HIghly advanced Probabilistic design and Enhanced Reliability methods for high-value, cost-efficient offshore WIND

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Contents

List of Abbreviations

LCOE	Levelized Cost Of Energy
O&M	Operations and Maintenance
WP	Work Package
T	Task
MILP	Mixed Integer Linear Problem
MIQP	Mixed Integer Quadratic Problem

1 Executive Summary

The HIPERWIND project aims at achieving a reduction in the Levelized Cost of Energy of offshore wind farms, through advancements of basic wind energy science which will lead to reductions in risk and uncertainty. The outcome is cost efficient offshore wind through a reduction in unnecessary use of materials, less unscheduled maintenance, and optimized operating strategy tailored at delivering power with high market value.

To fulfill this objective, among many other activities, we have developed a risk-based Operation and Maintenance model, which uses the improved component reliability modelling established in WP5, to devise Operation and Maintenance strategies which minimize financial risk. We have used this model to assess the value of wind farm assets depending on their Operation and Maintenance strategy and the state of the electricity market.

The O& M tool is composed of:

- 2 optimization models:
  - The short term model optimises the schedule of maintenance over the year, for a given number of operations to be planned, on a selected price and meteorological conditions scenario.
  - The long term model optimises the long term schedule, i.e. the number of maintenance to schedule each year.
- and a simulator which for each life-cycle expected failures scenario computes year after year the optimal number of maintenance to be scheduled the given year and the average yearly maintenance schedule and expected revenue.

The main results are:

- The short term optimization always leads to an increase in the expected revenue even though in some cases the optimal schedules include longer periods of maintenance thus an increased number of hours without generation;
- The long term optimization also leads to an increase in the expected revenue, which is highly dependent on the prices (in the case of price valuation);
- The short term optimization increases the market factor of the wind farm by an average of 3% with large variations due to the level of prices (from 0% to 5%);
- The long term optimization increases the market factor of the wind farm by an average of 3% with large variations due to the level of prices (from 0% to 5%).

2 Introduction

The HIPERWIND project aims at achieving a reduction in the Levelized Cost of Energy of offshore wind farms, through advancements of basic wind energy science which will lead to reductions in risk and uncertainty. The outcome is cost efficient offshore wind through a reduction in unnecessary use of materials, less unscheduled maintenance, and optimized operating strategy tailored at delivering power with high market value.

To fulfill this objective, among many other activities, we have developed a risk-based Operation and Maintenance model, which uses the improved component reliability modelling established in WP5, to devise Operation and Maintenance strategies which minimize financial risk. We have then used this model to assess the value of wind farm assets depending on their Operation and Maintenance strategy and the state of the electricity market.

The models outputs are also be used as an input to the final impact assessment study, which will be carried out to quantitatively verify how the technological achievements of HIPERWIND transform into reduction of LCOE.

The O&M model can be used to produce the following outputs:

- Compute a predictive optimised long-term schedule of future maintenance operations, on the whole life duration of a wind farm
- Evaluate the loss of energy linked to the maintenance
- Evaluate the cost (and loss of revenue) of a maintenance schedule
- Optimize for a given year and a given number of maintenance operations, the maintenance schedule

In practice we have implemented:

- 2 optimization models:
  - The short term model optimises the schedule of maintenance over the year, for a given number of operations to be planned, on a selected price and meteorological conditions scenario. Its outputs are both the dates when to schedule each operation and the cost (including maintenance cost and loss of revenue due to non produced electricity during the operation).
  - The long term model optimises the long term schedule, i.e. the number of maintenance to schedule each year. It uses as inputs the results of the short term model for every year, every possible combination of number of replacements, averaged on the price and meteorological scenarios. Its outputs are both the replacement schedule but also the optimal costs and revenues.
- a simulator which for each life-cycle expected failure scenario computes year after year the optimal number of maintenance to be scheduled the given year given the probability of failures which are expected to occur in the future years, as well as the average (on price and meteorological scenarios) yearly maintenance schedule and expected revenue.

We have ran the models and the simulators on different cases:

- Valuation with price scenarios or with a fixed strike price;
- Computation of the life-cycle maintenance schedule (number of maintenance per year) with the stochastic long-term optimization model or use of reference schedules;
- Computation of the annual maintenance schedules with or without using the optimization algorithm.

We obtained the following results:

- The short term optimization always leads to an increase in the expected revenue even though in some cases the optimal schedules include longer periods of maintenance thus an increased number of hours without generation;
- The long term optimization also leads to an increase in the expected revenue, which is highly dependent on the prices (in the case of price valuation)

- The short term optimization increases the market value factor of the wind farm by an average of 3% with large variations due to the level of prices (from 0% to 5%)
- The long term optimization increases the market value factor of the wind farm by an average of 3% with large variations due to the level of prices (from 0% to 5%)

Section 3 describes the real context of the study (the Teesside offshore wind farm); section 4 gives a summary of the optimization models; section 5 describes the simulation process; section 6 explains how price scenarios were created and section 7 presents the results of the study.

3 Context: scheduling the maintenance of a wind farm in the UK

Teesside offshore wind farm consists of 27 turbines. The turbines are arranged in three rows with 9 turbines in each row, see Fig. 3.1. Teesside offshore wind farm was fully commissioned in 2013, and is approximately 11 years old. MCR (Major Component Replacement) such as gearbox replacement plays an important role in its O&M (Operation & Maintenance). A good MCR strategy aims to minimize the resulting revenue loss as well as the maintenance cost. In case the electricity price is constant such as in a CfD (Contract of Difference) scheme, the revenue loss is directly proportional to the downtime of turbine caused by MCR work. In the scenario of variable electricity price such as after the CfD scheme, the revenue loss for the wind farm owner is determined by the downtime and the electricity price.

There are many challenges in the MCR. The first one may be the availability of the jack-up vessel. The offshore wind farm owner needs to plan about one year ahead and book the vessel in advance. Ideally it would be good to know when the turbine components are going to fail and how many turbine components are going to fail, particularly, the coming one year or two years. The second may be the uncertainty in the weather such as wind and wave conditions. When the vessel comes, the undesirable weather such as storms can significantly impact the accessibility to the site and consequently prevent the planned MCR work. Once the booked period passes, the vessel may need to leave due to its schedule, causing delay in the MCR work. In the HIPERWIND project, we looks at the MCR strategy from both a life-cycle optimization perspective and a short-term perspective. The turbine component reliability modelling enables the offshore wind farm owner to anticipate the turbine component failure through the life time of the offshore wind farm from the beginning. In a given year, the owner can anticipate the turbine component failure in all coming years til the end of the offshore wind farm. Through the optimization under different scenarios, we want to verify the benefits of having this probabilistic view of the failure events in the O&M strategy.

In the optimization, we considered a large number of failure scenarios through the life time of the wind farm, and a number of wind and wave time series, as well as a set of energy price scenarios.

The wind and wave time series are generated by the statistical models for weather time series generation developed for asset management for offshore wind farms (LJDP19). These models are variations of Auto Regressive Moving Average models (ARMA) and take into

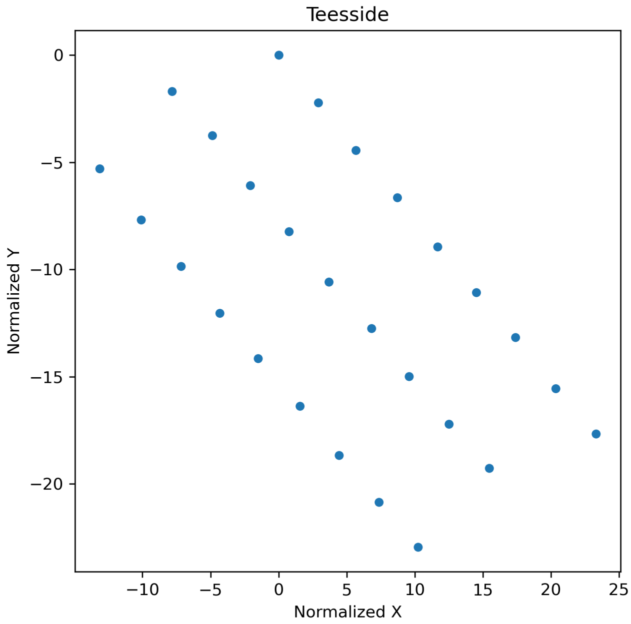

Figure 3.1: Turbine layout of Teesside offshore wind farm

account both the seasonality and the correlation between weather variables thanks to neural network models. A statistic criteria was used to select 200 different year-round time series that would capture the variability due to the stochastic nature of weather variables.

The wind and wave time series are used to evaluate the power production and the site accessibility. The energy price scenarios are essential to evaluate the revenue loss. It also enables us to investigate the optimal period for the MCR work in terms of wind and wave conditions that impact the power production and the site accessibility, and the electricity price that influences the revenue loss. Generally the MCR work should be placed in a time period with good site accessibility and low revenue loss. The latter means low power production and/or low electricity price.

4 The maintenance schedules optimization model

The scheduling optimisation problem is composed of 2 optimisation models as shown in Figure 4.1

- The short term model optimises the schedule of maintenance over the year, for a given number of replacements to be planned, on a selected price and meteorological conditions scenario. Its outputs are both the optimal dates when to schedule each operation and the resulting optimal cost (including maintenance cost and loss of revenue due to non produced electricity during the operation).
- The long term stochastic model optimises the long term schedule, i.e. the number of replacements to schedule each year. It uses as inputs the results of the short term model for every year, every possible combination of numbers of replacements, averaged on the price and meteorological scenarios. Its outputs are both the replacement

schedule but also the optimal costs and revenues.

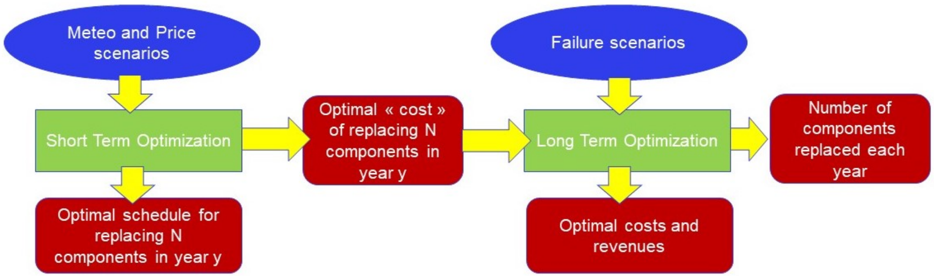

Figure 4.1: HiperWind Optimisation of maintenance models

We describe in the following subsection the assumptions taken, the data needed and the 2 optimization models.

4.1 Assumptions

The following assumptions have been taken in the model implementation:

- The model that we developed allows accounting for all components of big size (eg. gearboxes, main bearings....). In this case study we only account for gearboxes, due to lack of data for other components.
- Components could be replaced by new components or by refurbished ones, at a lower cost. The choice of refurbished or new component is not included in the model.
- Even though some planned maintenance may exist, we assume that the operation we are scheduling are always prioritized.
- A degradation factor is applied to the power generation of turbines.
- All turbines in a farm are identical, and the conditions applied to all turbines are also identical. This means that, without maintenance, all turbines of the same farm have the same power output, only depending on meteorological conditions, assuming that these conditions are identical for all turbines in the farm. In other words, the wake effects are not accounted for. It may be possible to integrate the wake effects later.
- Only one category of vessel (Jackup) is considered.
- The time for the vessel to reach the farm from the harbour is neglected.
- Components are always replaced before they fail. This assumption comes from the fact that the expected failure scenarios have a yearly granularity which means we have no information on the period of the year when failures may occur.
- Maintenance costs do not vary along the year. This assumption could very easily be removed.

4.2 Inputs

The following inputs are used:

- Description of a Maintenance operation for each component category: a maintenance operation is composed of a sequence of uninterruptible 'sub-operations'. Between sub-operations, there can occur interruptions (meaning than the vessel and crew will wait for better meteorological conditions).

  - Each sub-operation has a duration (expressed in days).
  - Sub-operations cannot be interrupted.
  - Each sub-operation is associated to given necessary conditions for accessibility (maximum waves height and maximum wind speed). The sub-operation can occur only when accessibility conditions are fulfilled.

- Constraints
  - The maximum number of replacement operations in a year is set to 5.
  - It is not possible to plan replacements in parallel.
  - The maximum duration of a whole maintenance operation (including all sub-operations and waiting periods) is set to 14 days.
- Failure probabilities: we used failures probabilities created during the project (Abr24): 1000 scenarios with the number of expected failures per year over 30 years.
- The maintenance cost is composed of:
  - A fixed cost depending on the number of gearboxes to be replaced during the year,
  - A vessel mobilization cost for a maximum period of 35 days and a maximum number of gearboxes of 5.
- Climate scenarios: we used 200 hourly correlated time series created during the project (Kel22). these series include wind speed, wave height, and maximum potential generation for one typical turbine.
- Price scenarios: we used 150 price scenarios. See section 6 for details about those scenarios.

4.3 The Short term optimization model

In this section we will summarize the short-term model which is deeply described in (Cha23). The short term model has the following characteristics:

- Time horizon: 1 year
- Time granularity: 1 day
- Decision variable: When in the year to plan each maintenance operation
- Objective function: minimize cost / maximize value (cost of maintenance, value of selling electricity on the market)
- Constraints: operation constraints (linked to the availability of materials, boats, how many items can fit on a boat, ...)
- Uncertainties: climate scenarios; price scenarios ; delays when vessels are available
- Results:
  - The cost matrix $C(y, \{N_{maint}, s)$ giving the optimal cost for each year y and each scenario s of replacing N_{maint} components.

  - For each year y and each scenario s, the best periods for replacing components, in the case of N_{maint} components

- Solving process: Monte-Carlo optimisation conducted on all scenarios, for all possible number of maintenance operations (from 0 to $N_{fail}^{max}(y) = 5$). For each year/scenario/number of gearboxes to be replaced, the optimization problem is solved by a mixed integer quadratic programming algorithm.

The results of the short-term problem for each year and each possible number of maintenance operations, averaged on all meteorological and prices scenarios (i.e. the optimal costs and optimal schedules) are used as inputs to the long-term problem which computes the optimal number of maintenance operations to be scheduled each year. The short term model is then used to define the optimal schedule in each year, given the optimal number of operations planned this year (results of long-term problem).

This problem can be written as follows:

$$C^{short}(y, \{N_y^{maint}\}) =$$

$$\min_{\{t_{i,j}, i\in[0,I_y-1], j\in[0,J-1]\}} \Big[FC(\{N_y^{maint}\}) + WC(\{t_{i,j}, i \in [0, I_y - 1], j \in [0, J - 1]\})$$

$$+LR(\{t_{i,j}, i \in [0, I_y - 1], j \in [0, J - 1]\}) + VM(\{t_{i,j}, i \in [0, I_y - 1], j \in [0, J - 1]\}) \Big]$$

with:

- $FC(\{N_y^{maint}\})$ is the fixed part of the maintenance cost, depending only on the number of maintenance. This cost is then fixed in our optimisation problem;
- $WC(\{t_{i,j}, i \in [0, I_y - 1], j \in [0, J - 1]\})$ is the waiting cost, depending on the schedule of the maintenance;
- $LR(\{t_{i,j}, i \in [0, I_y - 1], j \in [0, J - 1]\})$ is the lost revenue, corresponding to periods when some turbines are under maintenance, and then do not produce electricity. This value depends on the schedule of the maintenance;
- $VM(\{t_{i,j}, i \in [0, I_y - 1], j \in [0, J - 1]\})$ is the mobilisation cost; It depends on the number of necessary mobilisation, given that a mobilisation has a fixed cost for a given duration, and can include up to e.g. 5 operations.

