ALMA	Atacama Large Millimeter / submillimeter Array	

QA0 Pass Target and Downtime Characterization Analysis in Cycle 8

Draft A.0

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Change Record

Version	Date	Changes
A0.0	2022-10-26	Initial draft
A.1	2022-10-28	Final draft
A.2		
A.3		

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1 Purpose and Scope

This report presents the findings of the ALMA Downtime Working Group. The team was: Hector Alarcon, Juan Cortes, Priscilla Nowajewski, Roberto Price, Matias Radiszcz, Johnny Reveco, Tomas Staig, Ignacio Toledo, and Celia Verdugo. The work of this team took place over September to October 2022.

The purpose of the work of the team was to perform a study of downtime characterization at ALMA and report findings to the ALMA Director. The motivation for the study within a more global context, point to one of the main goal of the observatory of maximize the number of hours of QA0 Pass of science observations collected during an observing cycle (see ALMA Fundamental Statements - Prime Goal) , and more specifically, point to investigate the incidence of the different components of the downtimes in order to take actions that help to increase the number of hours dedicated to science observations, and at the end the efficiency of the observatory.

2 Key Goals of the Study

The key goals of this study are:

- Establish a critical analysis of the QA0 Pass Target for a whole cycle in the 12m array
- Explore a preliminary characterization of the different downtimes at a high level metrics
- Set up ideas and/or recommendations on the characterization of the downtimes
- Outline of a longer-term plan to align the lower level metrics used between different groups in ALMA (Engineering, Software and Science) with the higher level ALMA goals in order to set correctly the priorities for long term plan of mitigation of the different time losses components.

3 Format of the Report

3.1 Applicable Documents

The following documents contain additional information and are referenced in this document.

#	ALMA Doc. Number or link	Document Title
[AD01]	https://confluence.alma.cl/display/PMG/Downtime+Working+Group?preview=/104696761/104698547/ALMA%20Document%20v.09-1.pdf	Strategic KPI Development for ALMA
[AD02]	AEDM 2016-030-O_Rev.2	ALMA Steady State and Full Operations
[AD03]	https://confluence.alma.cl/display/SWO/KPI+Automation+Project+Documentation	KPI Automation Project Documentation
[AD04]	OPER-30.00.00.00-0020-H-PRO	AOS Antennas Survival Stow and Subsequent Restart Procedure
[AD05]	[pending reference]	ALMA Metrics

[RD01]	https://docs.google.com/document/d/1LLvk2-9oF2xtHtboXVQxueRSWEz-dLy-Quo0t3Jr6S4/edit?usp=sharing	PMG KPI Inventory

4 Report Intended Distribution

This report is intended to be used as support material by Sean Dougherty for the Board meeting presentation on 2022 November.

5 ALMA resources-based KPI framework

We have chosen the ALMA resource-based KPI, as a reliable framework to be used as a global context where to start our analysis. This KPI was defined as part of the work done during 2021 with the ALMA KPI Success Program Initiative together with a team from Universidad Adolfo Ibañez. The ALMA resource-based KPI, is a great starting point to have a complete high level characterization for the use of the antenna resources in ALMA observatory. We will do our analysis in this document based on this KPI [AD01], and specifically using the results for cycle 8. This initial characterization will help us to evaluate the incidence, in a global operational context, of each component, like downtimes, and others (see Table 1) in the final number of hours of QA0 Pass PI science execution collected during the previous cycle. Additionally, this characterization includes definitions and metrics for each component and group of components (different categories), leading us to the high-level ALMA resource-based KPI defined as Total Effective Array with Quality (TEA), that "aims to answer the strategic question: How can we use our limited resources in the best possible way?" [AD01 - page 18]

This KPI, points to "maximize the amount of time for successful science observations" [AD01], which metric is equivalent to the total accumulated time for QA0 Pass PI science executions within a whole observing cycle. This characterization of the different components will help to visualize the different downtimes as components within a more global context of the operations in ALMA; therefore, this will help to contextualize this work within one of the high-level goals in the observatory that points to maximize the amount of time for QA0 Pass PI science executions, and also connect this component and its investigation with the discussion about the QA0 Pass Target we will follow in the next section.

5.1 Definitions

The definition of the Total Effective Array with Quality (TEA) includes different categories used to characterize the different components of loss of time during the operations in the observatory. These categories group the different components of the total available time during a whole cycle. Below we summarize these categories:

- Scheduling Loss: "Time when antennas are not scheduled for observations."

Scheduling Loss = February Maintenance + Engineering Activities[1] *+ EOC*

- Availability of the Equipment: "The ratio of the amount of time that the tool is capable of running quality product to the total time it could be running."

Availability Loss = Weather Downtime + Technical Downtime + Successful Calibrations Time

[1] Here the Engineering Activities component involve both engineering and software activities

- Performance of the Equipment: "The ratio of the amount of product made to the amount of product that could have been made."

$Performance\ Loss = Remaining\ Time + Handover\ Time + Scheduling\ Downtime$

- Quality of Products: "The ratio of the amount of acceptable product made to the total amount of product made (including any unacceptable product)."

$Quality\ Loss = QA\mathbf{0}\ Semipass\ and\ Fail\ Time + Unsuccessful\ Calibrations\ Time$

These categories determine a series of times that converge in the Fully Productive Time that is the key number to obtain the metric used in the TEA. Here are shown the series of time definitions:

- $Planned\ Observation\ Time = Total\ Time - Scheduling\ Loss$
- $Run\ Time = Planned\ Observation\ Time - Availability\ Loss$
- $Net\ Run\ Time = Run\ Time - Performance\ Loss$
- $Fully\ Productive\ Time = Net\ Run\ Time - Quality\ Loss$

Finally we have the calculation of the TEA as:

$$TEA = \frac{(Total\ time - Scheduling\ loss - Availability\ loss - Performance\ loss - Quality\ loss)}{Total\ Time} = \frac{Fully\ Productive\ Time}{Total\ Time}$$

5.2 Results

Here we calculate the results of the different categories and components for the TEA in cycle 8 for the different array families.

The different components of the total time available within a year (cycle 8) are grouped by loss categories in Table 1, Table 2, and Table 3 for the 12m array, 7m array , and Total Power array, respectively. Moreover, the waterfall plot for the resource-based KPI for 12m, 7m, and TP for cycle 8 is presented in Figure I, Figure II, and Figure III, respectively.

Losses categories	Components	Hours	loss %	TEA %
Scheduling loss	**Engineering Activity, EOC, February Maintenance, Shared Resources**	2092	24 %	
Availability loss	**Eng. Tech. Downtime, Successful Calibration**	943	11 %	
Weather loss	**Weather loss**	1285	15 %	
Performance loss	**Handover, Remaining, Scheduling Downtime**	486	6 %	
Quality loss	**Fail, Unsuccessful Calibration**	292	3 %	

TEA		5098	58 %	42 %

Table 1: Table with the detailed information about losses categories used for the TEA metric calculation within the ALMA resource-based KPI for cycle 8 in the 12m array.

Losses categories	**Components**	**Hours**	**loss %**	**TEA %**
Scheduling loss	**Engineering Activity, EOC, February Maintenance, Shared Resources**	2129	24 %	
Availability loss	**Eng. Tech. Downtime, Successful Calibration**	2233	25 %	
Weather loss	**Weather loss**	1081	12 %	
Performance loss	**Handover, Remaining, Scheduling Downtime**	397	5 %	
Quality loss	**Fail, Unsuccessful Calibration**	214	2 %	
TEA		6053	69 %	31 %

Table 2: Table with the detailed information about losses categories used for the TEA metric calculation within the ALMA resource-based KPI for cycle 8 in the 7m array.

Losses categories	**Components**	**Hours**	**loss %**	**TEA %**
Scheduling loss	**Engineering Activity, EOC, February Maintenance, Shared Resources**	3611	41 %	
Availability loss	**Eng. Tech. Downtime, Successful Calibration**	1622	19 %	
Weather loss	**Weather loss**	1417	16 %	
Performance loss	**Handover, Remaining, Scheduling Downtime**	521	6 %	
Quality loss	**Fail, Unsuccessful Calibration**	75	1 %	
TEA		7247	83 %	17 %

Table 3: Table with the detailed information about losses categories used for the TEA metric calculation within the ALMA resource-based KPI for cycle 8 in the Total Power array.

