Comparison of Weather Window Statistics and Time Series Based Methods Considering Risk Measures

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Abstract. Offshore projects, like the installation of offshore wind farms, consist of a number of different and often weather dependent activities. These tasks and their relations are defined in project schedules, which have to be assessed for weather effects before the project realization. Here, often Weather Window Statistics are used to calculate probable weather delay times using relative frequencies of weather windows. Another possible approach is the Weather Time Series Scheduling (WaTSS) method which combines the given project schedule, weather restrictions and historical weather time series data for several decades. The aim of this paper is a comparison of the two approaches especially when it comes to risk analysis for project schedules using percentile values or related risk measures. The same ERA5 model data is used both as basis for the Weather Window Statistics and the WaTSS method. We calculate weather downtimes for each task, as well as for the total project, and apply the risk measures Value at Risk (VaR), Conditional Value at Risk (cVaR) and Upper Partial Moments (UPM). This is followed by an analysis of the results from Weather Window Statistics and the WaTSS method considering their applicability and consistence. We obtain that risk measurement for project schedules under use of Weather Window Statistics is not always practicable because certain risk values tend to overestimation. WaTSS method provides project adjusted modeling and leads to more realistic risk measurement for complex project schedules.

1. Introduction
Weather is one of the biggest risks in offshore activities, cf. [1]. Therefore, it is very important to provide risk management for assessment of weather-related delay times. These delay times affect the practicability of any offshore project, whose activities and their relations are often defined in project schedules. Thus, the latter have to be assessed for weather effects before the project realization. In this paper, we compare the two approaches Weather Window Statistics and Weather Time Series Scheduling (WaTSS) method for weather risk calculation, especially considering the application of risk measures.

Therefore we use project schedules and calculate the corresponding delay times using Weather Window Statistics and WaTSS method. As a first step we explain the different methods which both require weather data time series for several years. Calculating weather downtimes for a project schedule with Weather Window Statistics is quite common. The weather data is analyzed considering weather windows that fulfill the weather restrictions given for each weather dependent task. As a results we obtain the relative frequency of weather windows of different length for every month. We use the relative frequency of the minimum weather window length...
that is required for a task and calculate the probabilistic delay time. In WaTSS method, which is implemented in the Fraunhofer IWES COAST tool (presented in [2] or [3]), we use the complete project schedule with the given predecessor-successor-structure combined with historical weather data. We model the project plan starting at specific days in different years and check the corresponding weather data for weather windows to execute each task. An example project plan with three tasks is presented in Figure 1. In there, each task with its weather restriction is mapped in the weather time series plotted in blue. If weather is not adequate, the task execution is delayed. The delay times for the different years form a distribution of delay times for each task and for the whole project plan. These distributions are used for further analysis. All in all WaTSS method tends to be more realistic when it comes to risk management for project schedules because it takes into account the predetermined project schedule and thus the relations between and the sequences of the corresponding tasks. On the other hand Weather Window Statistics only uses single tasks without any dependencies or sequences.

After applying both methods, we apply the risk measures Value at Risk (VaR), Conditional Value at Risk (cVaR) and Upper Partial Moments (UPM) on the task and total project delays. As last step, we compare and discuss the obtained results for the different calculation methods and risk measures considering their applicability and statistical consistence.

The methodology may be applied on any activity that can be represented by a project schedule. This is mainly used in installation processes, but also covers complex maintenance activities, like replacing of blades or nacelles, as well as decommissioning.

2. Methodology

2.1. General Proceeding

We consider simple example project schedules containing \( m \) tasks of equal length without parallel processes. Every task has a duration of \( d \) hours and a lag to predecessor of \( l \). The lag is a predefined gap of a task to its predecessor, which is reduced as soon as the predecessor is shifted because of weather conditions. Each task is executable if the significant wave height undercuts...
the threshold $T$ for the complete task duration. We compare the results for the different months. Thus, the start date of the project schedule is set to the 1st of every month, 8 am. As weather data we use ERA5 model data, cf. [4], to avoid issues with measurement data gaps. The weather time series are presented for location of FINO1 in the German North Sea (cf. [5]) and cover $n = 40$ years.

In this study, we compared the following project schedules:

1. project with $m = 56$ tasks where each task has duration and lag of $d = l = 6$ hours
2. project with $m = 42$ tasks where each task has duration and lag of $d = l = 8$ hours
3. project with $m = 28$ tasks where each task has duration and lag of $d = l = 12$ hours

Not considering weather downtimes or lags, all project schedules cover a period of two weeks. We set the threshold for the significant wave height to $T = 1.5 \text{ m}$.  