The decisions variables are all the dates when a sub-block of a maintenance operation is starting: $\{t_{i,j}, i \in [0, I_y - 1], j \in [0, J - 1]\}$, with $t_{i,j}$ being the first day of the jth subblock of the ith maintenance operation.

submitted to the following constraints:

(C-1) All the maintenance sub-blocks are scheduled in the year:

$$\forall i \in [0, I_y - 1], \forall j \in [0, J - 1], t_{i,j} \leq T_y - 1$$

(C-2) Sub-blocks in a maintenance operations are scheduled one after the other:

$$\forall i \in [0, I_y - 1], \forall j \in [0, J - 2], t_{i,j+1} \geq t_{i,j} + d_j$$

(C-3) Maximum duration of a maintenance operation:

$$\forall i \in [0, I_y - 1], t_{i,J-1} + d^c_{J-1} - t_{i,0} \leq \overline{D}$$

(C-4) A turbine is not producing during a maintenance; We denote $op(t)$ the number of maintenance operations which are ongoing at time t with

$$op(t) = \sum_{i=0}^{I_y-1} op_i(t)$$

$op_i(t)$ is then defined as follows:

- Before the first day of the first sub-block:

$$\forall i \in [0, I_y - 1], \forall t < t_{i,0}, op_i(t) = 0$$

- Between the first day of the first sub-block and the last day of the last sub-block of a maintenance operation:

$$\forall i \in [0, I_y - 1], \forall t \in [t_{i,0}; t_{i,J-1} + d^c_{J-1} - 1], op_i(t) = 1$$

- Between 2 maintenance operations, ie between the last day of the last sub-block of a maintenance and the first day of the first sub-block of the next maintenance operation:

$$\forall i \in [0, I_y - 2], \forall t \in]t_{i,J-1} + d_{J-1} - 1; t_{i+1,0}[, op_i(t) = 0$$

- After the last day of the last sub-block :

$$\forall i \in [0, I_y - 1], \forall t \in]t_{I_y-1,J-1} + d_{J-1} - 1; T_y[, op_i(t) = 0$$

(C-5) Maximum number of parallel operations:

$$\forall t \in [0, T_y - 1], op(t) \leq \overline{P}$$

(C-6) Waiting periods occur between subblocks; We will denote $w(t)$ the number of maintenance operations that are 'waiting' at time t with

$$w(t) = \sum_{i=0}^{I_y-1} w_i(t)$$

$w_i(t)$ is then defined as follows:

- Before the last day of the first sub-block: no waiting:

$$\forall i \in [0, I_y - 1], \forall t < t_{i,0} + d_0 - 1, w_i(t) = 0$$

- During a sub-block of a maintenance operation: no waiting

$$\forall i \in [0, I_y - 1], \forall j \in [0, J - 1], \forall t \in [t_{i,j}; t_{i,j} + d_j - 1], w_i(t) = 0$$

- Between sub-blocks of a maintenance operation: waiting

$$\forall i \in [0, I_y - 1], \forall j \in [0, J-2], \forall t \in]t_{i,j} + d_j - 1; t_{i,j+1}[, w_i(t) = 1$$

- Between maintenance operations: no waiting

$$\forall i \in [0, I_y - 2], \forall t \in]t_{i,J^c-1} + d_{J-1} - 1; t_{i+1,0}[, w_i(t) = 0$$

- After the last day of the last sub-block of the last maintenance operation: no waiting

$$\forall i \in [0, I_y - 1], \forall t \in]t_{I-1,J-1} + d_{J-1} - 1; T_y[, w_i(t) = 0$$

(C-7) Maximum number of parallel operations:

$$\forall t \in [0, T_y - 1], w(t) \leq \overline{P}$$

(C-8) Accessibility conditions: the jth sub-block of a maintenance operation can occur only if the required accessibility condition is fulfilled

$$\forall i \in [0, I_y - 1], \forall t \in [t_{i,0}; t_{i,J-1} + d_{J-1} - 1] A_{t,s} \geq \underline{A}_j$$

(C-9) Schedule and availability conditions: the ith maintenance operation cannot start before a specific date,

$$\forall i \in [0, I_y - 1], t_{i,0} \geq \underline{T}_i$$

(C-10) Schedule and availability conditions: the ith maintenance operation cannot end after another specific date,

$$\forall i \in [0, I_y - 1], t_{i,J-1} + d_{J-1} - 1 \leq \overline{T}_i$$

(C-11) Mobilisation cost: a vessel is mobilised for a maximum duration. If it is necessary to mobilise it many times then the cost increases.

$$m = \sum_{i=1}^{I_y - 1} z_i$$

where:

- if the next operation ends before the end of the mobilisation period, no addtional cost:

$$\text{if } t_{i,J-1} \leq t_{i-1,0} + \overline{DM} \text{ then } z_i = 0$$

- if the next operation ends after the end of the mobilisation period, there is an addtional cost:

$$\text{if } t_{i,J-1} > t_{i-1,0} + \overline{DM} \text{ then } z_i = 1$$

where:

- y is the year index (useful for data depending on the year)
- $s \in S$ is the scenario index

- T_y is the number of days of the considered year
- $\{h_t\}$ are the indexes of the hours of the day t, with $\{h_t\} \in [24 * t; 24 * (t + 1)[$
- H_y is the number of hours in the year y
- $\{N_y^{maint}\}$ is the number of maintenance to be scheduled the year y
- $t_{i,j}$ is the start date of the jth block of the ith maintenance operation
- I_y is the number of maintenance operations to be scheduled the year y
- J is the number of sub-blocks composing a maintenance operation
- d_j is the duration of the jth sub-block of a maintenance operation
- $\overline{D}$ is the maximum duration of a maintenance operation
- $N_{turbines}$ is the number of turbines in the farm
- $op(t)$ the number of turbines in maintenance at time t
- $op_i(t) = 1$ if the ith maintenance operation is occurring at t, $op_i(t) = 0$ if not.
- $w(t)$ the number of turbines which are 'in the middle' of a maintenance operation (waiting)
- $w_i(t) = 1$ if t corresponds to a waiting period during the ith maintenance operation, $w_i(t) = 0$ if not.
- m the number of necessary vessel mobilisations
- M the unitary mobilisation cost of the vessel
- $\overline{DM}$ the maximum duration of one vessel mobilisation (which can be used for more than one operation)
- $\overline{P}$ the maximum number of parallel operations
- $W_{y,t}$ is the cost of waiting during 1 day, at day t, in the year y
- $\lambda_{h,s}$ is the marginal cost of electricity for the hour h of the year, in the scenario s
- $\overline{P}_{h,s}$ is the power generated by 1 turbine at hour h for the scenario s if the turbine is available.
- $A_{t,s}$ describes the accessibility conditions. $A_{t,s}$ can take a limited number of integer values $\{0, A^i, i \in [0; N_A]\}$ where N_A is the number of possible accessibility situations; The biggest $A_{t,s}$ is, the more accessible the conditions are, starting from $A_{t,s} = 0$ where it is impossible to conduct any kind of operation to $A_{t,s} = \max_{A^i, i\in[0;N_A]}$ where all operations are possible.
- $\underline{A}_j$ is the minimum required accessibility conditions for the jth sub-block of an operation. $\underline{A}_j \in \{0, A^i, i \in [0; N_A]\}$

Without the mobilisation constraints, the short term problem is solved using a MILP solver. With this constraint it is solved with a MIQC solver.

4.4 The Long Term optimization model

In this section we will summarize the long-term model which is deeply described in (Cha23). The long term model has the following characteristics:

- Time horizon: 25 years.
- Time granularity: 1 year (failure data are given with year granularity)
- Decision variable: How many gearboxes are replaced each year of the horizon
- Objective function: minimize cost (including maintenance cost, waiting cost, and cost of non-sold electricity). The objective function is a function of the costs computed by the short-term model.

- Constraints:
  - Maximum number of maintenance operations per year (set to 5)
  - Components are always replaced before failure; Here it means that if the failure model predicts a failure of a component in year y, it has to be replaced latest during the year y-1.
  - Budget constraints (not used in the simulations);
- uncertainties: failures probabilities, which are interpreted as the number of equipment which must have been replaced before year Y;
- Solving process: The long term problem is solved by a stochastic optimisation approach, which can either be a deterministic or a stochastic dynamic programming.

This problem can be written as follows:

$$\min_{N_{y,s}, y \in [0;Y[, s \in [0,S[} \left(\mathop{\mathbb{E}}_{s \in [0,S[} \left[\sum_{y=0}^{Y-1} C(y, \{N_{y,s}\right] \right)$$

$C(y, \{N_{y,s}\})$ is the mean optimal cost of scheduling $N_{y,s}$ operations in the year y.

The decision variables are $\{N_{y,s}, y \in [0;Y[, s \in [0,S[\}$, where $N_{y,s}$ is the number of maintenance operations scheduled the year y in the scenario s.

The constraints are the following:

(C-1) Enough maintenance operations are scheduled so that failures occur after replacements:

$$\forall y \in [0;Y[, \forall s \in [0,S[, \sum_{x=0}^{y} N_{x,s} \geq \sum_{x=0}^{y} \underline{N_{y,s}^{cum}}$$

(C-2) Upper bound on the number of replacements each year for each category:

$$\forall y \in [0;Y[, \forall s \in [0,S[, N_{y,s} \leq \overline{N_y}$$

(C-3) Upper bound on the total number of replacements each year:

$$\forall y \in [0;Y[, \forall s \in [0,S[, N_{y,c,s} \leq \overline{N_y}$$

(C-4) Upper bound on the budget per year:

$$\forall y \in [0;Y[, \forall s \in [0,S[, C(y,s,N_{y,s}) \leq \overline{B_y}$$

(C-5) Upper bound on the total budget:

$$\forall s \in [0,S[, \sum_{y=0}^{Y-1} C(y,s,N_{y,s}) \leq \overline{B}$$

(C-6) Upper bound on the total number of replacements:

$$\forall s \in [0,S[, \sum_{y=0}^{Y-1} N_{y,s} \leq \overline{CN}$$

where:

- Y is the number of years of the horizon;
- S is the number of scenarios (note that we are not referring to the same scenarios as in the short term model as here the uncertainties are the failure probabilities;
- $\overline{CN}$ is the maximum possible number of operations to be scheduled
- $CN^{y,s}$ is the cumulative number of expected failures occurred before year y in the scenario s;
- $\overline{N_y}$ is the maximum number of operations that can be scheduled during the year y
- $\overline{N_y}$ is the maximum number of operations that can be scheduled during the year y
- $\overline{B_y}$ is the maximum budget that can be spent during the year y
- $\overline{B}$ is the maximum budget that can be spent during the whole period.
- $C(y, \{N_{y,s}\})$ are the costs computed by the short term model.

This problem is solved by a stochastic dynamic programming algorithm.

5 Simulations

For being able to compare different maintenance scheduling strategies, we have implemented a simulator.

For doing so, we have simulated over all the failure scenarios the computation of maintenance schedules with different strategies:

- For the long term (how many replacements are scheduled each of the coming 25 years), 3 cases were simulated:
  - Use of a hand-made reference schedules. We detail below how we created different reference schedules.
  - Generation of a reference schedules by the simulator, from an optimistic reference hand-made schedule: this means that we simulated the operation process as it could happen. Each year, the chosen reference schedule is applied unless the expected number of failures for the given year leads to the situation where the total number of failures since the beginning of the period added to the expected number of failures in the current year is bigger that the total number of replacements already done plus the scheduled number of replacements in the given year. In this case the number of replacements of the current year will be increased (limited to 5);
  - Use of the results of the stochastic optimisation adapted in the simulation with the same method as the one described above to adapt the reference schedule.
- For the short term (when are the replacements scheduled during the year), 3 cases were simulated:
  - Optimisation of the schedule including minimisation of the loss of revenue in the case when the energy is sold at a market price;
  - Optimisation of the schedule including minimisation of the loss of revenue in

the case when the energy is sold at a given (and fixed) strike price;

– Optimisation of the schedule without accounting for the valuation of the energy sold (at market or fixed strike price); This case is used as the 'not optimised' case. In order to make the results closer to the real operational process, we added a few constraints to the short term optimisation:

  * not-before and not-after constraints in order to 'force' the model to schedule the maintenance mostly during the summer period (when prices are usually lower)
  * very low waiting costs in order to avoid non necessary waiting periods.

5.1 Probabilising the scenarios

The first step consisted in probabilising the failure scenarios. It appears that the same scenario is simulated many times in the 1000 scenarios which are available. In order to lower the computation times and analyse the scenarios, we applied the following methos to obtain a set of 104 probabilised scenarios:

From the S^c_{tot} failure scenarios of each component, we obtain S^c_{prob} scenarios, where scenario s has probability π_s. We then transform these scenarios which give the number of failures $F^c_{s,y}$ for the component c in year y for scenario s in scenarios of cumulated failures $CF^c_{s,y}$, where

$$\forall s \in [0, S[, \forall c \in [0, C[, CF^c_{s,y} = \sum_{x=0}^{y} F^c_{s,y}$$

Figure 5.1 shows how the 1000 scenarios are converted into 104 probabilised scenarios: each color represents one probabilised scenario. The probability of each probabilised scenarios is computed as the share of scenarios in each probabilised scenario.

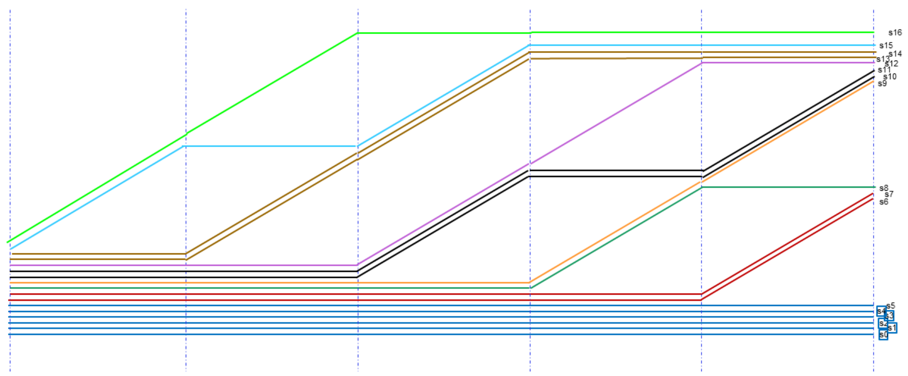

Figure 5.1: Methodology for computing probabilised scenarios

Figure 5.2 shows the 104 probabilised scenarios of expected failures per year.

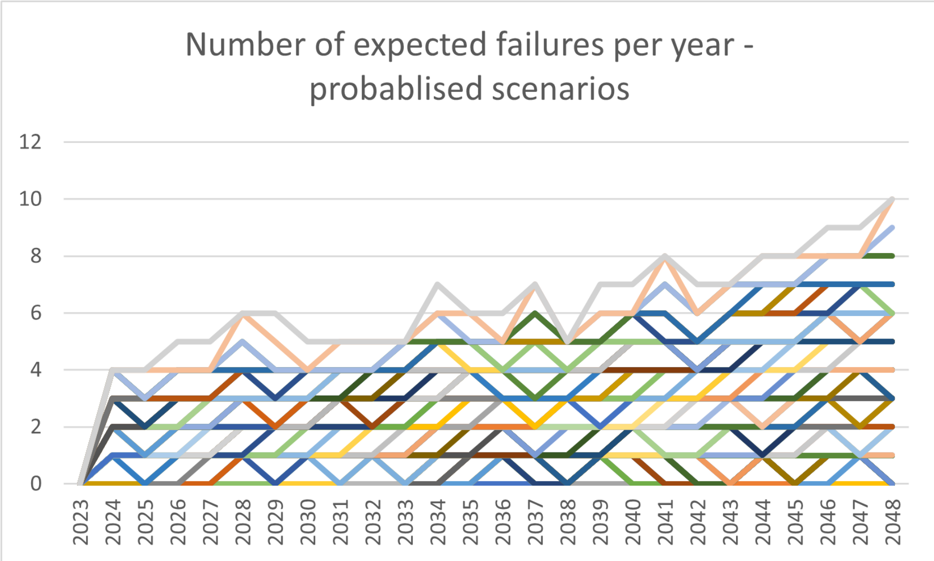

Figure 5.2: Expected number of failure expectations per year - 104 probabilised scenarios

Figure 5.3 shows the probability of each of the 104 probabilised scenarios of expected failures per year.

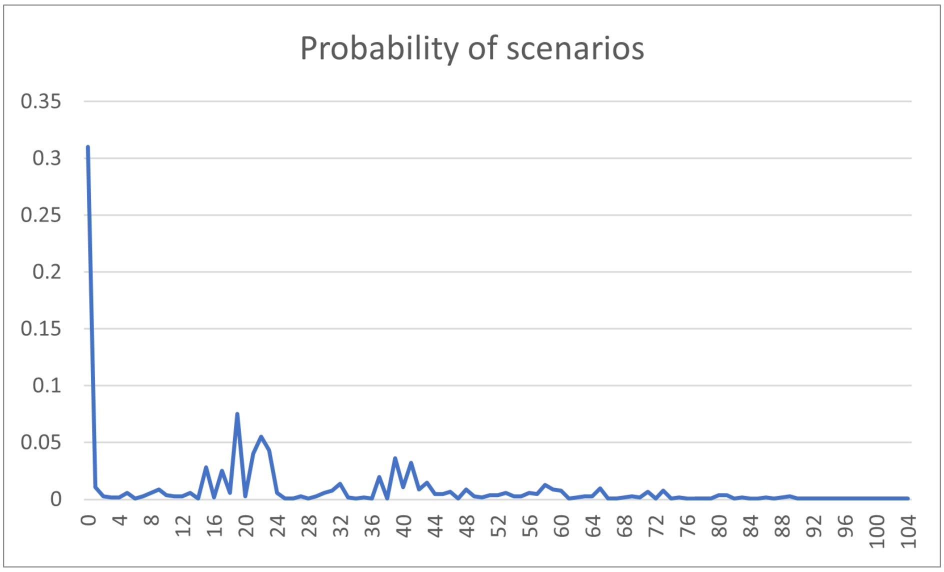

Figure 5.3: Probability of the 104 probabilised scenarios of expected number of failure per year

Figure 5.4 shows the total number of failures in each of the 104 probabilised scenarios.