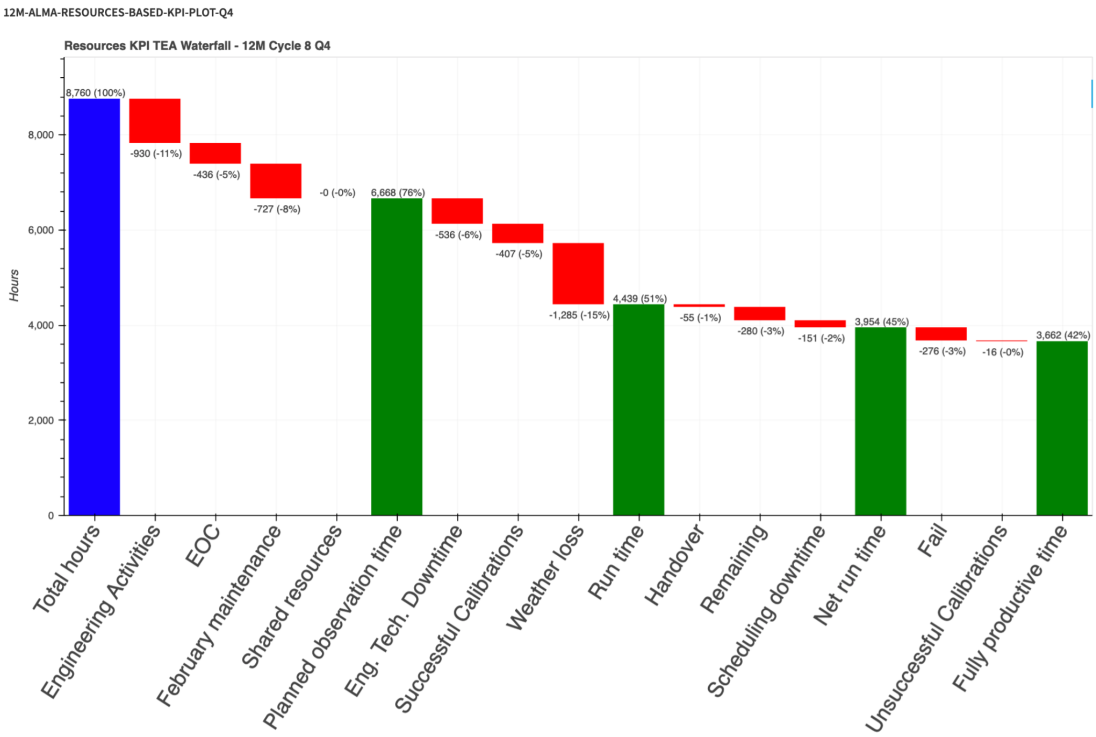

Figure I: Waterfall plot for the Resource-based KPI for the 12m array for cycle 8

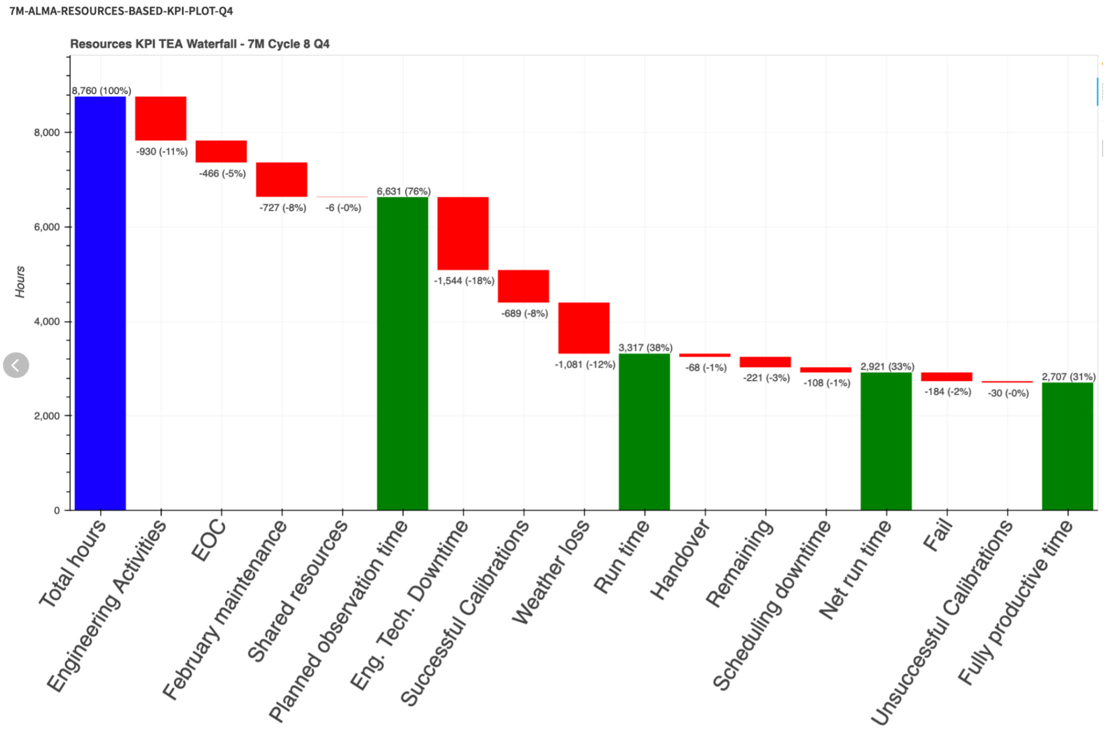

Figure II: Waterfall plot for the Resource-based KPI for the 7m array for cycle 8

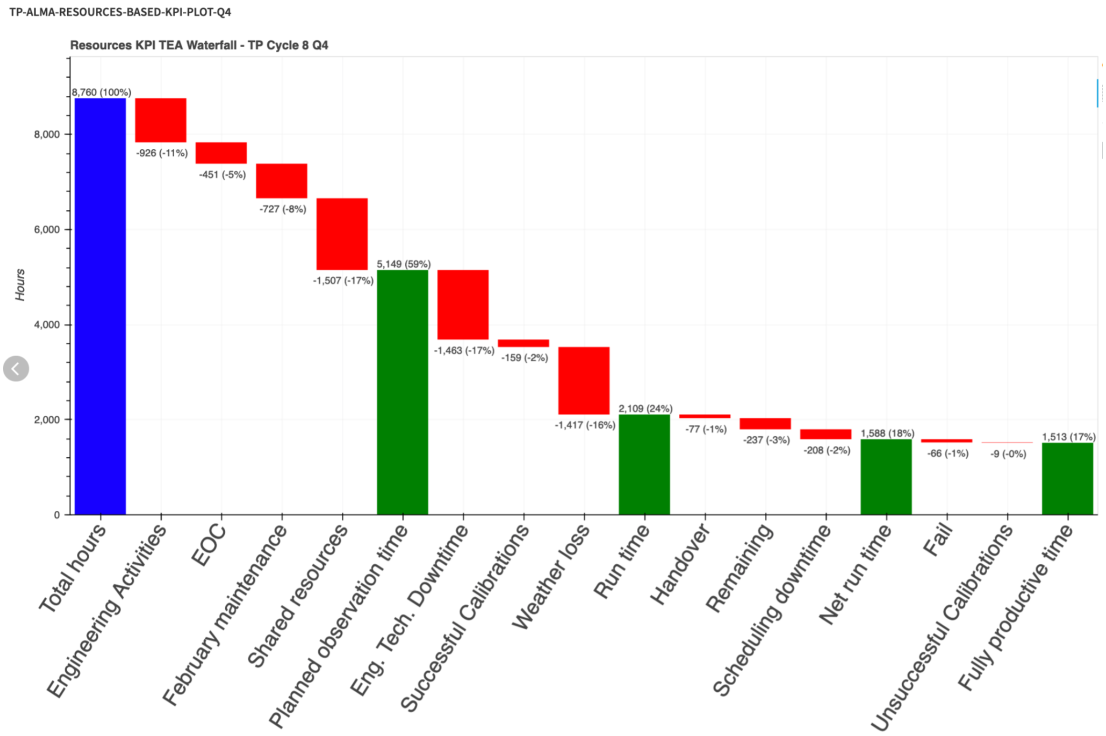

Figure III: Waterfall plot for the Resource-based KPI for the Total Power array for cycle 8

5.3 Discussion

These high-level metrics used to obtain the TEA KPI is a great opportunity to align the different groups (Engineering, Software, and Science) in ALMA, starting from the higher-level metrics and KPIs toward lower-level metrics and KPIs, that in the end respond to the same global ALMA goals. This work has not been properly developed in the past, so the different metrics and KPIs used by different groups may not be necessarily aligned with the higher-level ALMA goals. The fully productive time calculated in this KPI corresponds to the QA0 Pass time by the end of a cycle, which was the common metric used by the observatory in the 12m array associated with a target of 4300 hrs to evaluate the performance during a given cycle. However, this waterfall analysis could give us much more information about the different components that could affect this QA0 Pass target, revealing that the only use of QA0 Pass metric has several limitations for evaluating the observatory performance. Mainly, because some of the components do not depend directly on the efficiency, but on events that are out of our control, like weather conditions for a given cycle. Additionally some events that could be within our control area, do not necessarily depend on a situation that characterizes a given cycle but a longer-term technical issue carried over from previous cycles like correlator issues or power outage issues.

6 Critical analysis of the 4300 hours of QA0 Pass target in the 12 [m] array

As part of the ALMA call for proposals, a certain amount of time is anticipated for the 12-m Array and the Atacama Compact Array (ACA). This amount of time was different for every cycle, being, for the 12-m Array, 3000 hrs for Cycle 4, 4000 hrs for Cycles 5 and 6, and finally ramping up to 4300 hrs for Cycles 7, 8, and 9. The anticipated amount of time in steady state operations is defined by document [A02]. In this latter, the anticipated amount of time for the 12-m Array, called "Expected Time", is defined as the hours available per week modified by efficiencies, science time reserved for Extension of Capabilities (EOC) observations (including developments activities). The Expected time (ET) is expressed as follows:

$$ET = (52 - N) \times (16 \times (7 - X) + 24 \times X) \times \eta_{exec} \times (1 - EOC_{fraction})$$
$$= Total\ Allocated\ time \times \eta_{exec} \times (1 - EOC_{fraction})$$

Where

- N: is the number of shutdown weeks per year
- η_{exec} : is the execution efficiency.
- X: number of 24-hour days per observing week.
- $EOC_{fraction}$: the fraction of time in a year used for optimization activities (Enhancement of Capabilities, EOC, Development, etc.)

