.

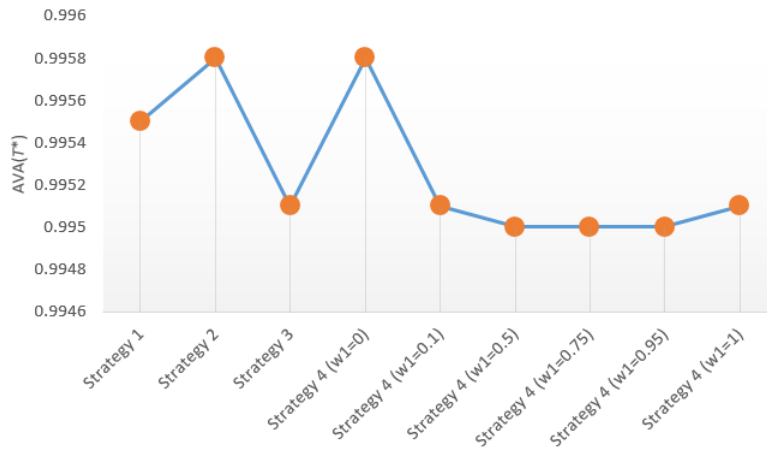


Figure 8: Optimal availability for each strategy.

433 6. Concluding Remarks

434 In the real world, there is no unrivaled solution for the optimal repowering
 435 topology in energy systems. Constraints such as costs and technological per-
 436 formances are the core of the decision-making tools for defining the optimal
 437 time and topology of repowering systems. Safety constraints are also crucial for

438 warranty reasons in order to avoid replacing the system while it is still under
439 warranty.

440 This paper has developed a decision-making tool for energy systems in order to
441 find the optimal repowering time and topology based on the following criterion:

- 442 • Repower the energy system taking into account warranty, cost, reliability,
443 failure rates of several versions of the system's components available in the
444 market and their warranty characteristics.
- 445 • Consider in each case a cost function to minimize, an availability function
446 to maximize, a joint function $AC(T)$ to maximize and a multi-objective
447 function $L(T)$ to minimize.

448 The core of replacement strategies of wind energy systems are within repowering
449 activities. One of the disadvantages of the proposed model is the fact that it
450 does not consider social and stakeholders criteria in the repowering decision, nor
451 environmental assessment of the chosen scenario was considered in this study.
452 A natural next step will be the incorporation of these two parameters in the
453 decision support tool.

454 Future studies will investigate other decommissioning scenarios of energy systems
455 and how they affect the levelized cost of energy-LCOE, since this phase received
456 little attention in the state of art of energy deployment and its sustainability.
457 Another perspective will be to consider system dependencies, weather conditions
458 and how it affects accessibility to the energy system. This paper consider full
459 repowering problem, one may also consider in future works partial repowering
460 and group maintenance.

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464 paper. This work was partially presented at the IEEE CODIT'19 conference
465 [20].

466 **7. APPENDIX**

467 In this section, expressions for the **availability** and cost functions are **devel-**
 468 **oped.**

469 The expected availability **and cost** functions for a series-parallel system can be
 470 **determined** as (G.1) and (G.2), respectively. The expected availability and cost
 471 functions for **the** case study can be **determined** as (G.3) and (G.4), respectively.

$$Cost(T) = \frac{c_F + (c_T - c_F)(1 - \prod_{j=1}^{d_1} F_{X_{k_i}}^{(i)}(T))(1 - \prod_{j=1}^{d_2} F_{Y_{k_i}}^{(i)}(T))(1 - \prod_{j=1}^{d_3} F_{Z_{k_i}}^{(i)}(T))}{\int_0^T \prod_{j=1}^n (1 - \prod_{j=1}^{d_1} F_{X_{k_i}}^{(i)}(t))(1 - \prod_{j=1}^{d_2} F_{Y_{k_i}}^{(i)}(t))(1 - \prod_{j=1}^{d_3} F_{Z_{k_i}}^{(i)}(t)) dt} \quad (G.1)$$

$$Availability(T) = \int_0^T \prod_{j=1}^n (1 - \prod_{j=1}^{d_1} F_{X_{k_i}}^{(i)}(t))(1 - \prod_{j=1}^{d_2} F_{Y_{k_i}}^{(i)}(t))(1 - \prod_{j=1}^{d_3} F_{Z_{k_i}}^{(i)}(t)) dt$$

$$\times \left[\int_0^T \prod_{j=1}^n (1 - \prod_{j=1}^{d_1} F_{X_{k_i}}^{(i)}(t))(1 - \prod_{j=1}^{d_2} F_{Y_{k_i}}^{(i)}(t))(1 - \prod_{j=1}^{d_3} F_{Z_{k_i}}^{(i)}(t)) dt + \mu_F + (\mu_T - \mu_F) \right. \\ \left. (1 - \prod_{j=1}^{d_1} F_{X_{k_i}}^{(i)}(T))(1 - \prod_{j=1}^{d_2} F_{Y_{k_i}}^{(i)}(T))(1 - \prod_{j=1}^{d_3} F_{Z_{k_i}}^{(i)}(T)) \right]^{-1}. \quad (G.2)$$

$$Cost(T) = \frac{c_F + (c_T - c_F)e^{-\left(\frac{T}{\lambda_i}\right)^{\beta_i} - \left(\frac{T}{\lambda_i'}\right)^{\beta_i'}} \left\{ 1 - \prod_{j=1}^2 (1 - e^{-\left(\frac{T}{\lambda_{i,j}''}\right)^{\beta_{i,j}''}}) \right\}}{\int_0^T e^{-\left(\frac{t}{\lambda_i}\right)^{\beta_i} - \left(\frac{t}{\lambda_i'}\right)^{\beta_i'}} \left\{ 1 - \prod_{j=1}^2 (1 - e^{-\left(\frac{t}{\lambda_{i,j}''}\right)^{\beta_{i,j}''}}) \right\} dt} \quad (G.3)$$

$$Availability(T) = \int_0^T e^{-\left(\frac{t}{\lambda_i}\right)^{\beta_i} - \left(\frac{t}{\lambda_i'}\right)^{\beta_i'}} \left\{ 1 - \prod_{j=1}^2 (1 - e^{-\left(\frac{t}{\lambda_{i,j}''}\right)^{\beta_{i,j}''}}) \right\} dt$$

$$\times \left[\int_0^T e^{-\left(\frac{t}{\lambda_i}\right)^{\beta_i} - \left(\frac{t}{\lambda_i'}\right)^{\beta_i'}} \left\{ 1 - \prod_{j=1}^2 (1 - e^{-\left(\frac{t}{\lambda_{i,j}''}\right)^{\beta_{i,j}''}}) \right\} dt + \mu_F + (\mu_T - \mu_F) e^{-\left(\frac{T}{\lambda_i}\right)^{\beta_i} - \left(\frac{T}{\lambda_i'}\right)^{\beta_i'}} \right. \\ \left. \left\{ 1 - \prod_{j=1}^2 (1 - e^{-\left(\frac{T}{\lambda_{i,j}''}\right)^{\beta_{i,j}''}}) \right\} \right]^{-1}. \quad (G.4)$$

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