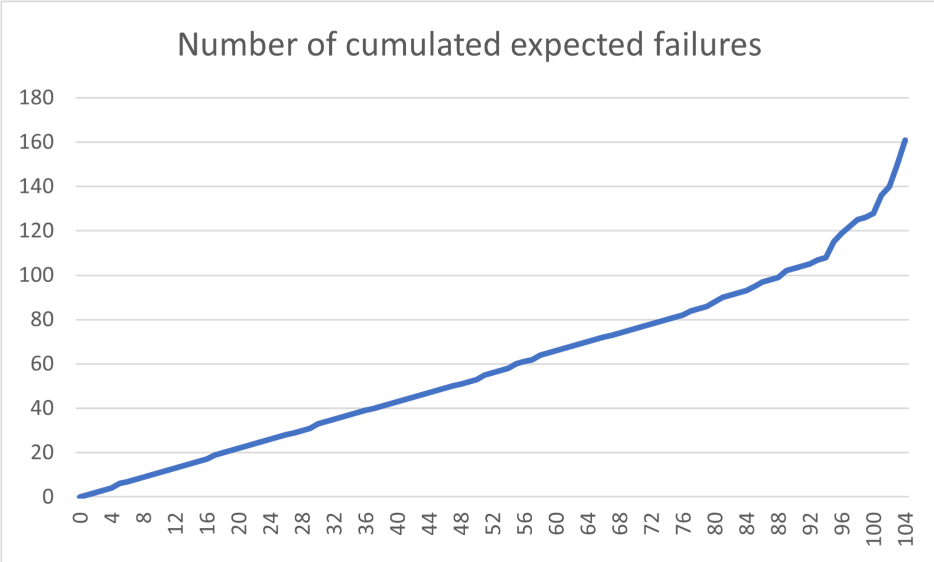

Figure 5.4: Cumulated number of expected failures in the 104 probabilised scenarios

5.2 The reference long-term maintenance schedules

As we do not have access to the real reference schedule used in the wind farm, we created a set of reference schedules that are consistent with the scenarios of expected failures. We used those reference schedules for conducting simulations using the short-term optimization only.

As the maximum number of cumulated gearbox replacement in our case is equal to 5 replacements $*$ 25 years $= 125$, we cannot create a reference schedule which would allow comparison with long term optimisation results based on the expected number of failures scenarios, as the worst scenarios accounts for 161 failures. We then chose to define 5 different reference schedules, each one consistent with the $x\%$ failure scenarios with lower cumulated number of failures. We created 5 different reference schedules which are shown in Figure 5.5:

- Schedule 85% replaces 2 gearboxes per year in the first 22 years, then 3 per year. This is consistent with the first 85% failure scenarios, in which the worst case scenario accounts for 52 cumulated failures;
- Schedule 86.7% replaces 2 gearboxes per year in the first 17 years, then 3 per year. This is consistent with the first 86.7% failure scenarios, in which the worst case scenario accounts for 57 cumulated failures;
- Schedule 90% replaces 2 gearboxes per year in the first 10 years, then 3 per year. This is consistent with the first 90% failure scenarios, in which the worst case scenario accounts for 64 cumulated failures;
- Schedule 95% replaces 2 gearboxes per year in the first 6 years, then 3 per year for 9 years, then 4 per year. This is consistent with the first 95% failure scenarios, in which the worst case scenario accounts for 77 cumulated failures;
- Finally, schedule 99.5% replaces 5 gearboxes per year. This is consistent with the first 99.5% failure scenarios, in which the worst case scenario accounts for 125 cumulated failures;

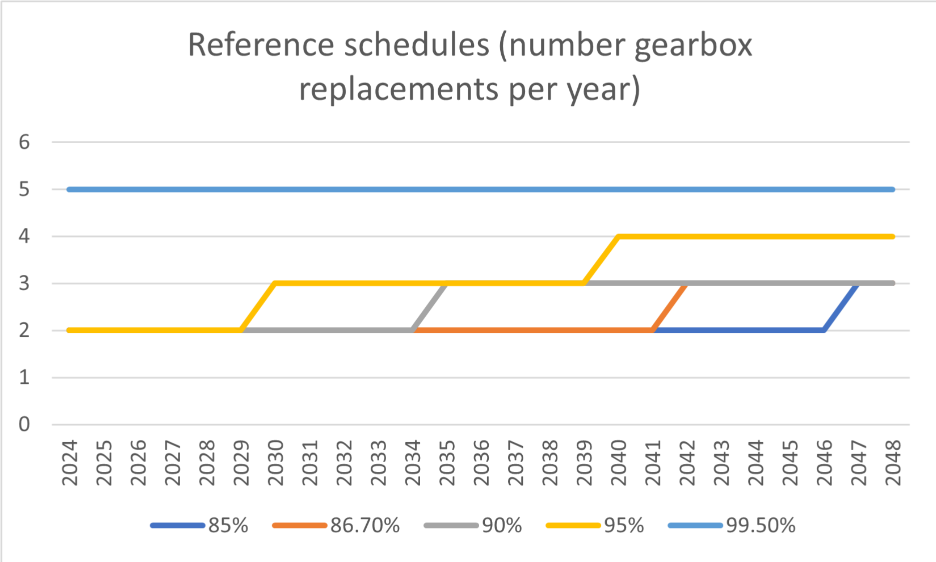

Figure 5.5: Reference long-term maintenance schedules

5.3 The optimised schedules

Optimised schedules are results of the stochastic optimisation which was conducted on a scenario tree. This scenario tree is created out of the probabilised scenarios as shown in Figure 5.6 (Note that these figures are only illustrating the tree generation and are not based on real data). At each time step, a leaf of the tree is created by grouping scenarios with identical past. During the optimisation decisions are taken at each of those leafs: the optimiser knows the past but has a a probabilistic view of the expected possible futures. Decisions are thus non anticipative.

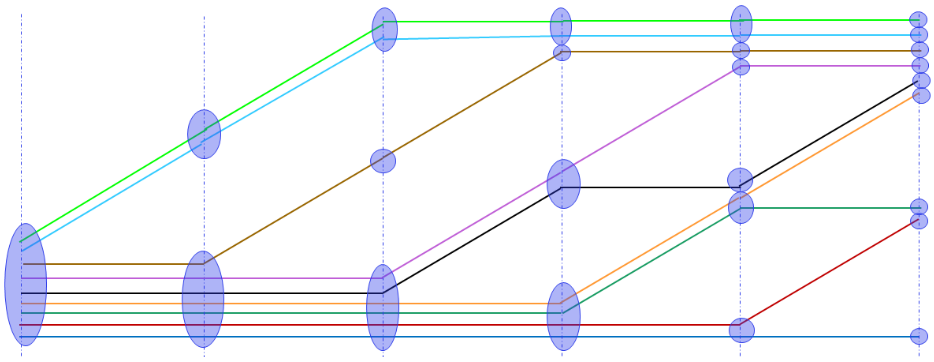

Figure 5.6: Illustration of creating the scenario tree out of probabilised scenarios

Figure 5.7 shows the resulting scenario tree.

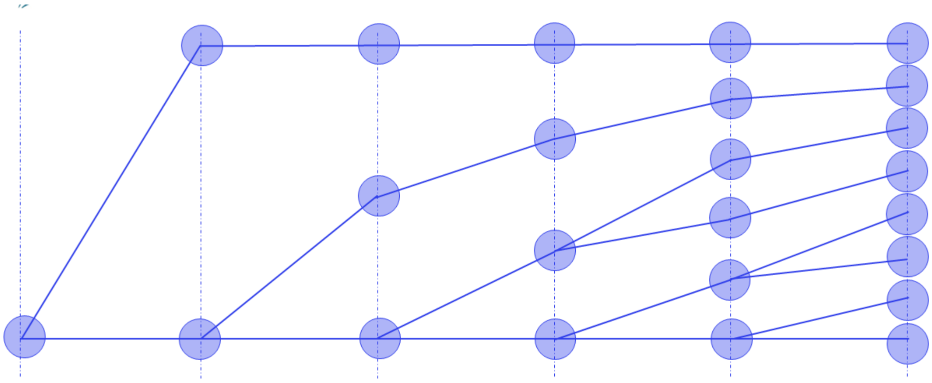

Figure 5.7: Illustration of scenario tree created out of the probabilised scenarios

We applied the long-term stochastic optimization algorithm to the scenario tree created by using the 99.5% "best" probabilised scenarios, in order to obtain results which can be compared to those obtained on the 99.5% reference schedule.

Figure 5.8 shows the optimal decisions to be taken for each of the probabilised scenarios. For 2 given probabilised scenarios, at a time step in which the past expected failures are identical, the optimal decision is be also identical. This long-term optimisation was conducted using the short-term optimisation with price valuation.

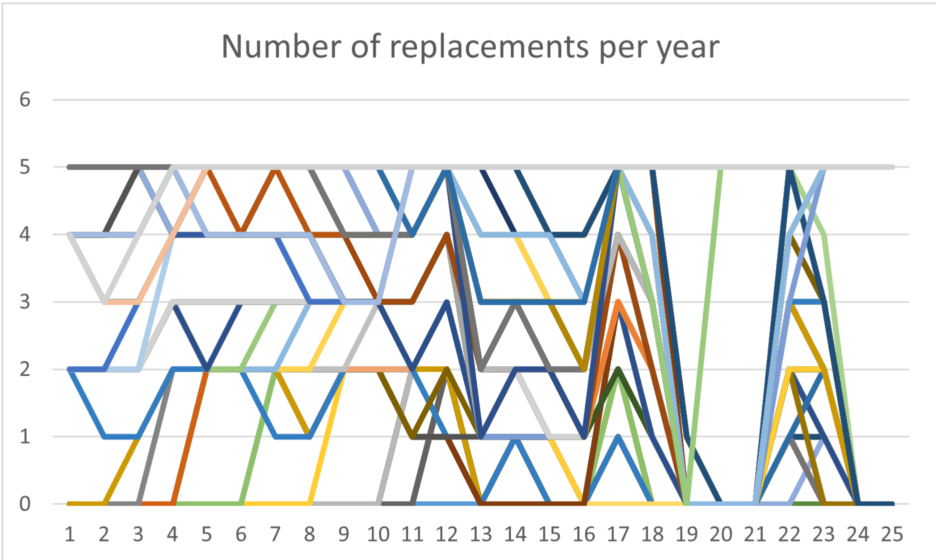

Figure 5.8: Optimal decisions computed by the stochastic optimization

5.4 The simulator

We have implemented a simulator which has the following behavior (see Figure 5.9):

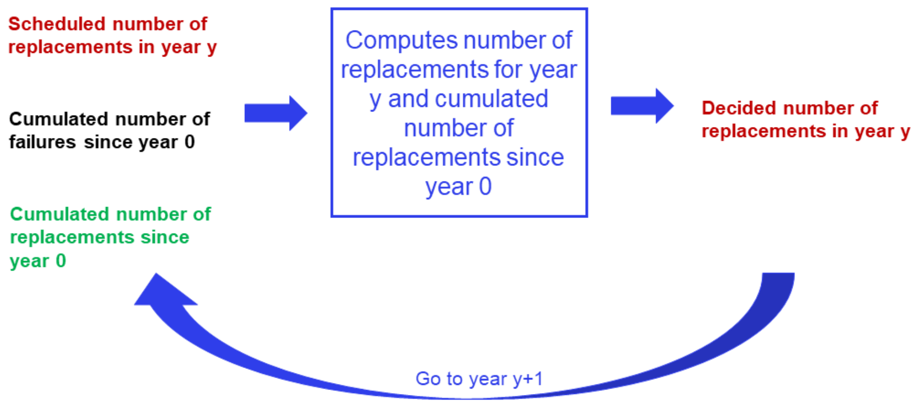

Figure 5.9: Hiperwind simulator process for one expected failures scenario

- For each probabilised scenario:
  - Get the reference schedule depending on the strategy:
    * For the case 'Reference schedule': we used a reference schedule with 1 replacement per year over the first 10 years, 2 replacement per year over the following 10 years and 3 replacements per year over the last years.
    * For the case 'Optimised': the schedule obtained by following the scenario s path in the decision tree.
  - Recompute the schedule to adapt it to the failures: for each year y:
    * Compute the number of cumulated failures $(CF(y-1))$ before year y in scenario s
    * Compute the number of cumulated planned replacements $(CP(y-1))$ before year y in scenario s
    * if the number of replacements for year y in the schedule is such that

      $$CF(y-1) + EF(y) < CP(y-1) + D(y)$$

      where $EF(y)$ is the expected number of failures in year y and $D(y)$ the decision proposed by the schedule, then increase $D(y)$ such that

      $$CF(y-1) + EF(y) = CP(y-1) + D(y)$$

      and $D(y)$ can not exceed 5.
  - Get the optimal cost and optimal short-term schedule for year y and scenario s. These optimal short-term schedules and costs have been pre-computed by the short term optimization which is applied to all years and all combinations of numbers of replacements.

6 The price scenarios

We have generated price scenarios by using an electricity system model: plan4res.

6.1 The plan4res electricity system model

plan4res is an electricity system optimization and simulation tool, composed of the 3 following models:

- A Capacity Expansion Model (CEM) aimed at adapting the electricity mix.
- A Seasonal Storage Valuation model (SSV) aimed at optimizing the management of seasonal storages. It computes the Bellman values (= cost-to-go functions) that represent the future expected economic value of the seasonal storages levels at time stages. This is necessary to know when to best use a "free" but limited and uncertain resource such as water inflows to large hydropower reservoirs: should the hydropower plant produce now and discharge part of its stored water, for example to avoid starting up a costly coal plant to meet demand, or should water be kept for a latter use, for example because present demand is low and RES generation is sufficient?
- A Simulation Model (SIM), aimed at optimizing the short-term operation of the system. The simulation is run on every scenario one after the other using a Unit Commitment model (UC) sequentially on the whole time period. The cost-to-go functions computed by the SSV are used as a variable cost for the generation of seasonal storages. The unit commitment problem (UC) solves the short-term horizon problem (short-term meaning "corresponding to a stage" usually weekly), where operational decisions are provided at one stage $s \in S$, in a deterministic setting, considering the expected future "value" that seasonal storage units can bring to the system via the cost-to-go function.

Various kinds of constraints and flexibilities involving both generation, storage and consumption are dealt with:

- Dynamic operation constraints of power plants (ramping constraints, minimum shutdown duration, ...)
- Dynamic operation of storage (including battery-like storages and complex hydro-valleys modelling)
- Demand-Response (including e.g. household dynamic consumption load-shifting or load curtailment)
- Transmission Network capacities...

The plan4res model has been developped in the Horizon 2020 plan4res project[1] (see (plab)). This model is open source and can be retrieved on github (see (plaa)). We have ran the plan4res model on datasets from the Open ENTRANCE project (see (ope)). Those dataset consist in pathways for the European energy system from 2018 to 2050, with a 5 years timestep. Those pathways consist in a description of the energy system: energy demands per uses and installed capacities. Those pathways are described in (Aue20) and the corresponding data can be retrieved in (Loe23). 4 different meta-scenarios were implemented.

The plan4res model was used to simulate the behavior of the European electricity system on the years 2018, 2025, 2030, 2035, 2040, 2045 and 2050 at country and hour resolution. We then obtained among other results marginal costs timeseries for each European country. As plan4res is a stochastic model which accounts for meteorological scenarios (tempera-

[1]This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 773897.

ture, wind, radiation, hydrology), we obtained 37 marginal costs scenarios for each Open ENTRANCE dataset.

In order to get timeseries from 2018 to 2050, we estimated the seasonnality on the existing years. Out of these estimated seasonnality, we interpolated the seasonality on the missing years and simulated a noise estimated on the values and seasonalities of the existing years in order to get data on the missing years.

Figure 6.1 shows an example of marginal costs time serie.

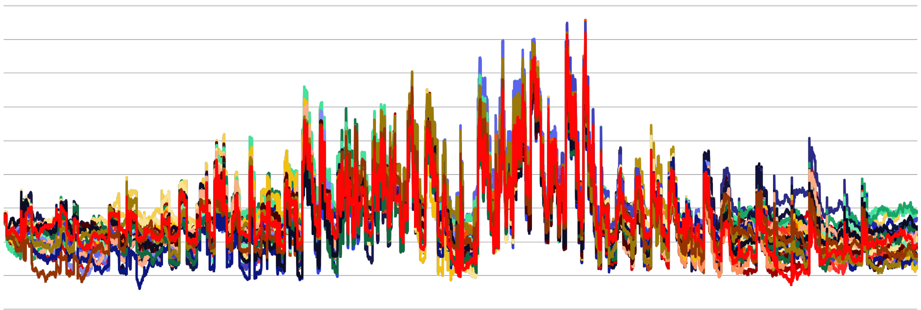

Figure 6.1: Hourly marginal costs over 1 year

7 Results

7.1 Results of the short-term optimisation

We have first ran the short-term optimisation on all years of the horizon, for all numbers of scheduled maintenance (from 1 to 5), on all meteorological and price scenarios (for the case with price valuation). We show below the results in terms of cost deviation between the optimised and non-optimised variants, averaged over all meteorological (and price for the case with price valuation) scenarios.