In [AD02], the execution efficiency is defined for the time offered to PI as

$$\eta_{exec} = ET / (Total\ Allocated\ Time \times (1 - EOC_{fraction}))$$

$$\eta_{exec} = Successful\ Execution\ Time\ /\ Total\ Allocated\ Time\ for\ Science\ ,\ \text{i.e.}$$

$$\eta_{exec} = QA0\ Pass\ time\ /\ Total\ Allocated\ Time\ for\ Science\ ,$$

For system availability, the execution efficiency is:

$$\eta_{exec} = \left(\frac{Successful\ Execution\ Time + Calibration\ Time}{Total\ Allocated\ Time\ for\ Science - Weather\ Downtime}\right) \equiv \eta_{observing}$$

$\eta_{\text{observing}}$ is called "Observing Efficiency" in several ALMA Documents.

According to [AD02], in steady state (starting Cycle 5) and full operations, expected time parameters should be as follows:

- $N = 4$
- $\eta_{\text{exec}} = 65\%$, $\eta_{\text{observing}} = 95\%$
- X: 5 days
- $EOC_{fraction} = 0.10$

Therefore, during the steady state the expected time (ET) is 4268 hrs ~ 4300 hrs, with a total allocated time for the science of 6566 hrs. Note that from [AD02] it is inferred that the anticipated technical time per week is just two 8-hours days for engineering and computing technical activities, i.e., 16 hours per week.

6.1 Assumptions and uncertainties with the current 4300 hrs target approach

In the previous section of this report, we developed the calculation for the current 4300 hrs of expected science time. We have to consider that in this calculation, some fundamental assumptions are hidden within the 65% expected execution efficiency and 95% expected observing efficiency. This includes the assumption of 15% of weather downtime (Corder, S. priv. comm) and that only 5% of the time is expended in losses such as technical downtime, QA0 fail/semi pass, remaining time, etc. Also, the expected engineering and computing technical time for steady state and full operations is only two days of 8 hours each, i.e., 16 hours per week, which contrasts with the actual formal 24 hours per week used. This is a serious underestimation of about 380 hours in expected technical time.

The fact that the granularity of high-level assumptions is too broad with fundamental assumptions hidden in the efficiency, such as; a non-explicit weather downtime, and calibration time, unrealistic assumption of 5% of losses, makes this approach unsuitable for analyzing if 4300 hours is an achievable goal, and for understanding the reasons of the current ALMA performance. To analyze if the 4300 hours target is achievable and understand the current ALMA performance, we use the ALMA resources-KPI waterfall approach described in section 5 since this latter gives more information on the different component losses that affect the observatory performance.

6.2 Analysis

6.2.1 4300 hours: A waterfall approach

To analyze the 4300 hours target in a waterfall approach, we follow [AD02] assumptions. These can be summarized as

- Technical time of 16 hours per week, i.e., two 8 hours days per week of engineering plus computing time[2].
- 4 weeks of February maintenance.
- EOC fraction of 10% of total allocated time multiplied by 65% execution efficiency.
- About 15% of weather downtime over the planned observed time.

These assumptions are not enough for reproducing a waterfall approach completely, but nevertheless, some parameters can be derived, as follows:

- Total Hours: 8760 hours.
- Technical Time: 770 hours.
- February Maintenance: 672 hours.
- Total Allocated Time: 7317 hours.
- EOC Time = Total Allocated Time x 0.9 x 0.65 = 476 hours.
- Planned Observed Time: 6841 hours
- Weather Lost: 1026 hours

Here, we don't have any information regarding successful calibration and other losses, and we have to do ad-hoc estimations regarding the rest of the waterfall components to try to satisfy the execution efficiency of 65% and an observing efficiency of 95%. If we do this, we can arrive at the following waterfall schema.

Waterfall Component	**Hours**	**Percentage**
Total Hours	8760	100%
Eng+Sofw Time	770	9%
Feb Maintenance	672	8%
EOC time	476	5%
Planned Obs Time	6841	78%
Eng. Tech Downtime	290	3%
Succ. Cal	902	10%

[2] In contrast, since Cycle 5 , the usual technical time allocation per week is 2 ADE blocks of 7 hours each per week (14 hrs) plus 2 ADC blocks of 5 hourrs each per week (10 hrs) = 24 hrs/week. This translates in 1152 hours per year. This is a big discrepancy with what is inferred from 4300 hours target document [AD02].

Weather Lost	1026	12%
Run Time	4623	53%
Handover	66	1%
Remaining	132	2%
Scheduling downtime	0	0%
Net RunTime	4426	51%
Fail	132	2%
Unsuccessful Cal	0	0%
Full Productive Time	**4294**	**49%**

Table 4: Waterfall schema for 4300 hours Target. Columns are Waterfall Components (1), hours used in each component (2), and percentage with respect to the total cycle hours (3). Total cycle hours are highlighted in light blue. Planned Observing Time, Run Time, Net Run time, and Fully Productive Time are highlighted in green. Fully Productive Time is equal to the QA0 Pass observing time.

This gives TEA KPI of 49%. Note that this distribution of losses is not unique; given the uncertainties in the assumptions, several other distributions can be possible. If we correct the TEA KPI by subtracting weather losses (which we don't have any control over), TEA Corrected by Weather is 56% for the 4300 hrs target. This distribution of losses has the following resulting efficiencies:

Efficiency	**Percentage**
Execution Efficiency	65%,
Observing Efficiency with Calibration	93%
Operation Efficiency with Calibration	95%

Table 5: Derived efficiencies for 4300 hours target. Columns are Efficiency (1), hours used in each component (2), and percentage (3). Efficiencies are execution efficiency, observing efficiency with Calibration, and Operation efficiency with Calibration.

The Observing Efficiency with Calibration is defined at [AD05], and the Operation Efficiency with Calibration at [RD01]. These are very high efficiencies, and we have never reached these efficiencies.

Regarding component losses, we can conclude the following:

- The assumption of 15% of weather losses seems reasonable. 4300 hrs target implies 1026 hrs of weather downtime, comparable to Cycle 6 and 7 weather losses.
- Assumption of 16 hrs per week of technical time seems very far from reality. The usual technical time allocation is 24 hours per week. During Cycle 6, we invested 1081 hrs in technical time and 929 hrs in Cycle 8. The target implies only 770 hrs expended in technical time, which is a major reduction of 170 hrs respect to Cycle 8.
- 93% observing efficiency with calibration implies a huge amount of time in calibration, which doesn't correspond to reality.
- Total losses other than weather downtime, calibrations, and technical downtime are only 9% of the total allocated time to PI science. This is less than half of the current losses. This is too small given our current performance.

Therefore, we conclude that 4300 hours cannot be achieved unless we make major changes to our technical time allocation and major reductions in our current losses.

6.2.2 Cycle 8 Performance: Why we couldn't reach 4300 hrs QA0 Pass time.

Cycle 8 was the second most "observed" cycle in ALMA history, with 3664 hrs of QA0 pass time in the 12-m Array. The most observed cycle was Cycle 5 with 3789 hrs of QA0 Pass time; anyway, the 4300 hrs of QA0 Pass time seems still far away. To establish the causes of why we couldn't reach our target, we compare Cycle 8 performance with respect to the actual 4300 hrs target in a waterfall approach.

Waterfall Component	**Target Hours**	**Cycle 8 Hours**
Total Hours	8760	8760
Eng+Sofw Time	770	930
Feb Maintenance	672	727
EOC time	476	436
Planned Obs Time	6841	6668
Eng. Tech Downtime	290	536
Succ. Cal	902	407

Weather Lost	1026	1285
Run Time	4623	4439
Handover	66	55
Remaining	132	280
Scheduling downtime	0	151
Net RunTime	4426	3954
Fail	132	276
Unsuccessful Cal	0	16
Full Productive Time	**4294**	**3662**

Table 7: Waterfall schema for 4300 hours Target vs Cycle 8. Columns are Waterfall Components (1), hours used in each component for 4300 hours target (2), hours used in each component for Cycle 8 (3). Total cycle hours are highlighted in light blue. Planned Observing Time, Run Time, Net Run time, and Fully Productive Time are highlighted in green. Full Productive Time is equal to the QA0 Pass observing time.

In the previous table, we see in red the Cycle 8 component losses where we have serious discrepancies with the target. We can see that the main discrepancies are:

- Eng + Software Time plus February maintenance excess of 215 hours.
- Excess in weather downtime of 260 hrs.
- Engineering Technical downtime of 246 hrs.
- Taking into account other expectations plus the overestimation of 4300 hrs target successful calibration, this gives

Fully Productive Time ~ 4300 - 600 = 3700 hrs approximately. Therefore, the main reasons for not reaching the target of 4300 hrs are weather downtime losses plus the time we use in technical times and engineering technical downtime. Note that 4300 hrs target technical time allocation implies just 16 hrs per week. We expend about 19 hrs per week, which leads to a difference of 160 hrs only to this issue. Moreover, contributions from other sources, such as remaining time and execution failures, cannot be undermined.