2.1.1. **Calculation of Delay Times with Weather Window Statistics** Using the weather data time series, we calculate for each month the values $\tilde{y}_j$. These give the relative frequency of weather windows with minimum length corresponding to task duration $d$ in year $j$. This implies that the proportion between working time (good weather) and corresponding waiting on weather time (bad weather) equals 

$$\tilde{y}_j : 1 - \tilde{y}_j.$$  

By multiplying the latter with $\frac{d}{\tilde{y}_j}$, the delay times $y_j$ for the tasks that are considered in the project schedule are given by 

$$y_j = \frac{d}{\tilde{y}_j} - d, \quad (1)$$  

for each year $j$. Hence, we get for each month a sample $y = \{y_1, \ldots, y_n\}$ of size $n$ with delay times for tasks with duration $d$. We only consider tasks with equal length, hence the total project delay in year $j$ can be expressed as 

$$Y_j = m \cdot y_j. \quad (2)$$  

The result is a sample $Y = \{Y_1, \ldots, Y_n\}$ of size $n$ for total project delay times in each month. We want to point out that we only use the statistics for single months and ignore shifts of tasks into the following one.

2.1.2. **Calculation of Delay Times with WaTSS method** On the other hand we use WaTSS method by simulating the given project schedule starting monthly at the 1st, 8 am, of every year and comparing its feasibility with the given weather data for each time step. Hence, we get monthly weather downtimes $x_{ij}$ for every task $i$ in year $j$ and with 

$$X_j = \sum_{i=1}^{m} x_{ij} \quad (3)$$  

weather downtimes for the whole project schedule $X_j$ starting in the corresponding month of year $j$. Thus, we get a sample of delay times for the whole project plan 

$$X = \{X_1, \ldots, X_n\}$$

as well as $m$ samples for every task $i$

$$x_i = \{x_{i1}, \ldots, x_{in}\}.$$
2.2. Risk Measurement
In this section, we apply risk measures on delay times calculated with Weather Window Statistics and with WaTSS method. We take into account

1. Value at Risk for confidence level \( p \in P = \{0.40, 0.75, 0.90, 0.99\} \),
2. Conditional Value at Risk for confidence level \( p \in P \) and
3. Upper Partial Moments for order 0 and 1 and threshold \( c = \overline{Z} \).

Some of the given risk measures are mostly used for financial risks, cf. [6]. For simplicity, we do not model costs in this case because they are usually almost perfectly correlated with task delay times. We calculate risk values for task delay as well as total project delay and compare the results from Weather Window Statistics and WaTSS method.

2.2.1. Value at Risk
The Value at Risk (VaR) is a risk measure which is often used for risk positions in finance, cf. [7]. However, this can be expanded to other risk related business, especially to weather risks, as presented in [8]. In our case, the VaR reflects the risk of weather dependent delay time without consideration of any corresponding financial fault.

**Definition 1** (Value at Risk). Let \( Z \) be a random variable and \( F_Z \) the corresponding distribution function. The Value at Risk for confidence level \( p \) is defined as

\[
\text{VaR}_p(Z) := F_Z^{-1}(p) = \inf\{z \in \mathbb{R} : F_Z(z) \geq p\}.
\]

For \( Z \) being a sample the VaR is just the quantile for confidence level \( p \% \) of the total observations may be found.

The VaR for confidence level \( p \) equals the value below which \( p\% \) of the total observations may be found.

For both, Weather Window Statistics and WaTSS method, we calculate the Value at Risk for confidence levels \( p \in P \) for total project delay times \( \text{VaR}_p(Y) \) and \( \text{VaR}_p(X) \) using the samples of delay times \( Y \) and \( X \) described in Section 2.1. For task delay times in Weather Window Statistics we directly use the sample \( y = \{y_1, \ldots, y_n\} \) to calculate the Value at Risk for each confidence level. However, due to VaR not being subadditive, we do not use the samples \( x_i = \{x_{i1}, \ldots, x_{in}\} \) for task wise calculation in WaTSS method. Furthermore, to calculate the VaR of delay time for task \( i \) we use the calibration factor \( \rho_i \), defined as

\[
\rho_i := \frac{x_i}{\overline{X}},
\]

where \( x_i \) is the Mean of task \( i \) delay time, thus

\[
x_i = \frac{1}{n} \sum_{j=1}^{n} x_{ij},
\]

and \( \overline{X} \) describes the Mean of total project delay time. Using the calibration factor we calculate the VaR for each task \( i \) with

\[
\text{VaR}_p(x_i) := \rho_i \text{VaR}_p(X).
\]