7.1.1 Price valuation case

Figures 7.1, 7.2 and 7.3 show the deviation between the case where the optimization was done with price valuation and the case with no real optimization:

- The average loss of energy : we can see in 7.1 that, depending on the years, the optimization may lead to losing more or less energy;
- The average number of 'lost' hours (7.3) -hours during which the turbine is 'in maintenance'- : the optimization always lead to more lost-hours.
- The average energy cost : we can see in 7.2 that for all years and numbers of maintenance scheduled, the short-term optimization leads to increased revenues. In the last years, the increase is much lower than in the first years, which can be explained by the global increase in prices from 2040 in the data that we used (the share of renewable increases in the system, making the prices more correlated to the renewable potential generation).

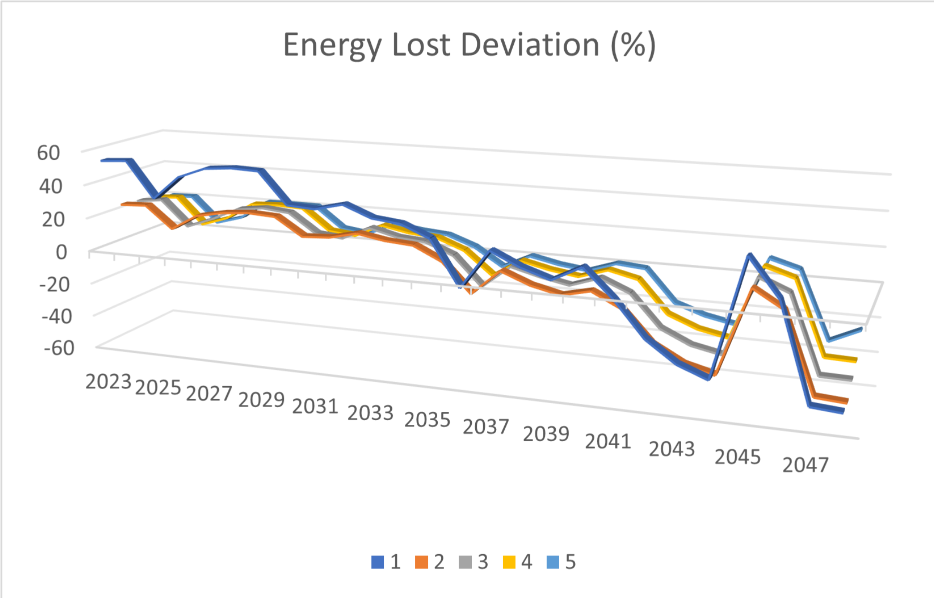

Figure 7.1: Difference in energy loss (optimised vs non optimised) - Price valuation

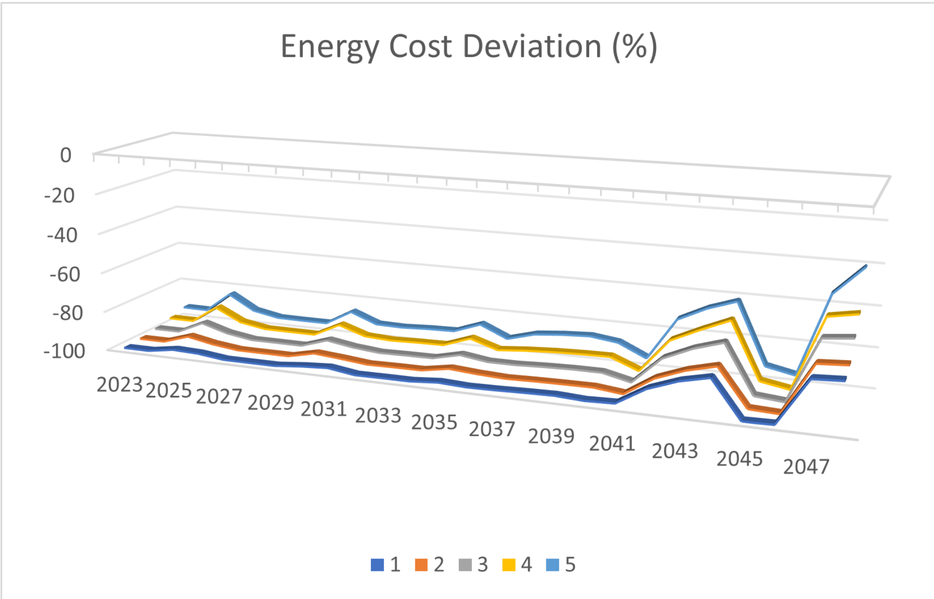

Figure 7.2: Difference in revenue loss (optimised vs non optimised) - Price valuation

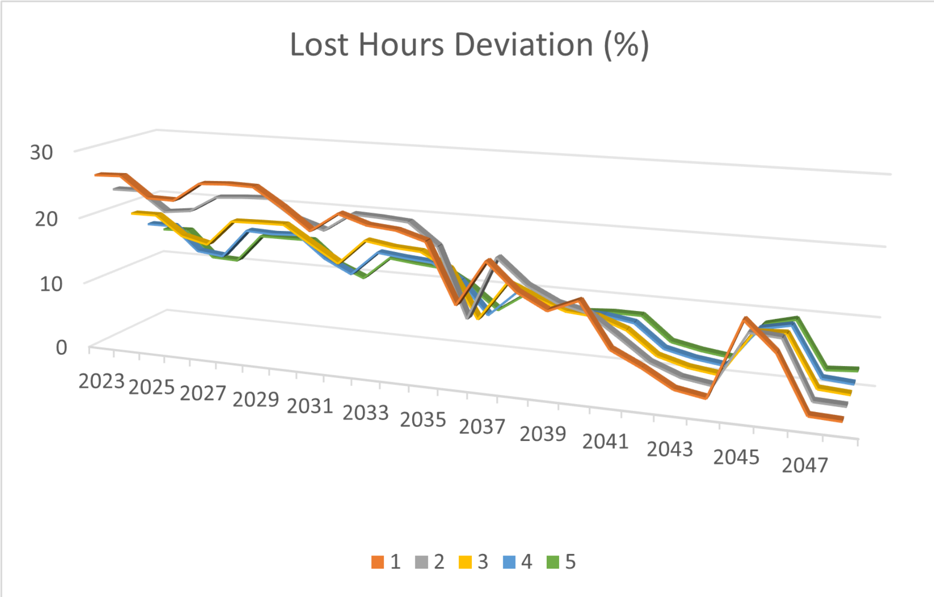

Figure 7.3: Difference in off-hours (optimised vs non optimised) - Price valuation

7.1.2 Strike valuation case

Figures 7.4, 7.5 and 7.6 show the deviation between the case where the optimization was done with strike valuation and the case with no real optimization:

- The average loss of energy : we can see in 7.4 that, the optimization always leads to losing less energy; The average loss of energy is nearly identical among the years.
- The average number of 'lost' hours (7.6)(ie hours during which the turbine is 'in maintenance'): the optimization always lead to less lost-hours.
- The average energy cost (7.5) is proportional to the average energy loss.

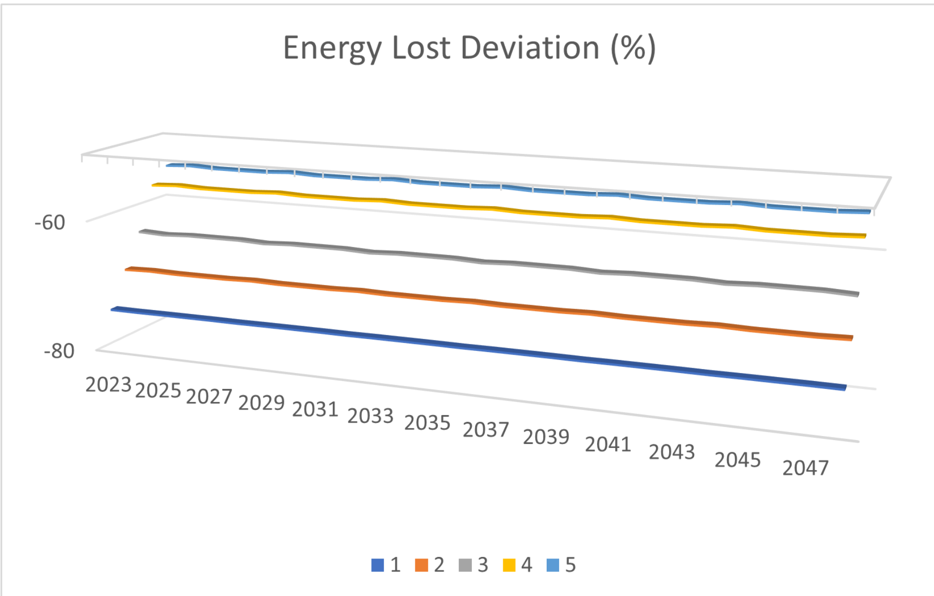

Figure 7.4: Difference in energy loss (optimised vs non optimised) - Strike valuation

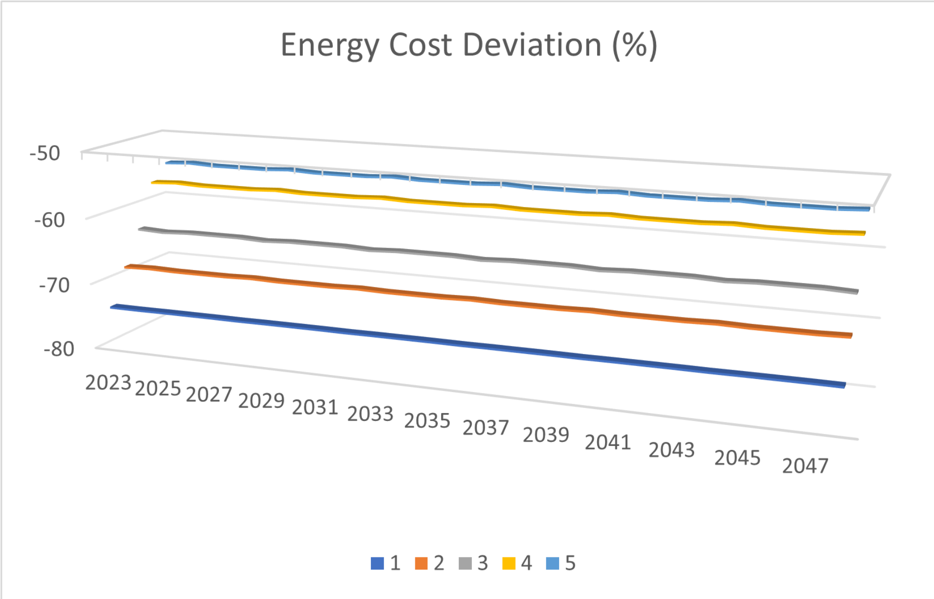

Figure 7.5: Difference in revenue loss (optimised vs non optimised) - Strike valuation

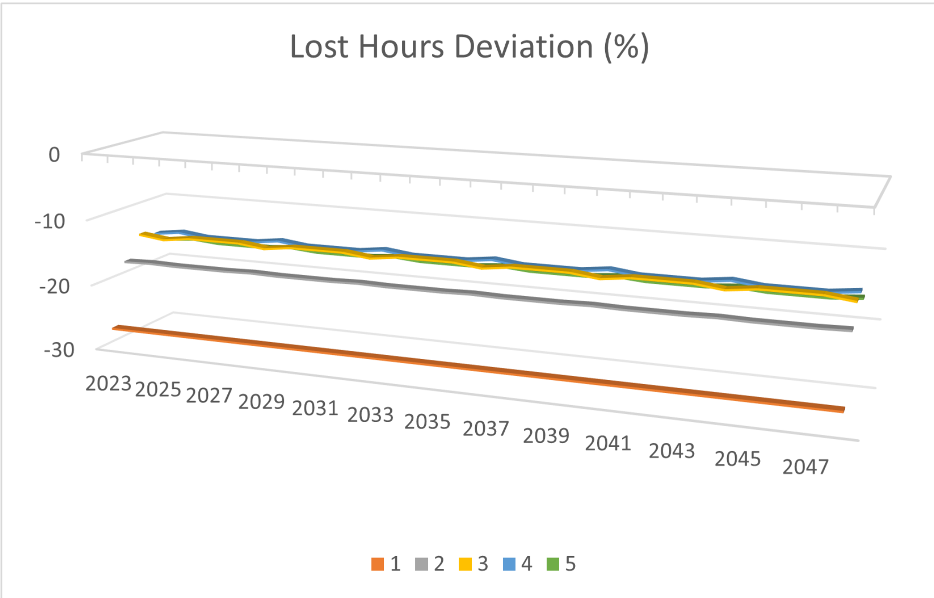

Figure 7.6: Difference in off-hours (optimised vs non optimised) - Strike valuation

7.2 Results on reference long-term schedules

In this section we will describe the results obtained when simulating on each on the 5 reference schedules as described in 5.2. For each schedule, we have conducted simulations on every failure scenario, following the simulation process in 5.4, and computed the average (over the failure scenarios) energy cost (ie value of the energy which could have been sold during the maintenance periods), energy loss and number of hours in which the turbine is down due to the maintenance. These simulations have been done in both cases: valuation by the price scenarios (see 6), or valuation by a fixed strike price (150 £). In order to get a basis, We also have ran simulations on the same long-term reference schedules using the 'no short-term optimisation' (i.e. valuation by a fixed price of 0, low waiting cost and force the algorithm to choose summer periods).

7.2.1 Price valuation case

Figures 7.7, 7.8 and 7.9 show the deviation to the basis for each of the 5 reference schedules for:

- The average loss of energy : we can see in 7.7 that apart from the reference schedule 99.5%, the short-term optimization leads to losing less energy.
- The average energy cost : we can see in 7.8 that for all scenarios, the short-term optimization leads to increased revenues.
- The average number of 'lost' hours (ie hours during which the turbine is 'in maintenance' : we can see in 7.9 that the short term optimization leads to more lost hours. This is explained by the fact that the short-term optimization may choose to wait between 2 sub-operations to take advantage of a period with very low price (and thus very low loss of revenue) but where it is necessary to interrupt the maintenance operation.

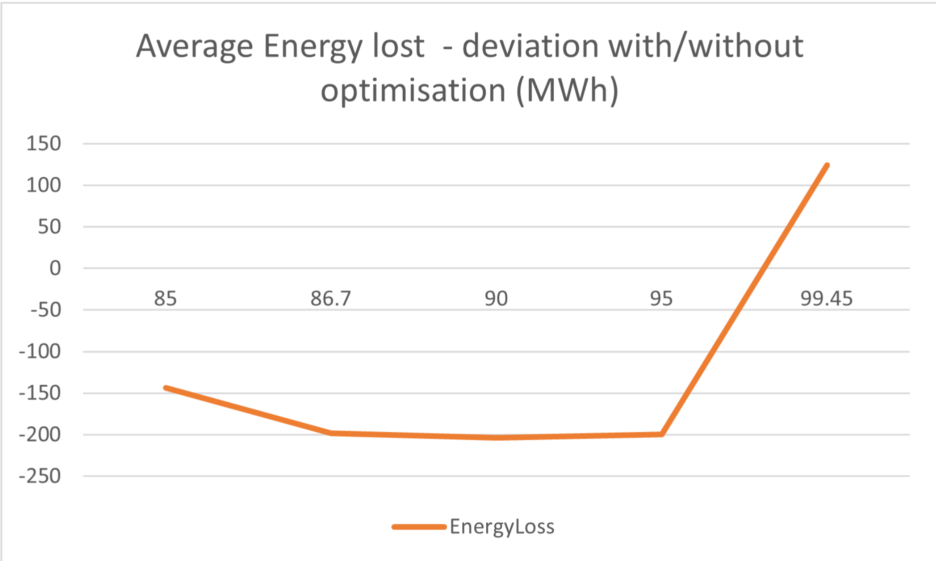

Figure 7.7: Difference in energy loss (optimised vs non optimised) - Reference schedules - Price valuation

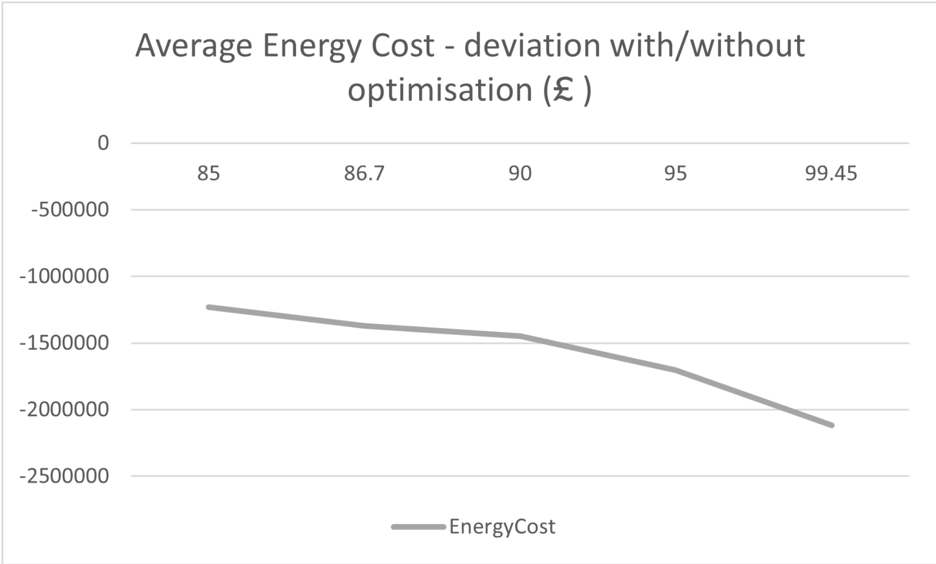

Figure 7.8: Difference in revenue loss (optimised vs non optimised) - Reference schedules - Price valuation