6.3 New QA0 Pass time Target definition

Since it is clear that 4300 hrs is hard to get due to serious underestimation regarding maintenance, and weather losses involved, we use the waterfall approach to elaborate a more educated estimation of our losses and, therefore, a more realistic target. To elaborate on this new target, we make the following considerations;

- HilSE and Flexible Technical times: According to 2022 Q4, flexible time allocation and HiLSE availability will allow the reduction of 500 hours in the technical time with respect to 1152 hours/24 hours per week allocation. We take a more conservative estimation of 80% for this 500 hours, i.e., 400 hours reduction, and so, an expected technical time of 752 hours per year, i.e. 15.7 ~ 16 hours per week.

- Weather losses: During Cycle 8, we experienced ~ 1285 hours in weather losses. We prefer to use this conservative figure since we don't have any control over weather losses themselves unless we somehow reduce the weather recovery. Therefore, we expect a realistic weather loss of 1300 hrs.

- Daytime focus: During Cycle 8, we expended 407 hours of calibration time. Considering that the daytime focus schema to be implemented in Cycle 10 will allow a reduction from 50 minutes to 30 minutes expended in focus calibration. This could reduce about 70 hours if we consider on-sky efficiency. Therefore, we should expect to invest about 340 hours in yearly calibration, where 185 hours is focus calibration.

- Fraction of failures and QA0 Semipasses: During Cycle 8, the amount of QA0 fails and semi-passes was 276 hours. We propose to lower this amount to 75 hours, using about 200 hours. DSO should analyze the feasibility of this proposal.

If we use these considerations and remaining losses similar to Cycle 8 losses, we should expect the following breakdown:

Waterfall Component	**Hours**	**Percentage**
Total Hours	8760	100%
Eng+Sofw Time	761	9%
Feb Maintenance	672	8%
EOC time	450	5%
Planned Obs Time	6877	79%
Eng. Tech Downtime	537	6%
Succ. Cal	340	4%
Weather Lost	1300	15%

Run Time	4698	54%
Handover	57	1%
Remaining	289	3%
Scheduling downtime	156	2%
Net Run Time	4196	48%
Fail	198	2%
Unsuccessful Cal	16	0%
Fully Productive Time	**3982**	**45%**

Table 8: Derived efficiencies for 4000 hours target. Columns are Efficiency (1), hours used in each component (2), and percentage. Efficiencies are execution efficiency, observing efficiency with Calibration, and Operation efficiency with Calibration.

Therefore, we propose a new target of 4000 hrs of QA0 Pass Time. 4300 hrs could be taken as a stretch goal.

As a result of this new target, we have the following resulting parameters:

- EOC fraction of 10% of total science time.
- Execution Efficiency of 61%
- Observing Efficiency with Calibrations of 82%
- Operational Efficiency with Calibration of 90%.
- TEA of 45%.

6.4 Proposed High-Level KPIs

6.4.1 Proposed Level 0 KPIs

To achieve this proposed goal of 4000 hrs of QA0 Pass time per cycle (with a stretch goal of 4300 hrs), we need a metric that is a strategic Key Performance Indicator (KPI) that allows us to track our performance with respect to the one necessary to achieve our proposal goal. Here, we propose to use the Total Effective Array with Quality (TEA) defined in [AD01] with a slight modification. TEA is defined as

TEA = (Total time – Scheduling loss – Availability loss – Performance loss – Quality loss)/Total Time
= Fully Productive Time / Total Time

The problem with the TEA is that it depends on the availability loss component of the weather downtime, which we have little control over. Therefore, we propose the introduction of a TEA corrected by weather loss defined as:

$$TEA_{corrected} = Fully\ Productive\ Time\ /\ (Total\ Time\ -\ Weather\ downtime),$$

as Level 0 KPI, so our KPI only depends on downtime components that we have control.

The TEA corrected by weather losses for different targets and Cycle 8 is as follows:

KPI	4300 Target	4000 hrs Target	Cycle 8
TEA	49%	45%	42%
TEA Corrected by weather	56%	53%	49%

Table 9: TEA and TEA corrected by weather downtime for different targets and Cycle8. Columns are KPI (1), derived metric for 4300 hours target (2), derived metrics for 4000 hours target (3), and derived metrics for Cycle 8 (4).

We see that the TEA corrected by weather losses for the target ranges between 56% - 53%. Therefore, we should aim to :

$$TEA_{corrected} = 53\%$$

as Level 0 KPI. If we reach this target of 53%, we should get a QA0 Pass time of 4000 hours if weather downtime is about 1300 hours, so it means that all the teams are doing their best to optimize time, and any underperformance should be due to weather downtime exclusively.

6.4.1 Proposed Level 1 KPIs

Here, we propose a set of Level 1 KPIs inspired in ALMA Resources-based KPI framework, that could be used by different ALMA departments to ensure we reach the goal of 4000 hrs with TEA corrected by the weather of 53%. It is important to note that this is just a recommendation, and every ALMA department must formulate sensical Level 1 KPI targets according to their resources and needs.

The proposed Level 1 KPIs are as follows;

1. February Maintenance duration. Target ≤ 4 weeks. Responsible: ADE, ADC

2. Planned Technical Time. Target ≤ 16 hours per week. Responsible: ADE, ADC
    a. Technical Returned to Science (HilSE, flexible time). Target ≥ 400 hours per cycle over the technical time benchmark of 1152 hours per year. Level 2 KPI . Responsible: ADE, ADC
3. Exclusive EOC Time. Target ≤ 450 hours per cycle (5% of Total Hours). Responsible: DSO/APG
4. Eng. Technical downtime. Target ≤ 540 hours per cycle (Cycle 8 benchmark). Responsible: ADE, ADC
5. Successful Calibration Time. Target ≤ 340 hours per cycle. Responsible: DSO
6. Weather Downtime Recovery Ratio.
    a. Ratio between the time expending recovery of the array and the actual weather downtime event duration.
    b. Target ≤ 1.
    c. Responsible: ADE/AMG
7. Handover time. Target ≤ 60 hours per Cycle. Responsible: ADE, DSO/AOG
8. Schedule downtime. Target ≤ 160 hours per Cycle. Responsible: DSO/OPG, DSO/PMG
9. Remaining Time. Target ≤ 290 hours per Cycle. Responsible: DSO/PMG
10. QA0 Failure + Semipass time. Target ≤ 200 hours per Cycle. Responsible: DSO/PMG, DSO/OPG.
11. Operations Efficiency with Calibration. Target ≥ 90%. Responsible: DSO/PMG.

7 Downtime characterizations and recommendations

From the critical analysis of 4300 hrs QA0 Pass target, becomes evident that assumption about losses are unclear, making hard to understand from where the time losses or downtimes are coming from. This is solved by proposing using ALMA Resource-based KPI framework, and new Level 0 and 1 kpis. The analysis reveals that the main drivers of Cycle 8 "underperformance" are weather losses, too optimistic technical time assumptions, and engineering technical downtimes, although other losses are not negligible. In this section, we perform a more detailed Cycle 8 losses analysis, including weather downtime, technical downtime, and scheduling downtime characterizations, and we give a set of recommendation and considerations regarding improvements to downtime definitions, tools, data sources, and operational procedures that would enable us to accurately track these downtimes to requires granularity level.

7.1 Weather downtime characterization

A weather downtime is recorded in the Shift log Tool and declared as an entry every time bad weather conditions do not allow to continue with PI science observations, even in band 3, during science operations in a given array family (12m, 7m and/or Total Power).

There are two main considerations to defining bad weather conditions.

- For observation scheduling: PWV > 12 mm and Phase RMS > 500 um.
- For antenna operations (according to AOS Antennas Survival Stow (Shutdown) and Subsequent Restart Procedure 2022-09-14 [AD04]):
    - Air temperature < -20 C

- Wind speed > 20 m/s for 12 m antennas
- Wind speed > 16 m/s for PM antennas (15 m/s prior to October 20th, 2022)
- Relative Humidity > 95% as indicative of Precipitation, Snow, Hail, and Frost.

Bad weather conditions mean:

- The array family is not operational because antennas are sent to survival stow (precipitation, snow, high wind, or T < -20 deg C)
- The number of antennas is not enough for science operations due to bad weather
- The sky conditions (PWV/phase rms) is not suitable for observations (go/nogo recommends to use Band 1, 2 or no Bands are available), or the conditions are marginal for band 3 (i.e. 30 rms frequency <= 120 GHz in the DSA scheduling GUI), and non-project are available in the DSA.

Visual inspection procedure on antennas after a weather downtime event could be triggered for the following conditions:

- Precipitation without interruption by more than 2 hours.
- Wind speed conditions higher than 30 [m/s].
- Ice detected in the surface of the antennas (is very important to check membrane and ice on the shutter mechanism).

In general, the weather downtime should supersede other downtimes.