Because the calculation is done in this way, we provide

\[
\sum_{i=1}^{m} \text{VaR}_p(x_i) = \text{VaR}_p(X).
\]

Equation (5) is not the usual definition of the Value at Risk for the corresponding set. But, because we are interested in total project level comparison mainly, we use the given equation for consistency reasons. Without this step, the risk measures for total project delay and task delay would not necessarily be related.
2.2.2. **Conditional Value at Risk** The Conditional Value at Risk (cVaR) is an advance from Value at Risk and gives information about values above the Value at Risk, which is very useful for risk analysis. This is also presented in [7].

**Definition 2** (Conditional Value at Risk). Let $Z$ be a random variable and $F_Z$ the corresponding distribution function. The Conditional Value at Risk for confidence level $p$ is defined as

$$c\text{VaR}_p(Z) := \mathbb{E}[Z \mid Z > \text{VaR}_p(Z)].$$

Thus, the Conditional Value at Risk for confidence value $p$ is calculated as the expected value from all values above the VaR. This is especially useful when only a few very high values occur - the VaR may not consider them, the cVaR does.

Similar to the calculation of VaR, we use the confidence levels $p \in P$ and calculate the cVaR for total project delay times with Weather Window Statistics $c\text{VaR}_p(Y)$ using the sample $Y = \{Y_1, \ldots, Y_n\}$ and with WaTSS method $c\text{VaR}_p(X)$ using $X = \{X_1, \ldots, X_n\}$. Single Tasks Conditional Value at Risks in Weather Window Statistics are also computed with the sample $y = \{y_1, \ldots, y_n\}$. However, for WaTSS method we use the calibration factor, defined in (4) and the formula

$$c\text{VaR}_p(x_i) := \rho_i c\text{VaR}_p(X)$$

(6)

to provide $\sum_{i=1}^{m} c\text{VaR}_p(x_i) = c\text{VaR}_p(X)$ and consistence between task and total project delay.

2.2.3. **Upper Partial Moments** The Upper Partial Moments (UPM) is a risk measure that only considers a part of the whole probability distribution. It only captures the positive differences between a given benchmark, where the benchmark can be fixed or stochastically like $\mathbb{E}[X]$. Additional information can be found in [9].

**Definition 3** (Upper Partial Moments). Let $Z$ be a random variable with $\mathbb{E}[Z] < \infty$. The Upper Partial Moments for benchmark $c$ and order $k$ is defined by

$$\text{UPM}_k(c,Z) := \mathbb{E}\left[\max(Z - c, 0)^k\right]$$

where we set $0^0 := 0$

In case of wind farm planning, the UPM can be useful when penalties are considered. In that case, a penalty payment is due as soon as a given threshold of delay time is exceeded and therefore it is helpful to measure the associated risk above the threshold.

The order $k$ gives different results for UPM:
- $k = 0$: $\text{UPM}_0(c,Z)$ gives the probability to exceed the threshold $c$
- $k = 1$: $\text{UPM}_1(c,Z)$ gives the average exceeding value

For total project delay we calculated the UPM for order 0 and 1 using the Mean $\overline{X}$ in WaTSS method and $\overline{Y}$ in Weather Window Statistics as threshold $c$.

In calculation of task wise delay time UPM in Weather Window Statistics, the given distribution of weather windows is used and the threshold is set to $c = \overline{y}$. Within WaTSS method we take the Mean of task delay $\overline{x}_i$ for each task $i$ as threshold and calculate the UPM for order 0 and 1 for every task in a month. Afterwards we calculate the mean over all tasks, because as mentioned before they have the same duration and same lags.

3. **Results**

We have applied each risk measure on the three different project schedules, specified in Section 2.1. Because there was no significant difference obtainable in the results of the different project inputs, there is only the example with 12-hour tasks presented in this section.
Figure 2. Value at risk for project with 12-hour-tasks.

Figure 3. Conditional value at risk for project with 12-hour-tasks.
3.1. Value at Risk and Conditional Value at Risk

In Figure 2 and Figure 3 we have the VaR and the cVaR calculated for task delays. This comparison is sufficient because the VaR and the cVaR for total project delay corresponds to the latter due to the calculation with the calibration factor.