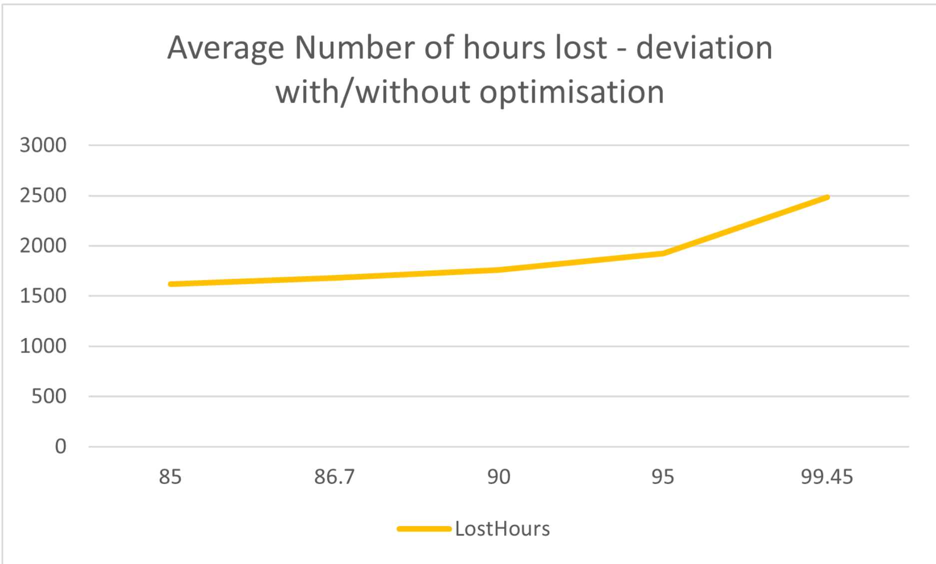

Figure 7.9: Difference in off-hours (optimised vs non optimised) - Reference schedules - Price valuation

7.2.2 Fixed Strike price valuation case

Figures 7.10, 7.11 and 7.12 show the deviation to the basis for each of the 5 reference schedules for:

- The average loss of energy : we can see in Figure 7.10 that the short-term optimization leads to losing less energy.
- The average energy cost : we can see in Figure 7.11 that for all scenarios, the short-term optimization leads to increased revenues.
- The average number of 'lost' hours (ie hours during which the turbine is 'in mainte-

nance' : we can see in Figure 7.12 that the short term optimization always leads to less lost hours.

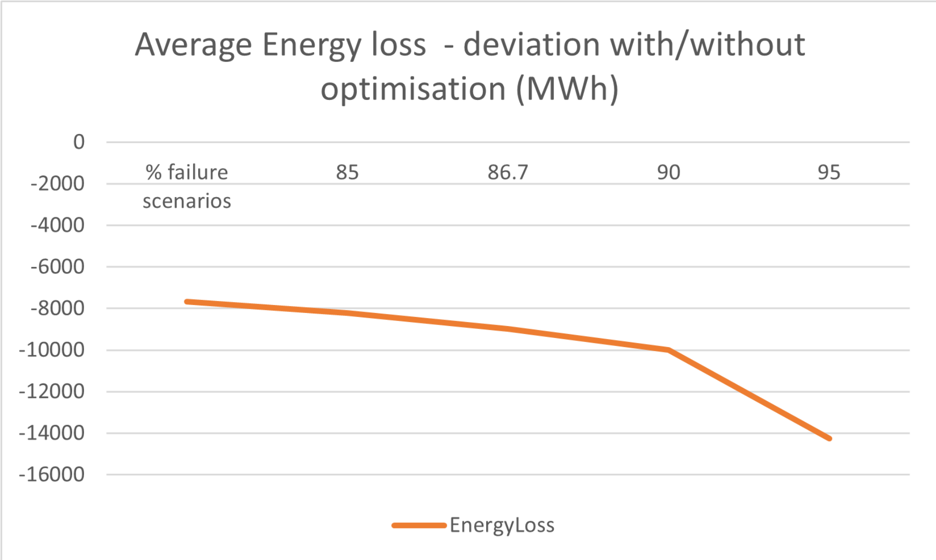

Figure 7.10: Difference in energy loss (optimised vs non optimised) - Reference schedules - Strike valuation

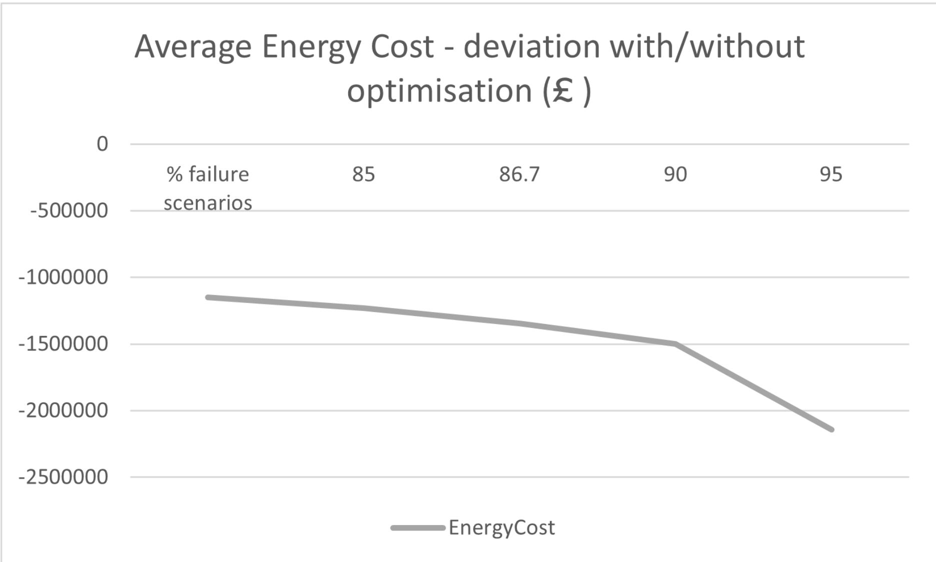

Figure 7.11: Difference in revenue loss (optimised vs non optimised) - Reference schedules - Strike valuation

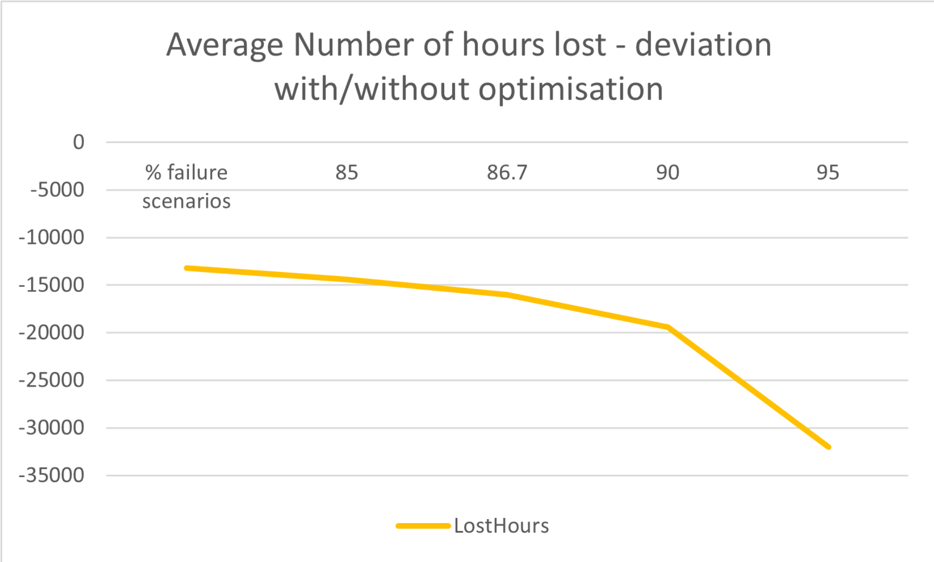

Figure 7.12: Difference in off-hours (optimised vs non optimised) - Reference schedules - Strike valuation

7.3 Results of the long-term optimization

In this section we will show comparisons of the cases:

- Simulation over the recalculated reference schedule without short term optimization;
- Simulation over the recalculated reference schedule with short term optimization;
- Simulation over the recalculated optimised schedule without short term optimization;
- Simulation over the recalculated optimised schedule with short term optimization;

in the cases with price valuation and with strike valuation.

7.3.1 The optimized long-term schedules

We ran the long-term optimization algorithm on all different cases. We show below the log term optimized schedule as computed by the algorithm and the schedule which was adapted by the simulator as described in 5.4.

- **Case without short term optimization**

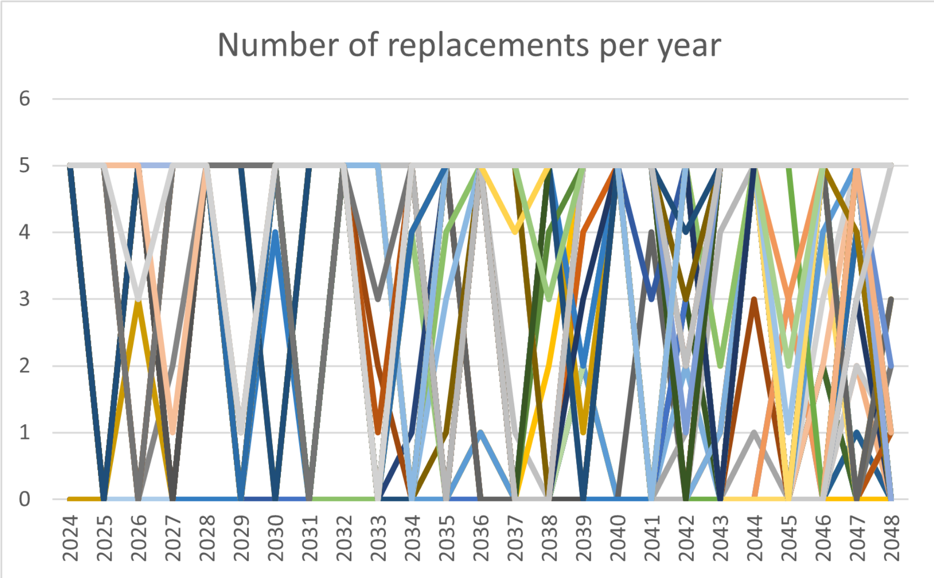

Figure 7.13: Optimised long-term schedule without short-term optimization

The adapted schedule is very close to the original optimised schedule.

- **Case Strike valuation**

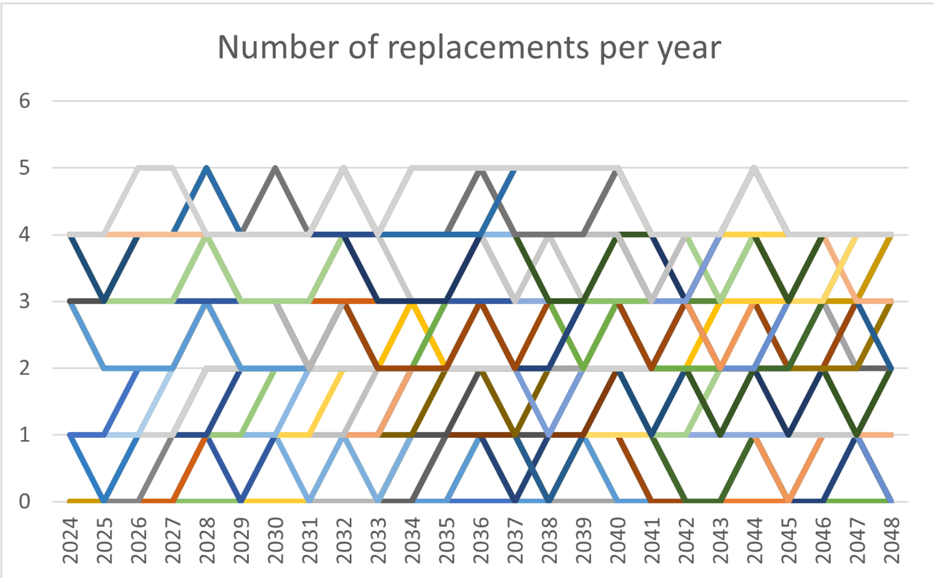

Figure 7.14: Optimised long-term schedule with strike valuation

The adapted schedule is very close to the original optimised schedule.

- **Case Price valuation**

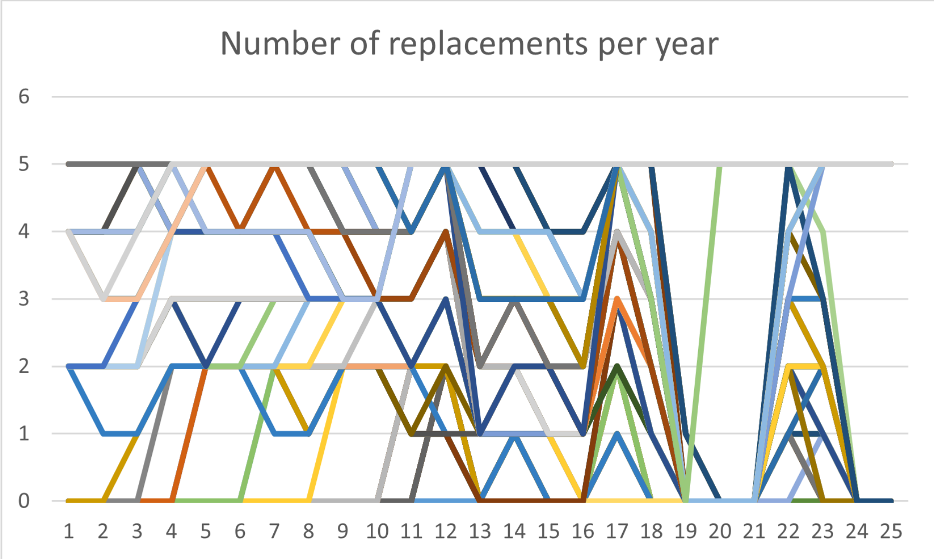

Figure 7.15: Optimised long-term schedule with price valuation

The adapted schedule is very close to the original optimised schedule.

7.3.2 The reference long-term schedule

Within the simulation (see section 5.4), we created an adapted long-term reference schedules, which was used in the comparison with the optimized reference schedules. This schedule is shown below in Figure 7.16

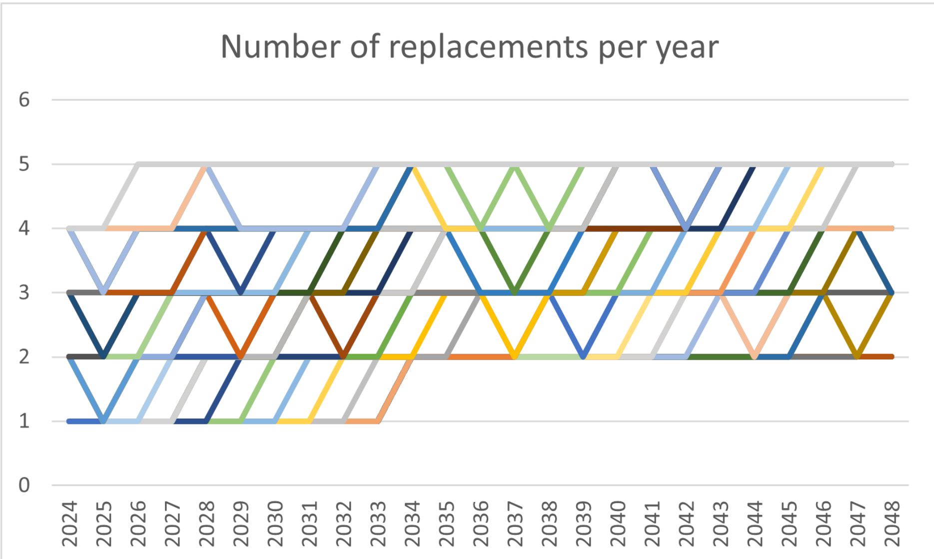

Figure 7.16: Adapted reference long-term schedule

7.3.3 The resulting maintenance schedules

We will show examples of the schedules obtained when simulating on the 57^{th} probabilised scenario, in the case with price valuation. (We chose the 57^{th} scenario by chance, we could have chosen any other...).