Although this is not part of the weather downtime entries procedure, SLT users have usually characterized this entry with a brief sentence in the "Subject" field of the downtime entry and/or with a PRTSPR Jira ticket associated to the downtime (included as a comment in the downtime entry), and created specifically to characterize the weather event. Some examples are :

- PRTSPR-45792 : (For Statistics) APE2: Observation aborted because AOS precipitation ... (generic ticket)
- PRTSPR-55212 : (For Statistics) Antenna availables below the blocker number (generic ticket)
- PRTSPR-44711 : (For Statistics) Aborted because wind speed alarm (> 20 m/s). all to survival-stow (generic ticket)
- PRTSPR-54263 : [Statistics] APE2: BL: High wind speed at AOS: Number of available antennas is below the blocker

However, this is not clearly established as a procedure to use these specific tickets as a comment or any specific keywords in the Subject to be used as characterization tag for the different kinds of weather downtimes. Therefore, this depends on the Array Operator/AoD in how these resources, the "Subject" or commented Jira tickets, are used in the downtimes entries in order to be characterized.

Therefore, in short, we do not have rules on how to characterize weather downtimes. Understanding these limitations on the source of data, we will try to do some analysis based on the existing sentences in the "Subject" of the downtimes entries and PRTSPR tickets associated.

7.1.1 Analysis

7.1.1.1 Preliminary analysis

We've obtained a preliminary characterization of the weather downtime by using keywords found in the sentence included in the "Subject" of the weather downtime entries in the SLT as well as the title of the JIRA tickets associated with those entries. The used tags associated with those specific keywords are: "wind", "precipitation", "snow", "vir", "pwv", "phase", "ice", "not suitable for b3", "antenna not available", and "Other".

Below in the Table 10, Table 11, and Table 12 we show the time duration of each characterization tag component for the weather downtimes in the 12m array, 7m array and Total Power array, respectively. In the tables is also included the number of events (number of weather downtimes entries created) and the calculated total weather recovery time for each tag component from the Start Recovery Time information in the weather downtime entries associated.

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	TIME RECOVERY [hrs]	Number of events
12 [m]	wind	482.53	326.55	118
12 [m]	precipitation	308.36	158.02	58
12 [m]	snow	176.79	120.66	18
12 [m]	vir	121.66	106.21	8
12 [m]	Other	70.16	32.16	36
12 [m]	not suitable for b3	59.45	53.42	25
12 [m]	antennas not available	31.91	14.92	2
12 [m]	pwv	16.56	12.5	9
12 [m]	phase	15.12	5.58	8
12 [m]	ice	2.73	1.83	1

Table 10: Weather downtime characterization for the 12m array using keywords from the weather downtime entry summary and PRTSPR ticket title associated.

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	TIME RECOVERY [hrs]	Number of events
7 [m]	wind	397.86	230.04	87
7 [m]	precipitation	291.31	184.3	28

7 [m]	snow	153.76	104.88	15
7 [m]	vir	126.01	114.02	8
7 [m]	Other	61.11	31	16
7 [m]	antennas not available	31.82	14.92	2
7 [m]	not suitable for b3	11.25	10.62	1
7 [m]	pwv	5.88	5.54	3
7 [m]	ice	1.82	1.82	1

Table 11:Weather downtime characterization for the 7m array using keywords from the weather downtime entry summary and PRTSPR ticket title associated.

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	TIME RECOVERY [hrs]	Number of events
Total Power	wind	799.72	555.23	157
Total Power	precipitation	206.48	110.31	21
Total Power	snow	148.23	97.32	15
Total Power	vir	139.02	123.65	8
Total Power	Other	78.25	35.73	10
Total Power	antennas not available	31.92	14.92	2
Total Power	not suitable for b3	11.34	10.6	2
Total Power	ice	2.46	1.83	1

Table 12: Weather downtime characterization for the Total Power array using keywords from the weather downtime entry summary and PRTSPR ticket title associated.

From this preliminary analysis is clear that the high wind conditions in cycle 8 appear as a relevant actor for the weather downtimes, especially for the Total Power array that use a lower limit for the wind speed allowed at AOS to operate (of 15 m/s instead of 20 m/s for the other antennas), where the wind is the dominant component of the weather downtime (with ~800 hrs).

On the other hand, precipitation ("precipitation") in liquid (rain) or solid ("snow") state together are also a relevant component of the weather downtime, especially in the 12m and 7m arrays (485 hrs, and 445 hrs respectively) that are similar and slightly higher than the wind component. Then, further down in importance, we have the Visual Inspection required after a strong weather event like relevant snow accumulation in the antennas and around the antennas in the route, or too high wind conditions like gusts surpassing the 30 m/s at AOS that trigger a Visual Inspection requirement, and is tagged as "vir". We can also see the tag component "antennas not available", which could include cases where Visual Inspection is ongoing, so that not enough array elements have been recovered after a weather event in order to start PI science. But also, this could include high wind conditions affecting some antennas when we are in a long baseline configuration, where those antennas are associated with a different weather station located close to one of the branches of the current antenna configuration that is affected by high wind conditions.

In terms of big weather downtimes entry events with time durations (longer than 12 hours), in general, could account for around half of the total weather downtime in each array family. In this case, again the precipitations as liquid ("precipitation") or solid ("snow") are dominant in the 12m and 7m arrays, followed by Visual Inspection ("vir") and then the wind ("wind"). In the Total Power array, now the precipitations as liquid ("precipitation") or solid ("snow") together are dominant, followed very close by the wind ("wind") and then by Visual Inspection ("vir"). In general, big downtimes events could be associated also with long periods where a Visual Inspection Requirement is ongoing, even when the weather conditions have improved.

7.1.1.2 Weather recovery

In the preliminary analysis we also include for each weather tag component, an estimation of the Weather Recovery time (TIME RECOVERY [hrs]). This should correspond to the time required to recover the minimum of array elements, and/or hardware components to start PI science observations, that required a Visual Inspection after a strong weather event. This recovery time starts when the weather event has finished and the Visual Inspection actions have started.

In order to calculate the weather recovery time from the SLT record, we use the timestamp recorded in the Start Recovery Time field within each weather downtime entry. So, we use that time as the start of the recovery until the end of the weather downtime. However, there are several uncertainties about how this time is recorded in the SLT, specifically how systematic is the editing of the start recovery timestamp following any policy.

On the other hand, when a weather downtime is created, by default the recovery start time is set equal to the timestamp when weather downtime was created, which in general tends to overestimate the recovery time in case this time is not edited later. This behavior needs to be modified in order to avoid any bias in the calculations, in this case tending to overestimate the weather recovery. In general, the weather recovery calculations seem to be affected by too many uncertainties; so the current calculations are not reliable at all to be used as a metric at this time until some improvements in the login system and login procedures are in place.

For the weather component tag "vir" in the previous analysis, the TIME DURATION [hrs] and TIME RECOVERY [hrs] should be the same, although they are close, they are not exactly the same. This reveals part of the limitations we have on the recording of this time duration component.

7.1.1.3 Current limitations and validation of the used classification

The next relevant weather tag component in our preliminary analysis is the one labeled as "Other". This classification includes all those Weather Downtimes that contains sentence too vague in the "Subject" like "Bad weather", or "Weather" or "bad weather to observe" or "no project to run", that does not allow any clear characterization of the weather downtime; and not useful jira ticket associated; or do not include any sentence at all in the subject neither ticket associated; so, it is not possible to characterize the downtime, as non-useful information is included.

In general, the use of vague or random sentences in the "Subject" of the weather downtimes as well as in the jira ticket titles associated with the downtimes is very problematic for a correct and systematic characterization of the Weather Downtimes. For the preliminary analysis, the use of keywords to characterize the Weather Downtimes became a very chaotic exercise. We need something better in terms of the organization of the information used to characterize the downtimes.

7.1.1.3.1 Weather downtime characterization validation

The following characterization was performed by identifying the dominant atmospheric condition for each cycle. In order to make a comparison of the weather conditions for each cycle, the analysis was performed by using wind speed (m/s), relative humidity (%), and precipitable water content (mm). The data was obtained by using the MeteoCentral weather station data from Cycle 5 to Cycle 8 (October 2017 to September 2022). Weather data with unusual pressure values of 700hPa, relative humidity higher than 100%, and date 1970 were discarded.

No further data cleaning was performed for precipitable water content (PWV). In this case, a maximum limit (bad weather) was defined following the indications of Bill Dent by internal communication. A shiftlog entries table was created for this report, helping to cross the weather downtime information with the weather station data.

Figure IV presents a summary of the main keywords related to atmospheric events since cycle 5 in order to highlight the importance of having a correct way to register the event that triggers a weather downtime.