As we can see in Figure 2, if VaR is used, we have to differentiate between higher and lower confidence levels. The Value at Risk for \( p = 0.40 \) or \( p = 0.75 \) tends to be higher when WaTSS method is used for calculation of task delay times. On the other hand, high confidence levels like \( p = 0.99 \) imply extremely high Value at Risks for task delay times calculated with Weather Window Statistics. Furthermore, there is significant difference between summer months with less and winter months with more adverse weather conditions. In good condition months (April - September), the results from Weather Window Statistics tend to be lower at any confidence level. On the other hand, in months with adverse weather conditions occurring more often (October - March) the Value at Risk nearly explodes for high-level quantiles in Weather Window Statistics. Compared to VaR, for cVaR the difference between winter and summer months is even more distinctive. In winter months the cVaR calculated with Weather Window Statistics is significantly higher than WaTSS cVaR. However, in summer months and low confidence levels the cVaR from WaTSS method tends to be a higher. For high confidence levels and summer months, the results are almost equal.

A reason for the different results from WaTSS method and Weather Window Statistics might be the way the WaTSS method’s VaR and cVaR are calculated. We use the total project risk and the calibration factor for the calculation. Thus, we provide the impact of Knock-On Effects: Good weather conditions may occur for quite some time after adverse weather. This has the effect that the first task might have a huge delay while the following tasks do not have any delay at all and thus, the total project delay might be acceptable. By using the calibration factor method for calculation, we make sure to not overvalue the first huge delay, because the total project’s delay was not high at all due to the successors not having any delay. Similarly, we prevent undervaluation in reverse effects: A short period of favorable weather followed by a long period of adverse weather conditions result in high total project delays while the first tasks were not delayed at all.

3.2. Upper Partial Moments

Besides the results of VaR and cVaR, we have calculated the task wise UPM without consideration of calibration factors. Thus, we present both, total project delay UPM and task delay UPM, in Figure 4. We obtain that the percentage for exceeding the Mean in task delay is quite low for WaTSS method, but the exceeding height is much higher than the results from Weather Window Statistics. This shows that there are only a few delay values for a task, which exceed the mean, but these few values are very high. The Knock-On Effect also attributes this.

However, when the total project delay is considered, we have the 0-Order-UPM being higher in WaTSS method, while the exceeding height for Weather Window Statistics shows high values especially in winter months. Hence, we have fewer values exceeding the mean, but these values being high in Weather Window Statistics. This also shows that the distribution of total project delay times from Weather Window Statistics tends to have heavier tails in winter months while the distribution from WaTSS method is more concentrated around the mean. This also explains the high risk values for high confidence levels in Weather Window Statistics. Illustrated in Figure 5, we calculated the histograms using the months February and October as examples for autumn/winter months.

4. Discussion and Conclusion

The WaTSS method as well as Weather Window Statistics are established methods to calculate weather risk. To compare their applicability we have calculated delay times with both methods
Figure 4. Upper partial moments for project with 12-hour-tasks.

Figure 5. Histograms of total delay in project with 12-hour tasks for February and October.
and applied risk measures. Referring to the results for complex project schedules presented above, there are significant differences in risk values calculated with Weather Window Statistics or WaTSS method. There are some points we want to outline:

- Using Weather Window Statistics and calculating the risk with high confidence level, VaR leads to overestimation in winter months. Thus, we reserve more time than required in reality.
- Referring to the last point, the effect of overestimation is even stronger when cVaR is used as risk measure.
- On the other hand, VaR and cVaR calculated with Weather Window Statistics tend to underestimation in summer months. In that case, we reserve less time than required in reality.
- The 1-Order UPM on total project level in Weather Window Statistics also leads to overestimation in winter months, while the 0-Order UPM tends to underestimate.

Another point is that WaTSS method provides the predetermined predecessor-successor-structure of the project. Thus, we ensure to model the relation between tasks in the project schedule as well as its explicit sequence during the time horizon. On the other hand, Weather Window Statistics only assesses each task an 'average' delay for the corresponding month. However, if we analyze single activities, which do not belong to any complex project plan, the latter may adequate due to its simple application.

Finally, one should always keep in mind that the method, that was used to calculate the delay times, has an impact on the results. To provide realistic risk values, it is important to consider whether a total project is analyzed or whether only a few independent tasks are considered. For complex offshore installation projects a risk analysis calculated with WaTSS method models certain effects while risk values calculated with Weather Window Statistics tend to over- or underestimation. Thus, we suggest using WaTSS method in that case.

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