- **Optimised (adapted) long-term schedules** Figures 7.17, 7.18 and 7.19 show the schedules for each year in the case with short-term optimization (blue lines) and without short term optimization (red lines). The schedule used is the one computed by the long-term stochastic optimization, which has been adapted during the simulation.

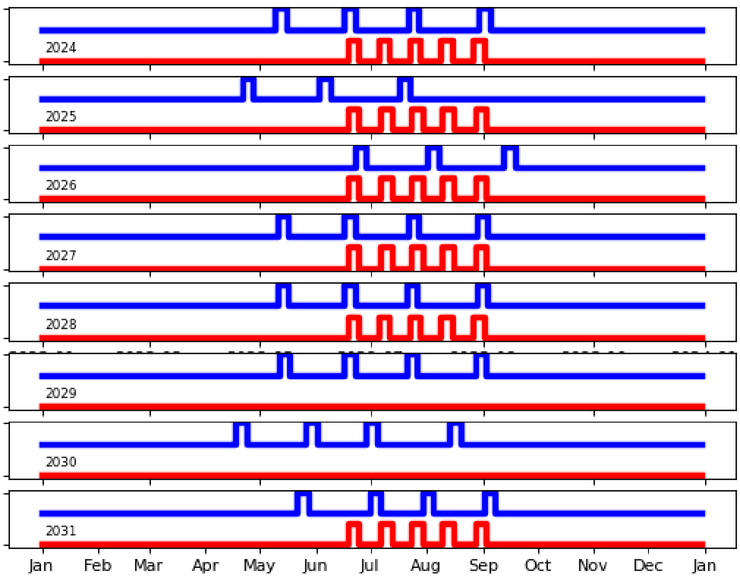

Figure 7.17: Maintenance schedules: case with optimized long-term schedules, price valuation, years 2024-2031

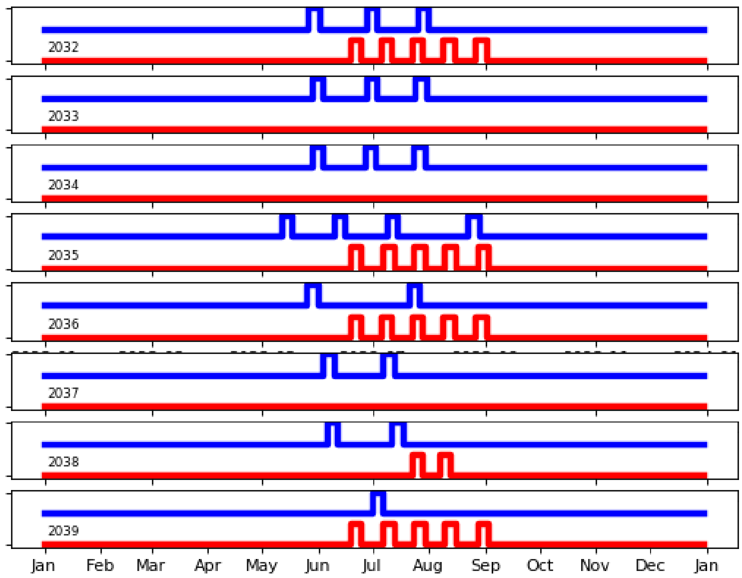

Figure 7.18: Maintenance schedules: case with optimized long-term schedules, price valuation, years 2032-2039

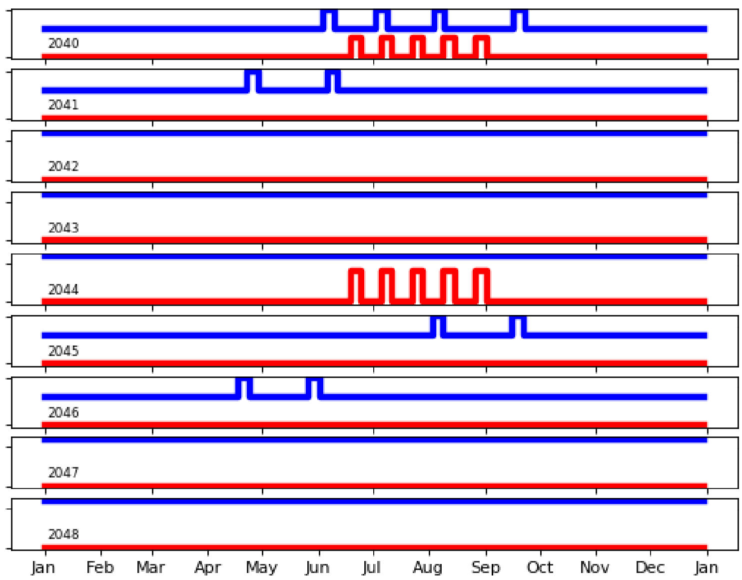

Figure 7.19: Maintenance schedules: case with optimized long-term schedules, price valuation, years 2040-2048

- **Reference (adapted) long-term schedule** Figures 7.20, 7.21 and 7.22 show the schedules for each year in the case with short-term optimization (blue lines) and without short term optimization (red lines). The schedule used is the long-term reference (as defined in section 7.3.2), which has been adapted during the simulation.

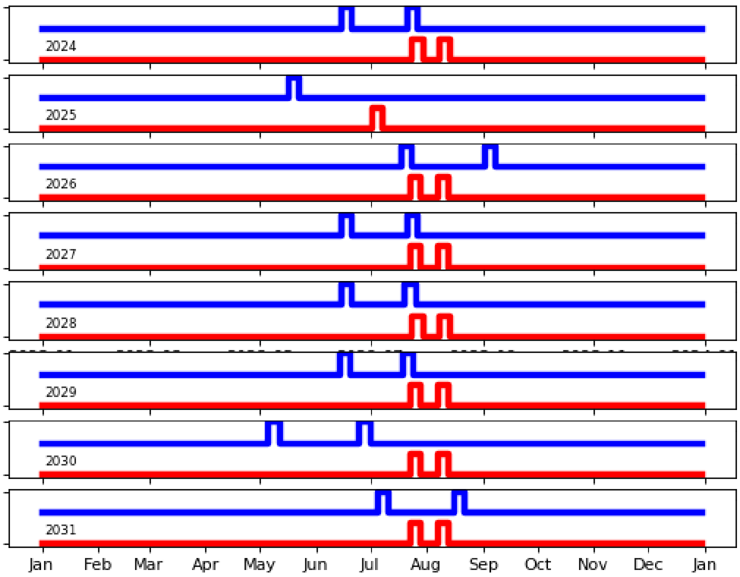

Figure 7.20: Maintenance schedules: case with reference long-term schedule, price valuation, years 2024-2031

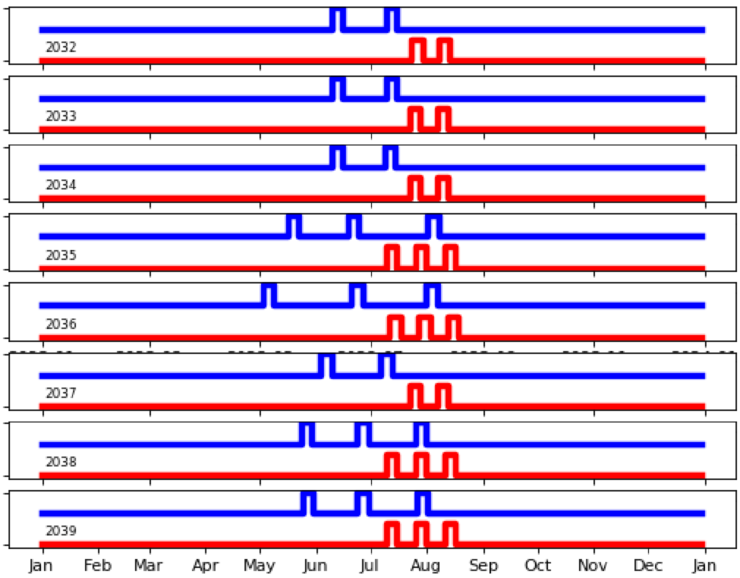

Figure 7.21: Maintenance schedules: case with reference long-term schedule, price valuation, years 2032-2039

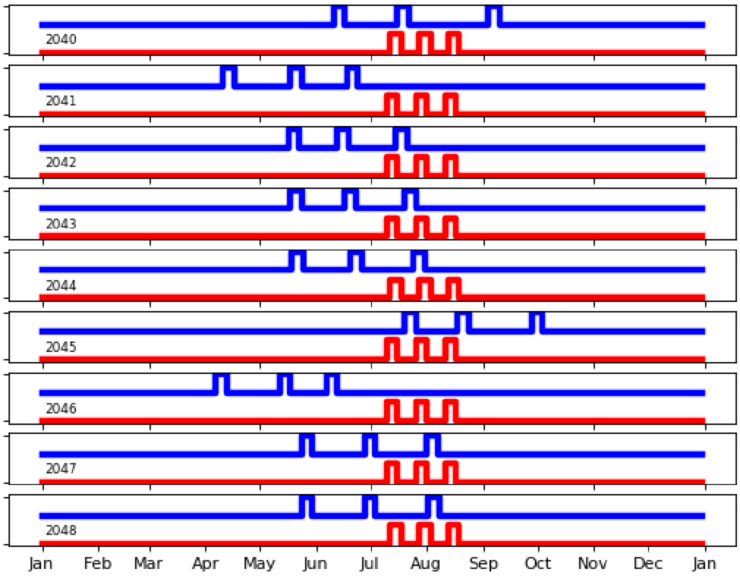

Figure 7.22: Maintenance schedules: case with reference long-term schedule, price valuation, years 2040-2048

7.3.4 Impacts on energy and revenue losses

We show here the impacts in terms of average (over the price - for the price valuation case - and meteorological scenarios and over the years) number of maintenance, loss of energy, energy cost and number of lost hours (ie hours during which one turbine is off dur to maintenance) on each probabilised expected failure scenario that was simulated.

Case Price valuation

Figure 7.23 shows the average number of maintenance per failure scenario. We can see that using the long term stochastic optimization leads to less maintenance in the easier scenarios. The number of maintenance is the same in the cases with/without short term optimization (as the number of maintenance only depends on the expected failures scenarios and on the long-term algorithm).

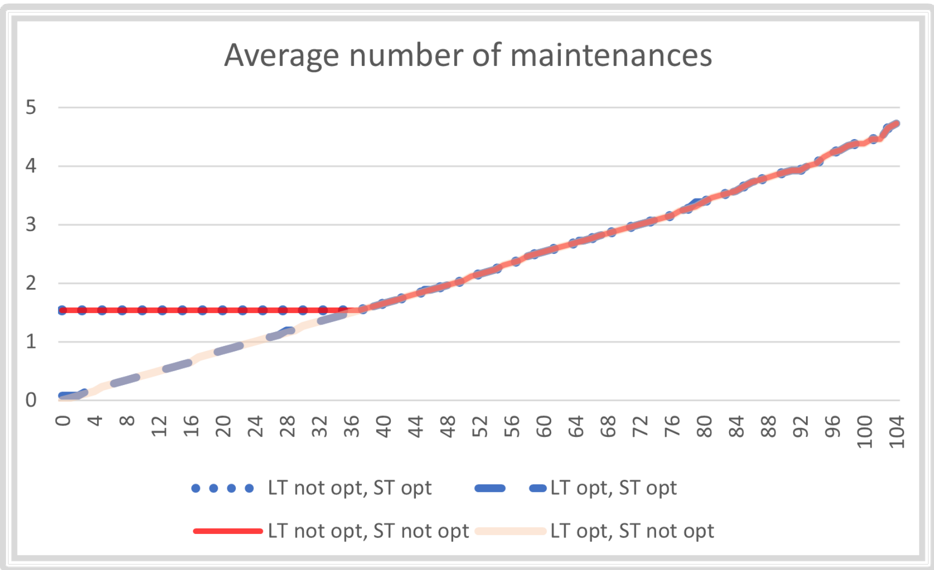

Figure 7.23: Average number of maintenance per failure scenarios - Case with price valuation

Figure 7.24 shows the average loss of energy (in MWh) per failure scenario. We can see that using the long term stochastic optimization leads to less lost energy, in particular in the easier scenarios (which is mainly due to the lower number of maintenance). In the cases with optimised long-term schedules, the energy loss is slightly higher in the case with short-term optimization in most of the scenarios. This is consistent with what was observed in the analysis of deterministic long-term scenarios (see section 7.1).

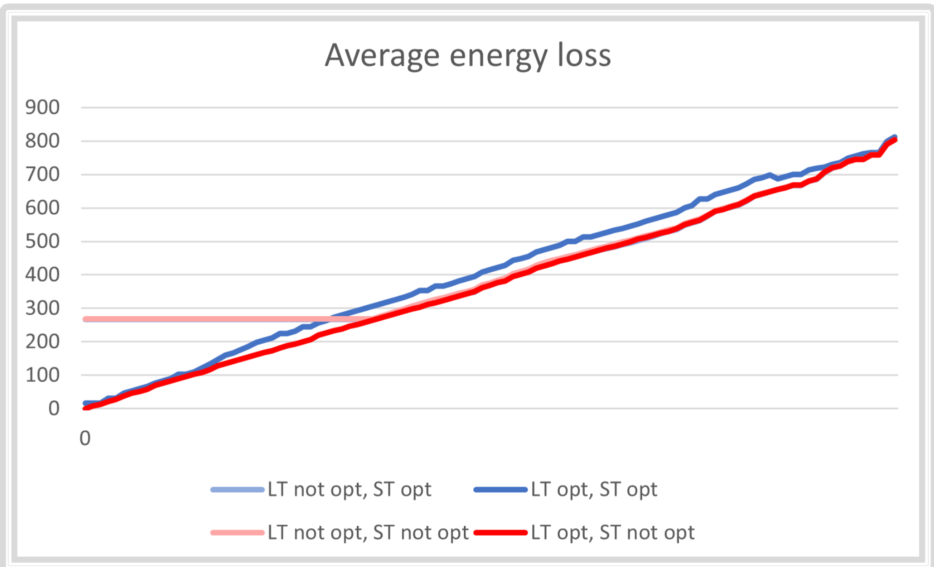

Figure 7.24: Average loss of energy per failure scenarios - Case with price valuation

Figure 7.25 shows the average loss of revenue (in £) per failure scenario. We can see that using the long term stochastic optimization leads to less revenue loss in all scenarios. Also using the short-term optimization allows to lower this loss of revenue in most cases apart from the very difficult scenarios with high number of failures (in which there is a reduction but it is quite low and thus not visible on the graph).

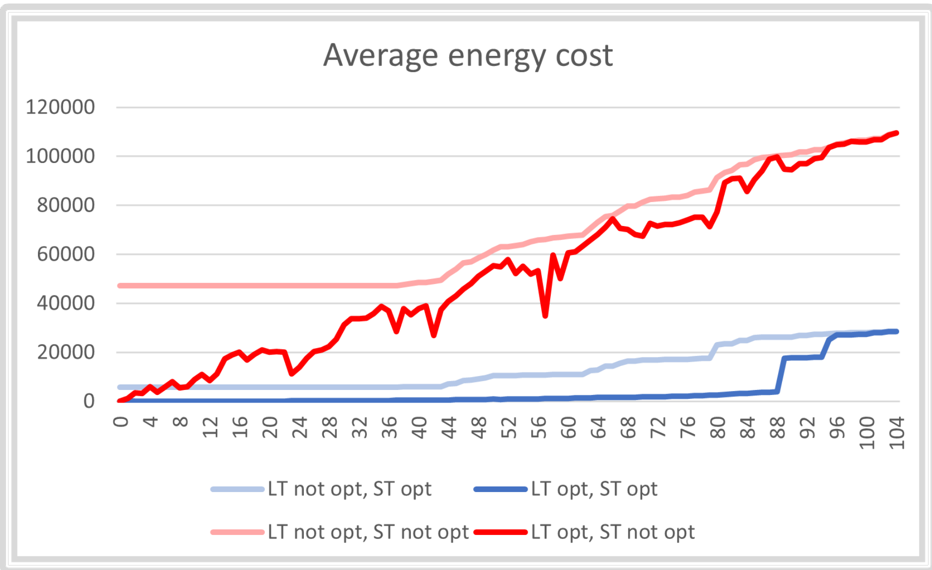

Figure 7.25: Average loss of revenue per failure scenarios - Case with price valuation

Figure 7.26 shows the average number of hours without production due to maintenance operations per failure scenario. We can see that using the long term stochastic optimization leads to less lost hours in the easier scenarios (and slightly more in some difficult scenarios although the difference being very small it is not visible in the graph). We can also see that in the cases with short-term optimization, the number of lost hours is slightly increased, which is consistent with the results on the deterministic long-term schedules (see section 7.1).