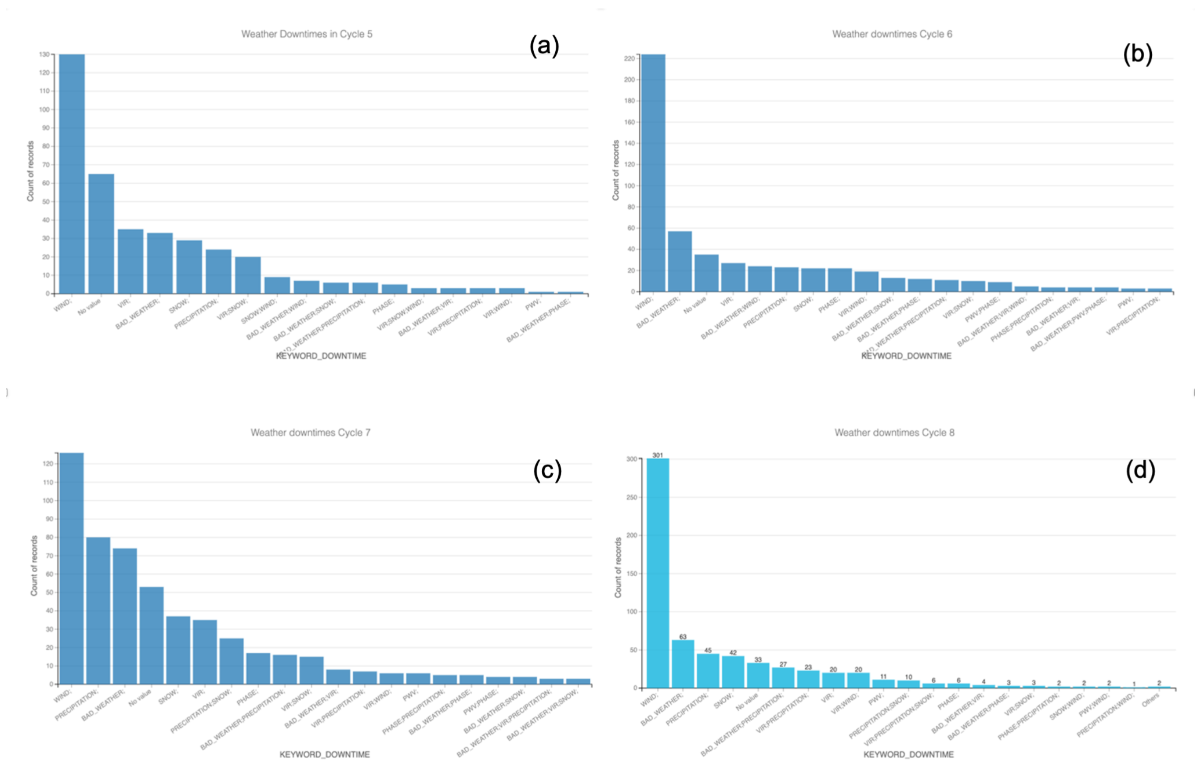

Figure IV: Weather downtimes presented by keyword for each cycle. The analysis shows the dominant atmospheric conditions for each cycle: winds and precipitation (rain, snow). Also shows the importance of having a correct way to register the downtimes to avoid loss of information depending on the event. Each figure shows the weather downtimes keywords for each cycle. Cycle 5 is presented in (a), where winds and issues with the registration of events dominate, (b) shows the weather downtimes keyword for cycle 6, same as cycle 5, winds dominate and also undetermined bad weather entries, then (c) shows a predominance of downtimes by winds and precipitation in Cycle 7 as expected, and (c) Cycle 8 again shows a predominance of wind and undetermined bad weather entries.

Weather downtime due to high winds

The protocol indicates that a weather downtime, due to high winds, is declared when wind speed is over 15 m/s in Total Power arrays, and 20 m/s for 12 m and 7m (cycle 8), meaning the antennas are sent to survival mode. Moreover, the protocol defines a maximum wind speed of 30 m/s to trigger a visual inspection.

The lack of a fixed entry in the shiftlog tool makes it difficult to identify the origin of the issue as several entries were declared as weather downtime without reaching the required speed limit. As it was presented in Figure IV, most of the entries are declared when high winds had a speed over 15 m/s, but several of them are also declared with wind speed under the limit value mainly due to other weather downtimes (precipitation or snow).

Table 13 presents the amount of time in hours of the total high wind event with wind speed over 30 m/s events for cycles 5, 6, 7, and 8, also including the maximum wind speed reached and the date when the maximum value event occurred. The duration of the wind speed event over 30 m/s was calculated by using the MeteoCentral weather station data, identifying the duration of each event.

Cycle 8 has the major high winds registered since cycle 5. The total time registered for wind speed over 15 m/s was 2496.3 hrs. Taking into account the new wind speed limit for PM antennas, the total time registered for wind speed over 16 m/s is 2094.5 hrs. The total time gain due to this change is 401.6 hrs.

According to these numbers, 16% of the total weather downtime would be gained due to wind conditions. For cycle 8 in Total Power, we have ~799.72 hrs of wind, so we would have gained ~129 hrs, assuming the wind hours are well characterized as the wind only and do not include visual inspection.

Cycle	Duration of wind speed event over 30 m/s (hrs)	Max Wind Speed [m/s]	Date of maximum wind speed [utc]
5	35.1 hrs	37.80	2018-09-01 17:52:07
6	19.5 hrs	39.20	2019-07-24 19:53:46
7	28.3 hrs	37.30	2021-06-23 18:54:04
8	102.5 hrs	41.1	2022-07-16 02:03:30

Table 13: The table shows the duration of wind speed events over 30 m/s, the max wind speed reached, and the date of the maximum wind speed registered since cycle 5. Cycle 8 presents a higher amount of high wind events than the maximum value registered.

Figure V shows the amount of weather downtime entries related to wind speed, identifying the keyword "wind" in the subject or description of the downtime entry. Most of these downtimes were declared when wind speed was between 15 and 20 m/s as can be expected. It is interesting to observe that in some cases the weather downtime due to high wind was declared when the wind was under 15 m/s, even though there are cases when the downtime is declared with a wind speed between 0 to 5 m/s.

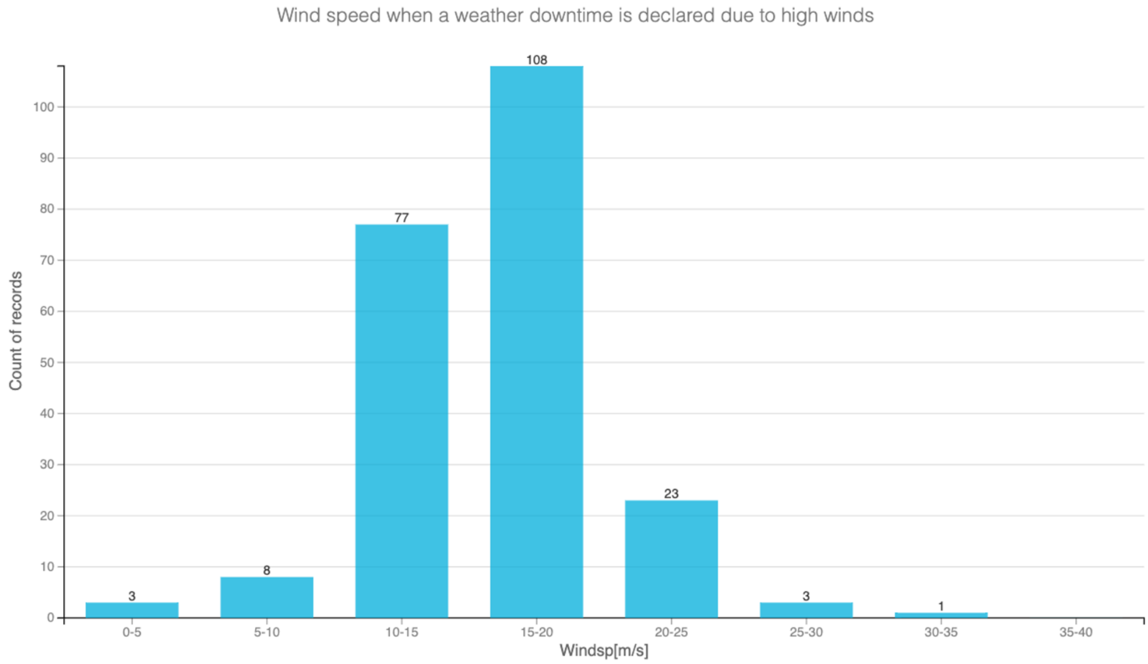

Figure V: Amount of weather downtimes due to high winds during cycle 8, depending on the wind speed registered when the downtime was declared.

Weather downtime due to Precipitation

The protocol indicates that a weather downtime, due to bad weather, is declared when PWV is over 12 mm, also according to the protocol, precipitation (rain, snow, and hail) is expected with a Relative Humidity higher than 95%.

As can be seen in Table 14, taking into account only the maximum values of PWV, the relation with precipitation and relative humidity was accomplished during cycle 7 when the maximum PWV was registered, confirming bad weather conditions and snow using the keyword of the shiftlog entry. In this case, the duration of the weather downtime was 4.6 hrs. Also, for cycles 6 and 7, bad weather was identified with PWV > 12 mm as the protocol indicates, but only for cycle 7, the relative humidity was over 95% when the downtime was declared due to snow in the AOS.
The number of weather downtimes declared due to precipitation during cycle 8, depending on the relative humidity is presented on Figure VI. It can be seen that at least three values of relative humidity are related to precipitation in cycle 8: 15% - 20%, 75%-80%, and 95%-100%.

Cycle	Date of Max PWV [mm]	Max PWV [mm]	RH [%] when Max PWV	Keyword of Weather downtime declared	Duration of the downtime (hrs)
5	2017-10-13 03:56:09	15.52	27.5	High winds	-
6	2019-01-27 17:41:11	17.55	66.7	Bad weather and Precipitation	18.2
7	2020-01-23 08:10:16	18.78	99.9	Bad weather and snow	4.6
8	2021-12-20 01:31:21	8.26	62.8	Snow	3.78

Table 14: Show the date when the maximum PWV was registered, with its corresponding relative humidity and the weather downtime reason declared. The duration of the downtime is presented only for bad weather, precipitation, and snow keywords.