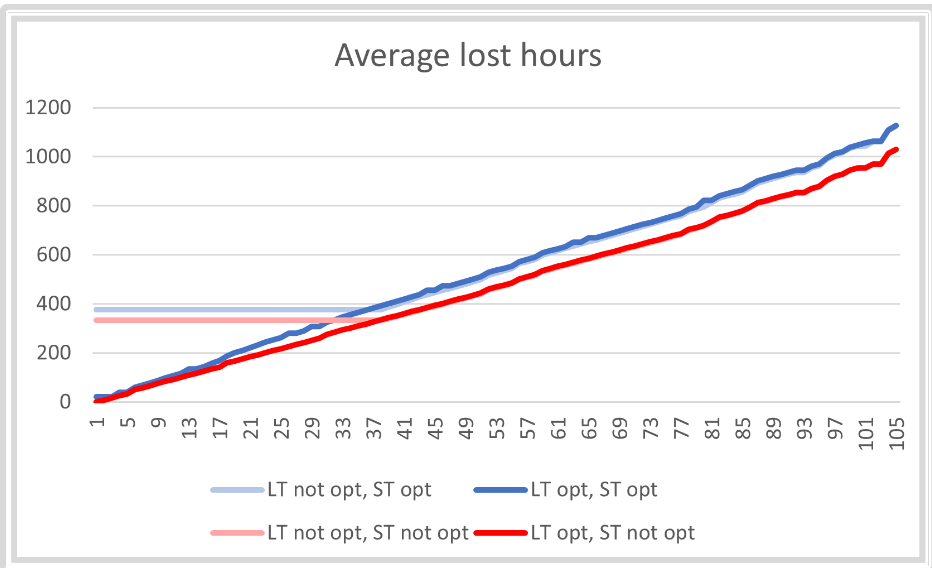

Figure 7.26: Average number of lost hours per failure scenarios - Case with price valuation

Case Strike valuation Figure 7.27 shows the average number of maintenance per failure scenario. We can see that using the long term stochastic optimization leads to less maintenance in the easier scenarios. The number of maintenance is the same in the cases with/without short term optimization (as the number of maintenance only depends on the expected failures scenarios and on the long-term algorithm).

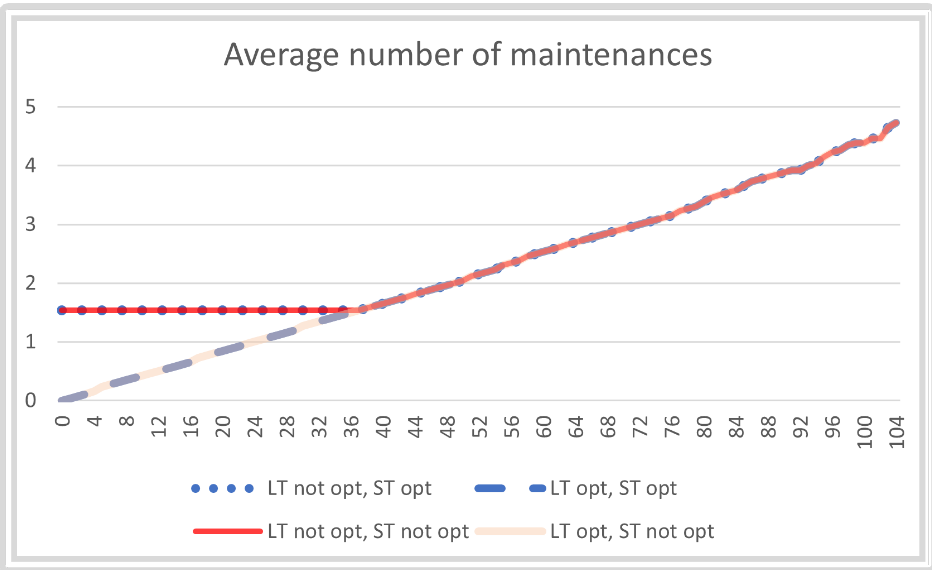

Figure 7.27: Average number of maintenance per failure scenarios - Case with strike valuation

Figure 7.28 shows the average loss of energy (in MWh) per failure scenario. We can see that using the long term stochastic optimization leads to less lost energy in the easier scenarios (which is mainly due to the lower number of maintenance). Using the short-term optimization leads to high reduction of energy losses in all cases. This is consistent with what was observed in the analysis of deterministic long-term scenarios (see section 7.1).

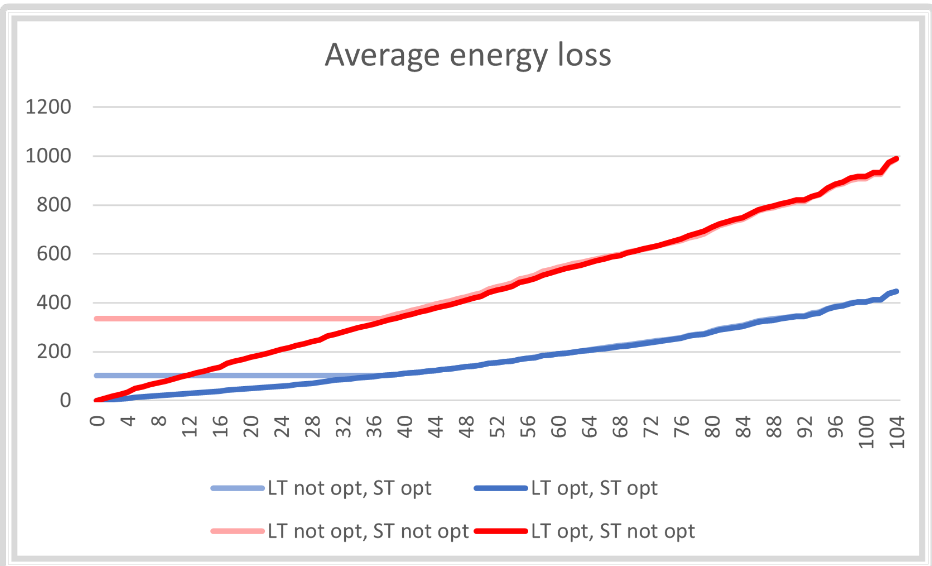

Figure 7.28: Average loss of energy per failure scenarios - Case with strike valuation

Figure 7.29 shows the average loss of revenue (in £) per failure scenario. The graph is strictly identical as the above (figure 7.28, as loss of revenue is in the strike cas proportional to loss of energy.

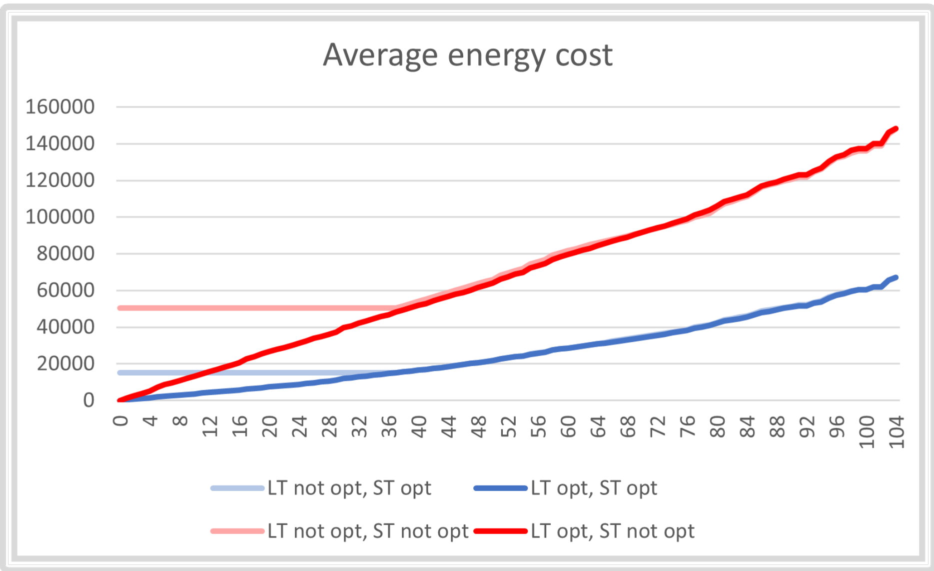

Figure 7.29: Average loss of revenue per failure scenarios - Case with strike valuation

Figure 7.30 shows the average number of hours without production due to maintenance operations per failure scenario. We can see that using the long term stochastic optimization leads to less lost hours in the easier scenarios (and slightly more in some difficult scenarios although the difference being very small it is not visible in the graph). Using the short-term optimization also reduces the number of lost hours, which is consistent with the results on the deterministic long-term schedules (see section 7.1).

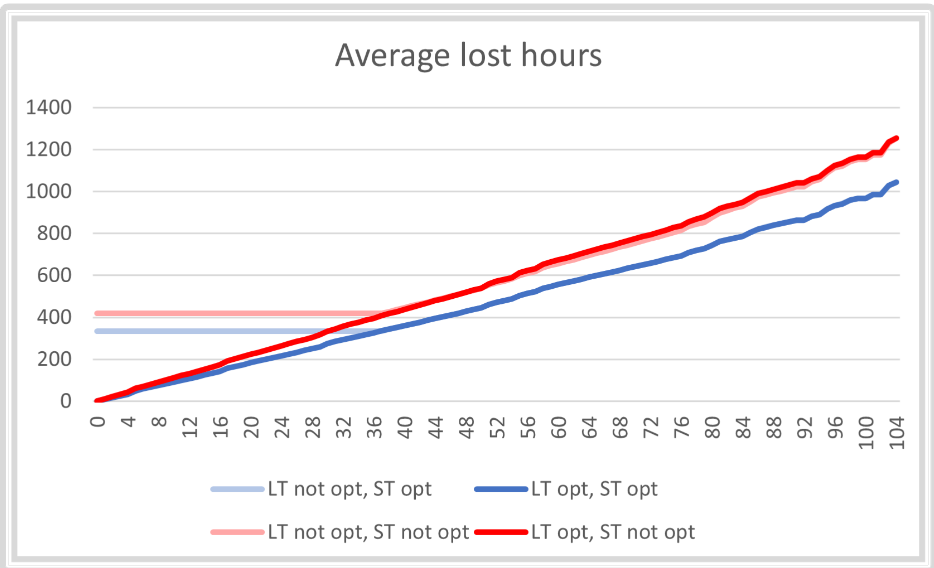

Figure 7.30: Average number of lost hours per failure scenarios - Case with strike valuation

7.4 Market Factor

7.4.1 Definition

In order to get some indicators of the market value brought by the maintenance schedules potimization, we computed the market factor in all different cases with Price valuation, such as:

$$\text{for each year } y, MF = \frac{Revenue(y)}{Energy(y)}$$

with

$$Energy(y) = \frac{1}{S_p * S_m * S_f} \sum_{s_p \in S_p} \sum_{s_m \in S_m} \sum_{s_f \in S_f} \sum_{h \in y} W(h, s_m, s_p, s_f)$$

and

$$Revenue(y) = \frac{1}{S_p * S_m * S_f} \sum_{s_p \in S_p} \sum_{s_m \in S_m} \sum_{s_f \in S_f} \sum_{h \in y} p(y, h, s_p) * W(h, s_m, s_p, s_f)$$

with:

- S_p is the number of price scenarios, $\{s_p \in S_p\}$ is the set of price scenarios
- S_m is the number of meteorological scenarios, $\{s_m \in S_m\}$ is the set of meteo scenarios
- S_f is the number of expected failures scenarios, $\{s_f \in S_f\}$ is the set of expected failures scenarios
- $\{h \in y\}$ is the set of all hours in year y
- $p(y, h, s_p)$ is the price at hour h of year y for the price scenario s_p
- $W(h, s_m, s_p, s_f)$ is the generation of the wind farm at hour h of year y for the price scenario s_p, the meteo scenario s_m and the expected failures scenario s_f. This generation is a results of the optimisation, it accounts for the energy not produced during optimally scheduled maintenance.

7.4.2 Impact of short-term optimization

For each of the 5 reference long-term scenarios such as described in 5.2 we have computed the average market factor on each year. They are shown in Figures 7.31, 7.32, 7.33, 7.34, and 7.35. We can see that the market factor is always higher in the case with short term optimization.

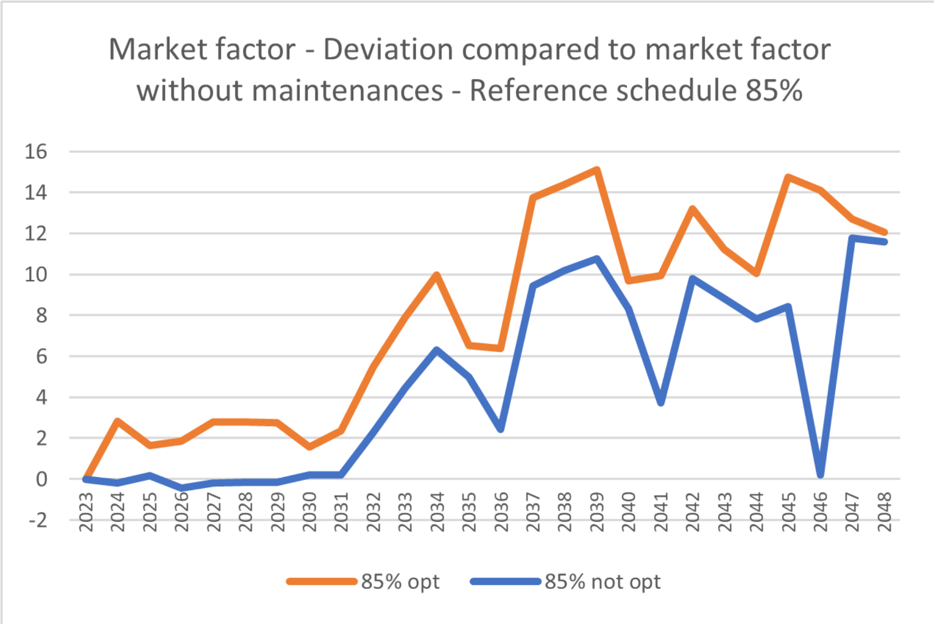

Figure 7.31: Market factor - reference long-term schedule 85% - cases with/without short-term optimization

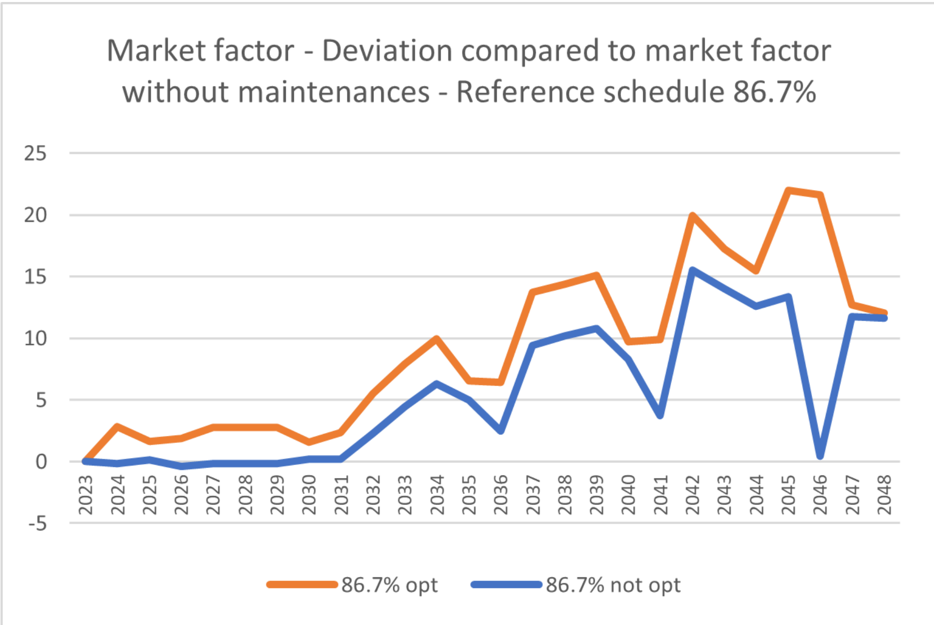

Figure 7.32: Market factor - reference long-term schedule 86.7% - cases with/without short-term optimization

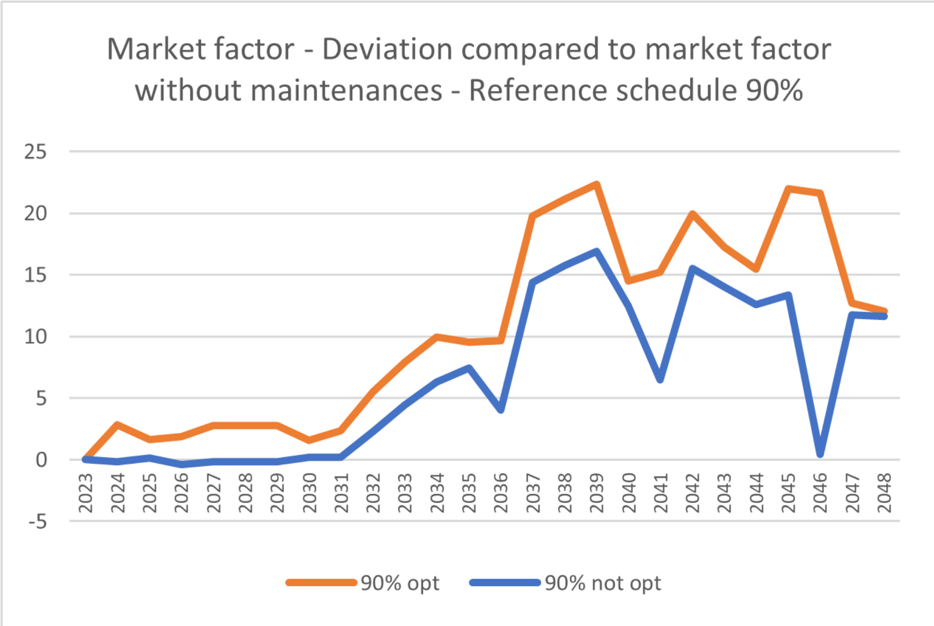

Figure 7.33: Market factor - reference long-term schedule 90% - cases with/without short-term optimization