Also, the amount of weather downtimes due to snow depending on the relative humidity during cycle 8 is presented in Figure VII. Unlike precipitation, in this case, we can observe a higher amount of weather downtimes related to snow when the relative humidity is in the range of 90% - 95%. Unfortunately, in this case, the description of the shiftlog entry did not always give a specific cause of the atmospheric phenomena. Even when snow is identified, some cases describe frost in the antennas, which is described as “icing”, terminology not appropriate to describe the atmospheric condition observed, as it makes reference to a different phenomenon.

The lack of instruments to measure precipitation or snow, make it difficult to obtain the real duration of the event. Based only on the shiftlog entries to declare the weather downtimes, is not enough to understand the impact of the event on the operations, as the description can be descriptive but not accurate as *“no projects to observe”* or *“after foggy night and after sunrise ice on dish was evident then now all point to the sun”* as was identified in the subject entry for the cycle 7 event presented in Table 14.

Further investigation needs to be done to identify the impact of the precipitation events in the AOS and the accurate downtime duration, its relation with PWV, and Relative humidity to improve the operations protocol.

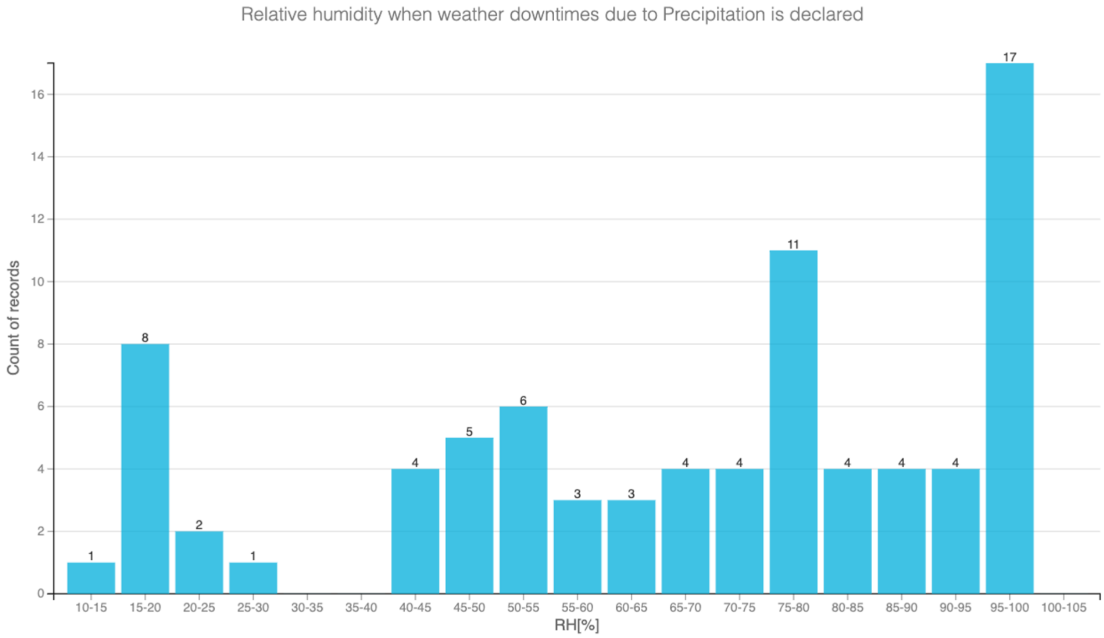

Figure VI: Amount of weather downtimes due to precipitation during cycle 8, depending on the relative humidity registered when the downtime was declared.

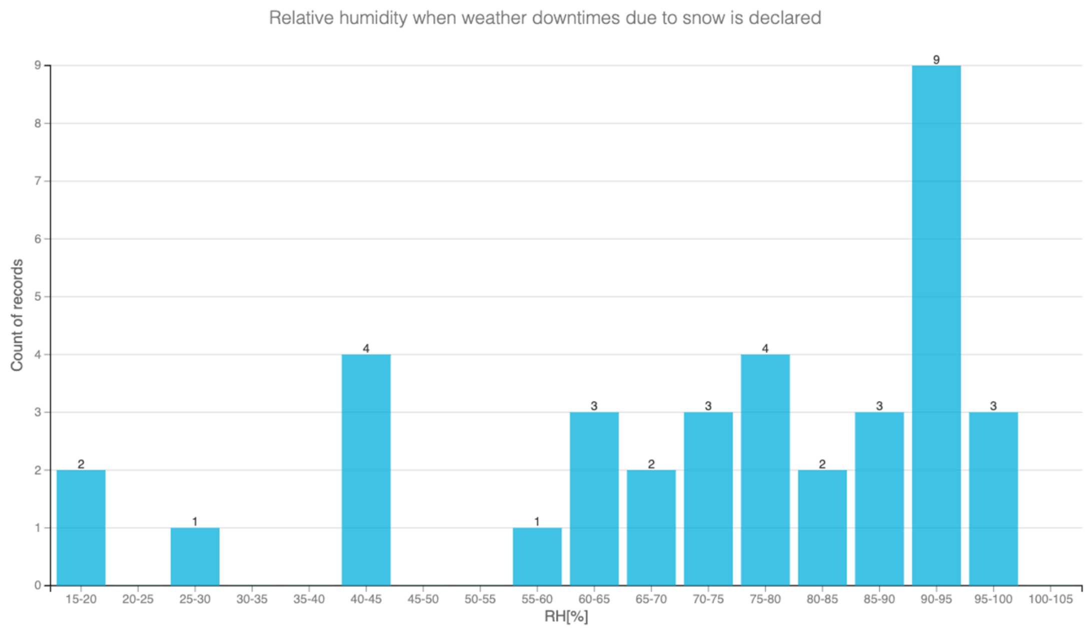

Figure VII: Amount of weather downtimes due to snow during cycle 8, depending on the relative humidity registered when the downtime was declared. In this case, the description of the shiftlog entry does not always give a specific cause of the atmospheric phenomena (snow or frost).

7.1.1.4 Band 1

The components that could potentially be overcome partially by band 1 receivers available for PI science observations are the tags corresponding to "pwv", "phase", and "not suitable for b3". This sums a total of ~91 [hrs] in the 12 [m] array, ~17 [hrs] in the 7 [m] array, and ~11 [hrs] in Total Power array. The "Other" classification tag could also provide potentially some additional time.

The limitations we have now on characterizing the marginal weather conditions leave our analysis with a significant uncertainty about the impact of band 1 availability on QA0 Pass science data acquisition. This would be great to overcome these limitations in order to know how relevant band 1 would be in terms of increasing the efficiency in the observatory. This analysis is not only concerning to the weather downtime component, but also to misclassified scheduling downtimes and QA0 Fail or QA0 Semi-Pass executions due to marginal weather conditions (that is the Fail component in the ALMA resource-based KPI waterfall schema - see section 5).

7.1.2 Discussion

Regarding the limitations we currently have in terms of recording the weather downtime characterization, and the validation of these records, the following points appear relevant for the discussion about how to improve this characterization.

7.1.2.1 New required policies for weather downtime characterization

1. In order to improve the recording of the Weather Downtime characterization, it should be mandatory to use a well-delimited number of tags for each weather downtime event, when the weather downtime entry is created. In this way we avoid the use of vague words or random sentences that do not follow any clear rule, making it difficult to characterize any Weather Downtime event. The different tags should cover the different kinds of possible weather events or actions required after the weather event. The suggested tags could be:

    - High phase (not suitable or marginal even for band 3)
    - High pwv (not suitable or marginal even for band 3)
    - High wind speed (VIR/non VIR)
    - Rain (VIR/non VIR)
    - Snow (VIR/non VIR)
    - Frost (VIR/non VIR)
    - Too low temperature
    - Ongoing recovery after VIR due to high wind
    - Ongoing recovery after VIR due to rain
    - Ongoing recovery after VIR due to snow
    - Ongoing recovery after VIR due to frost
    - Waiting for VIR after the end of high wind conditions
    - Waiting for VIR after the end of precipitation/snow/frost conditions

2. This should be included in the procedure explicitly to separate the weather downtimes entries for each kind of event characterized by the tags defined in the previous point (1.). So, we should avoid using the same Weather Downtime entry for different weather event characterizations, following the granularity described in point 1.

3. This needs to be discussed, between all the relevant stakeholders, a detailed procedure about when should be declared the start of the weather recovery time (the start of the Visual Inspection), who is responsible to declare it, and how is this properly recorded. This procedure needs to be improved as at this time it is not reliable at all.

4. Also, this needs to be discussed between relevant stakeholders about the need of recording the time between the end of a weather event like high wind and the start of the recovery after VIR. Actually, possibly this is only available to be fully implemented for the wind, as we have the weather stations monitoring the wind potentially covering 24 [hrs] and 365 days of a year. But, this is not the case for precipitation (see the discussion below).