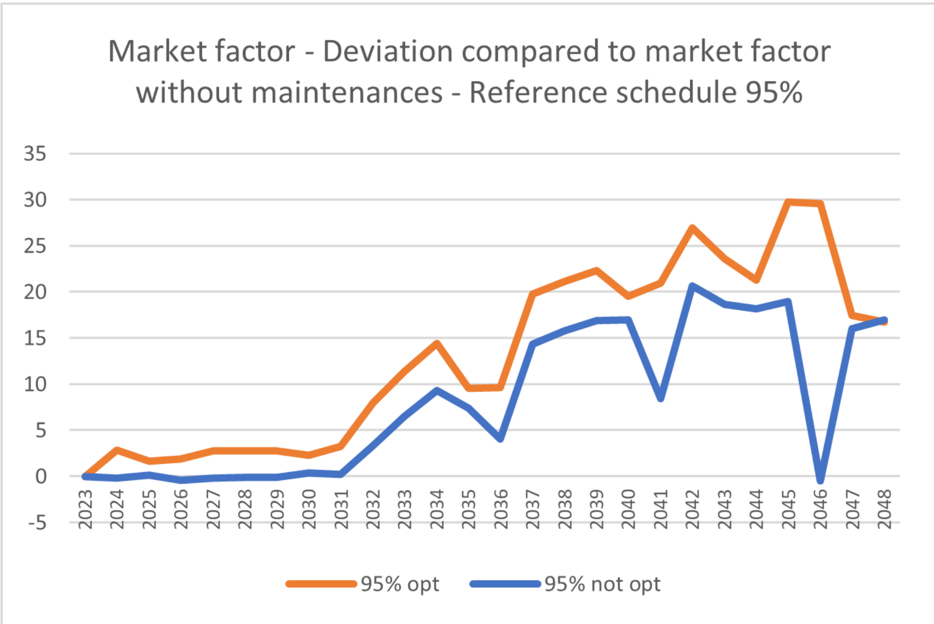

Figure 7.34: Market factor - reference long-term schedule 95% - cases with/without short-term optimization

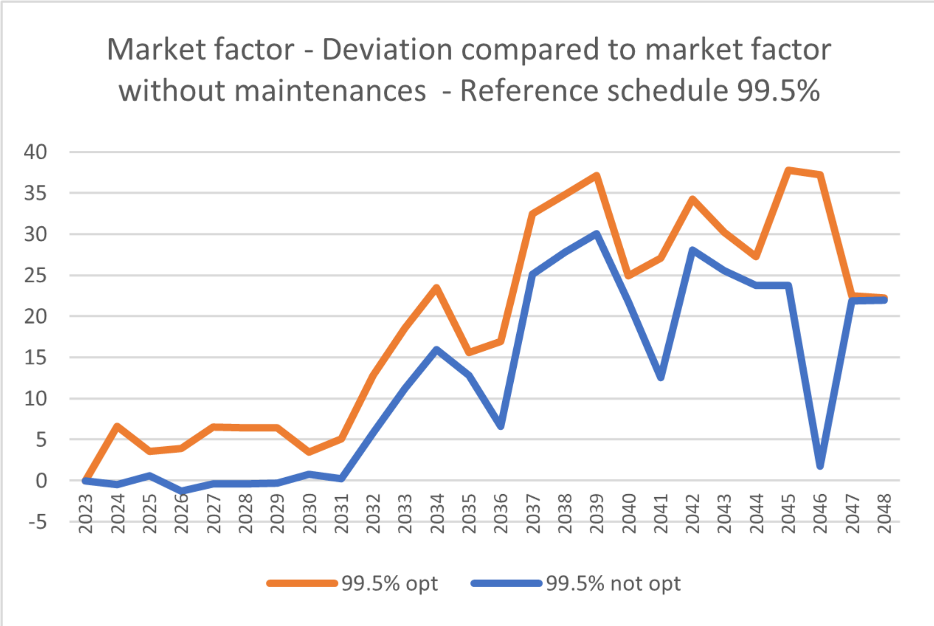

Figure 7.35: Market factor - reference long-term schedule 99.5% - cases with/without short-term optimization

7.4.3 Impact of long-term optimization

We have computed the average market factor on each year for the cases simulated by our simulator. Figure 7.36 shows the result in the cases with long-term optimization/adapted reference schedule and short-term optimized or not optimized.

We can see that the long-term optimization increases the market factor only in years between 2034 and 2047, while the short-term optimization always increases it (as shown in previous section).

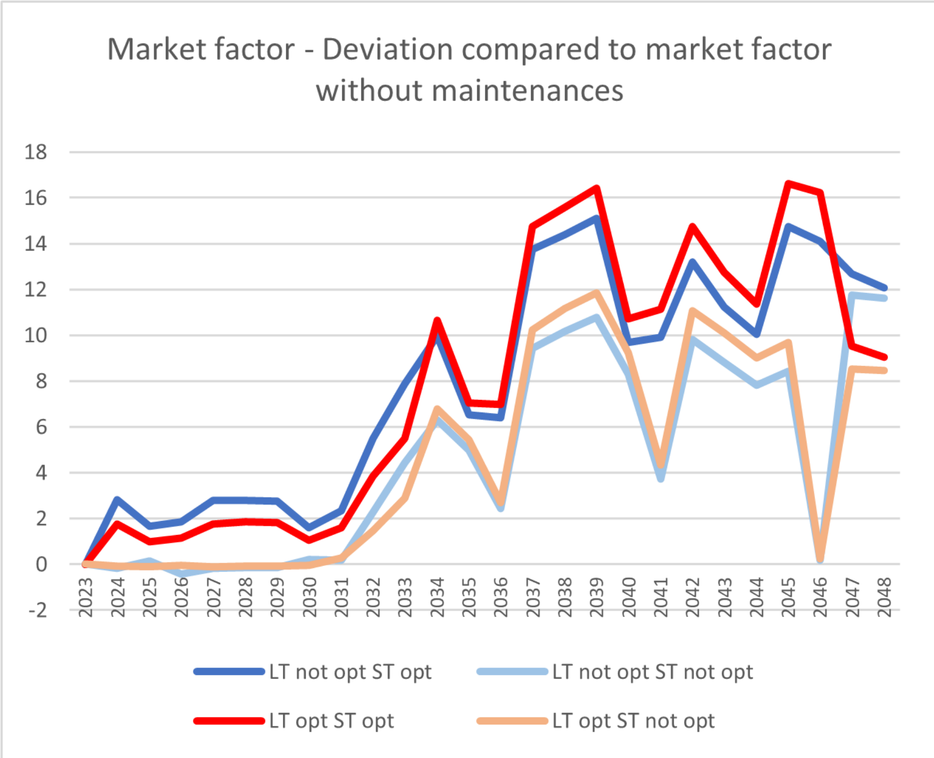

Figure 7.36: Market factor - optimised vs not optimised long-term schedule

This may be linked to an increase in the prices and in the share of the offshore windpower in the electricity mix in UK as shown in figures 7.37 and 7.38

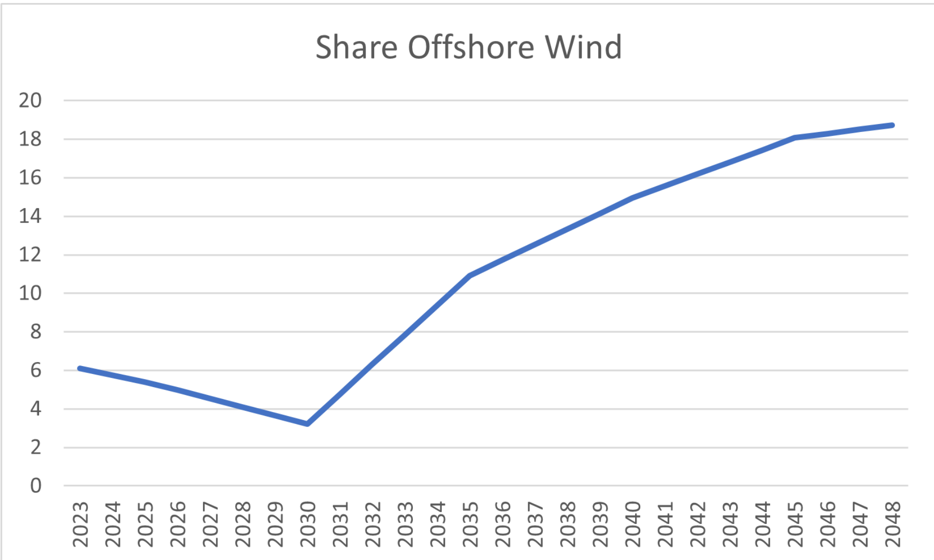

Figure 7.37: Share of Offshore Wind Power in the UK electricity mix in the Open ENTRANCE scenarios, average on scenarios

We can see an increase in the Offshore wind share in the electricity mix of the United Kingdom from 2031, reaching 10% in 2034 and nearly 20% in 2050.

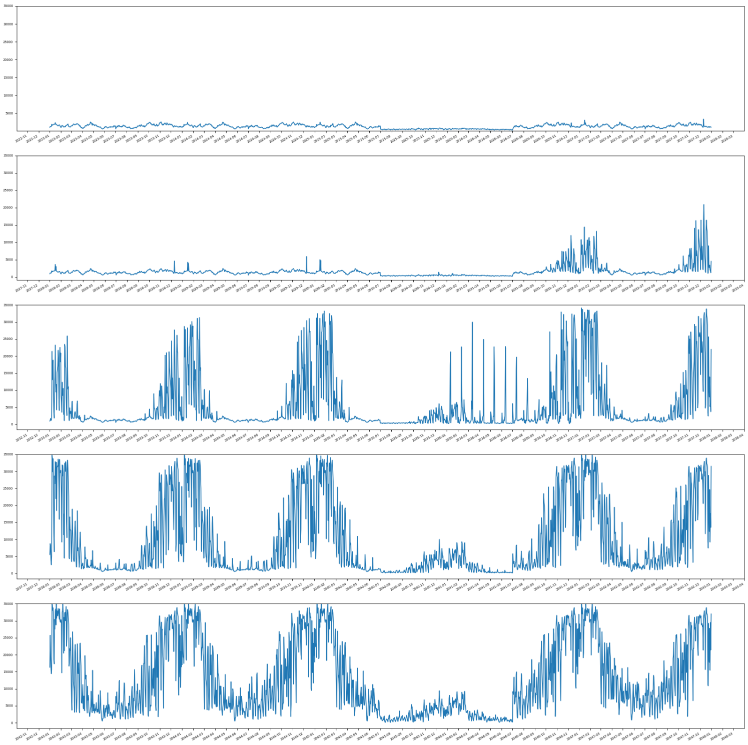

Figure 7.38: Value of the generation of the Teesside offshore wind farm, per day from 2023 to 2050, based on marginal costs

Figure 7.38 shows the average over all price and meteorological scenarios of the value of the electricity, every day from 2023 to 2050. This value for one day is computed as the sum on all hours of the day of the product between the price and the maximum possible generation (depending on meteorological scenarios) of the farm, without any off period due to maintenance. We can see a high increase starting in 2031, mainly due to an increase in the electricity prices, due to a more tense electricity system.

8 Conclusion, limitations and perspectives

8.1 Main results

The main conclusions of our study are:

- Using optimization algorithms to compute the maintenance schedules of a wind farm leads to an increase in the expected revenue;
- In some cases the optimal schedules may comprise longer periods of maintenance thus an increased number of days without generation;
- The increase in the expected revenue is highly dependent on the prices (in the case

of price valuation);

- Optimising the schedules within a year increases the market value of the wind farm by an average of 3%;

8.2 Limitations

The case study was conducted with the following limitations:

- Only one type of wind turbine component (gearboxes) was included;
- Some assumptions were taken on the modelling of the maintenance operations (only one kind of vessel, not accounting for delays in the vessel arrival to the windfarm...)
- The prices and the meteorological scenarios were generated out of 2 different models and hypothesis although there may exist a correlation between the market prices and the meteorological conditions.
  - The prices generated by the plan4res model are indeed correlated with meteorological scenarios -including among others meteorological variables such as temperature and wind speed as well as hourly maximum wind power depending on the wind speed (Cha20)-. Nevertheless, the scenarios used as plan4res inputs are available only at a Nuts2 (Nut) granularity and as the plan4res runs were done for the whole Europe with country resolution, these scenarios needed to be aggregated at country level. Moreover, the scenarios used as inputs to plan4res do not include the waves height.
  - For the current study it was necessary to use :
    * meteorological scenarios which:
      · include not only the wind speed but also the wave heights;
      · in which wind speed and wave height were generated alltogether as a correlation between those 2 variables does exist;
      · were generated at very low granularity (a few kimometers around the wind farm) given that wind speed and wave heights can be very local phenomena.
    * price scenarios which:
      · cover the whole life duration of the wind farm,
      · include correlations between meteorological conditions (wind speed, temperature) and power generation of renewable energy (in particular wind farms) as well as electricity demand

      This excludes the statistical approaches based on using historic price scenarios (as those approaches are valid only if the electricity system does not change too much, which will not be the case in the 25 coming years, given the planned energy transition in Europe), meaning that physical electricity system models need to be used. Because of the high level of interconnection in Europe, prices in one country are strongly correlated with prices in other countries, meaning that a model at european level should be used. Solving this (stochastic) model at the necessary granularity for accounting for the local meteorological conditions is today out of reach, meaning that studies including correlated prices and low-granularity wind-speed and wave eights are not yet available.

This explains that We couldn't account for the correlation between prices and the wind speed/wave height used in this study at the wind farm level. meteorological scenarios were computed for a small area around the Teesside offshore wind farm.

- The price scenarios which we used were generated out of the OPEN Entrance dataset ((Aue20)) which were created in 2021, with assumptions based on the situation in 2019. Since then, the prospective assumptions on the energy system future changes have drastically changed in particular following the Ukraine war and the gas crisis in europe, which led to new European objectives in terms of energy independance (in particular the REPpowerEU program - see (rep)). New datasets are currently being worked on in many research projects and should be published in the coming months.
- The used price scenarios show very high price values in the latest years, due to the fact that the electricity mix in the dataset is characterised by a lack of peak capacity, as it was computed by an energy system model which is mostly deterministic and computed the demand/supply equilibrium with a yearly granularity. Although it includes a modelling of the peak demand and the variability of wind and PV power, this modelling is not accurate enough to allow creating a perfectly adequate electricity mix.

8.3 Perspectives

- Regarding the implemented software, the following tasks could be envisaged:
  * Re-write a more 'industrial' version (the one we have is a research code, usable only for the benefit of the research conducted within this project)
  * Optimize the solving process, in particular for the short-term problem. For MINLP problems, the computation time can be drastically reduced by adding additional constraints (called cuts), which do not change the result of the optimisation, but may drastically (or not) reduce the computation time as they will help the branch and bound solver to find the optimal solution much faster. This would require consequent research time and is not feasible in the time frame and resource allowance of the HIPERWIND project but could be envisaged in the future.
  * Parallelize the resolution of the short term problems. We have used a parallel approach for solving the short-term problems and the simulation but it was restricted to parallel runs of models on different cases. The code could benefit from internal parallelisation. Nevertheless, it requires some expertise on parallelization techniques, which are out of the scope of the HIPERWIND project.
- Regarding the modelling, it could be improved first by including the modelling options which are already implemented but were not used due to lack of data, and second by adding some modelling features such as accounting for delays in the vessel arrival.

- Regarding the price scenarios:
  - Recomputing new scenarios based on new energy system prospective assumptions as well as enhanced modelling of the energy system model, which now better accounts for electricity flexibility needs and thus creates electricity mixes which are more able to cope with high shares of variable renewable energy assets;
  - By using electricity system models with a lower granularity for the region around the wind farm, it may be possible to generate market prices which are correlated with the meteorological scenarios used to account for the wind speed. The computations in particular of the market factor would then be much more accurate and representative. This nevertheless would require a 2 steps approach in order not to lose the European correlations.

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[plaa] plan4res github repository.

[plab] plan4res website.

[rep] plan4res website.

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