7.1.2.2 Automatic monitoring of the weather conditions

It would be desirable to validate the different Weather Downtime entries with the different weather station monitoring points + antenna WVR measurements + antenna phase rms measurements. In fact, it would be great to use all this information to automatize the Weather Downtime Characterization (like it was mentioned in the previous point 4.). However, in addition to the fact that some work is still needed in terms of preparation and consolidation of the data sources to be used, there are also some limitations, especially in the case of precipitations both liquid and solid.

The use of the SLT as a reference for weather downtime characterization has its cons side, as the weather downtime entries are declared and edited manually usually asynchronously, so that the AO have to discriminate the affected families and the specific triggered weather condition while after the event have started. This could results in inaccurate logging .This would be much more sense that a weather station server take care on triggering the different alarms about the different weather conditions and they are properly recorded to be used on the weather downtime characterization. The development of this system would result in a great improvement on the characterization of the weather conditions. Currently we should explore the current weatherStation-server to provide these alarms to be used as an starting point for weather downtime characterization automation.

The case of precipitation: Actually, using the current procedures, precipitation monitoring, depends on the guards and the visualization by cameras. The guards are not always available for monitoring the conditions at AOS, and the cameras are not always a good way to determine the real conditions at AOS, especially during nighttime. On the other hand, the evaluation of the conditions is more qualitative than quantitative in terms of the amount of water or snow accumulation, as we do not have the instruments needed in order to get a reliable measurement of the amount of precipitation. This is a weakness of the current procedure used for Weather Downtime due to precipitation and could be improved significantly by having reliable instruments for precipitation and snow accumulation measurements.

Additionally, as suggested before some important work needs to be done in order to consolidate the data sources to be used for weather condition monitoring, as well as long-term studies about weather patterns at AOS.

7.1.2.3 Weather year-to-year variability, in terms of El Niño-Southern Oscillation (ENSO) climate pattern

According to McPhaden et al. 2006[3], El Niño-Southern Oscillation or ENSO is the cycle in which the sea surface temperature (SST) is unusually warm (El Niño) or cold (La Niña) in a period of 2 to 7 years, affecting winds and precipitation in western and eastern Pacific.

Main weather downtimes are due to wind or precipitation, which corresponds to the atmospheric behavior in the altiplano. During South hemisphere winter (June, July, and August), the altiplano exhibits high wind speed mainly due to the dry/cold westerly winds coming from the Pacific Ocean. Meanwhile, during the southern hemisphere summer (December, January, and February), the altiplano is influenced by the warm/wet easterly winds coming from the Amazonian basin, favoring the increment of water vapor content in the atmosphere (Garreaud et al. 2001[4], 2003[5]).

Precipitation occurs when the water vapor content is high in the atmosphere. The type of precipitation, liquid (rain) or solid (snow), will depend on the air temperature. When the temperatures are below the water freezing point (0 C in 5000m), the probability of snow increases; meanwhile, when temperatures are over 0 C, the probability of rain increases.

The National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Center (CPC) defines the Oceanic Niño Index (ONI[6]) to identify the SST anomalies in a specific tropical Pacific Ocean region called Niño 3.4 (5N-5S, 170W-120W) by using a 3-month running mean. If the anomalies exceed ± 0.5 C in a five months period, the event is classified as La Niña (cold) or El Niño (warm).

The daily mean wind speed and the daily mean precipitable water vapor content from 2017 to 2022 are presented in Figure VIII and Figure IX, respectively. Figure VIII shows that the wind speed increases during the La Niña period, getting higher values when the La Niña pattern is maintained for several years. The current La Niña period began in 2019, decreasing the SST by three years in a row[7], which enhances the heat absorbed by the ocean, translated into decreasing the air temperature and the humidity. As we can observe in Figure IX, the water vapor content decreases in La Niña periods and increases during El Niño, which means that weather downtimes are closely related to ENSO.

Further investigation needs to be done to improve operations based on ENSO patterns, thinking primarily of extended configurations and periods of high-frequency observations per cycle. The high variability of atmospheric conditions due to the El Niño and La Niña events would provide a variable range of observation time to offer to the scientific community. For this reason, it is necessary to understand how ENSO has historically affected the Chajnantor Plain, looking for large ENSO events that have occurred in the past in order to have an idea of what atmospheric conditions could be expected for the future, always taking into account the intensity of these events due to the current climate crisis.

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[3] McPhaden, Michael J., Stephen E. Zebiak, and Michael H. Glantz. "ENSO as an integrating concept in earth science." science 314.5806 (2006): 1740-1745.

[4] Garreaud, RenéD, and Patricio Aceituno. "Interannual rainfall variability over the South American Altiplano." Journal of climate 14.12 (2001): 2779-2789.

[5] Garreaud, René, Mathias Vuille, and Amy C. Clement. "The climate of the Altiplano: observed current conditions and mechanisms of past changes." Palaeogeography, palaeoclimatology, palaeoecology 194.1-3 (2003): 5-22.

[6] https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php

[7] Jones, Nicola. "Rare 'triple' La Niña climate event looks likely-what does the future hold?." Nature 607.7917 (2022): 21.

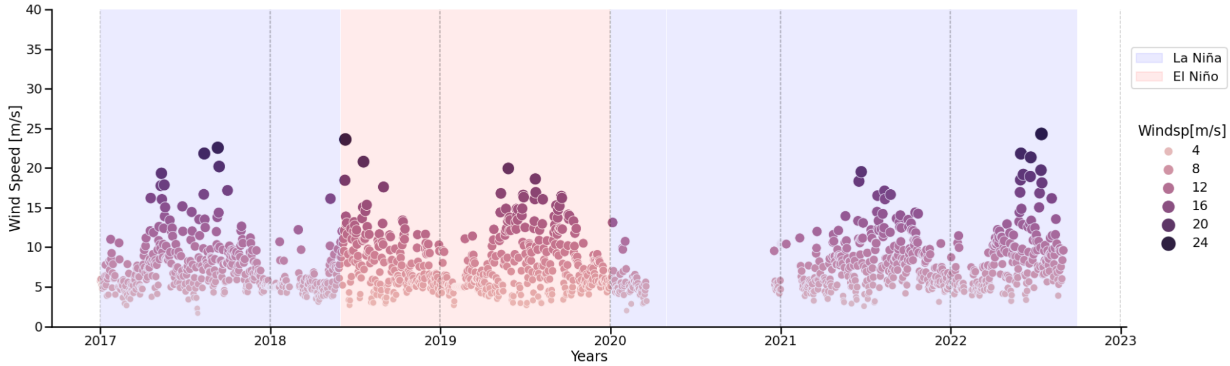

Figure VIII: The figure shows the evolution of the daily mean wind speed since 2017 (cycle 5) to 2022 (cycle 8), compared with the years defined as La Niña(blue) and El Niño (red).

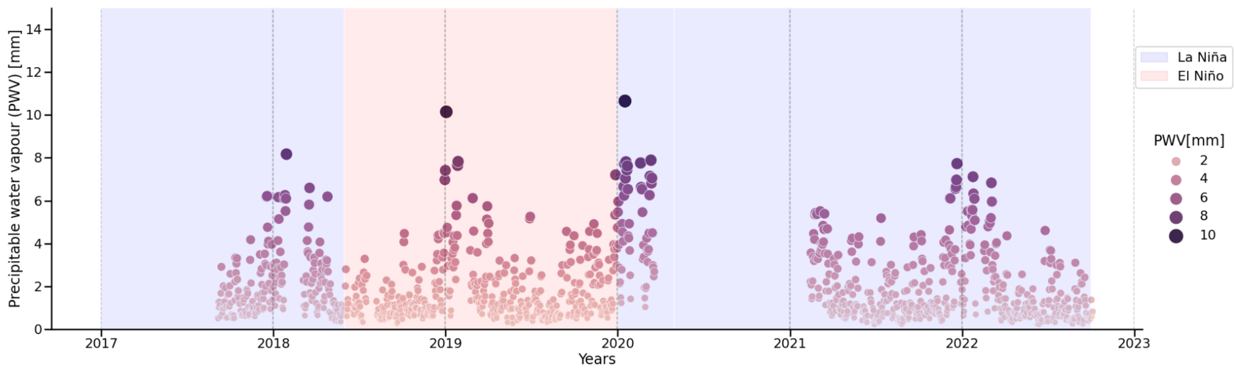

Figure IX: The figure shows the evolution of the daily mean Precipitable water vapor content from 2017 (cycle 5) to 2022 (cycle 8), compared with the years defined as La Niña (blue) and El Niño (red).

7.1.2.4 Other recommendations

- Due to the great intra-annual variability of ENSO, it is recommended to establish a time range to offer to the scientific community, based on the fact that there are years, such as cycle 8, with higher wind events over 30 m/s. It is also necessary to take into account the impact that the climate crisis will have in the coming years, so it is also proposed to generate climate projections.
- In order to establish a criterion regarding precipitation, it is fundamental to complement the existing instrumentation.
- It is recommended to establish a protocol where the meteorological stations continue working, even when there are shutdown periods, to obtain a detailed historical compilation of the atmospheric conditions in the AOS. For this reason, it is also recommended to keep a set of radiometers working in engineering or computing times or any shutdown period and to recover instruments that are not in use, such as the oxygen sounder that provides detailed information about the water vapor in the atmospheric column.
- It is recommended to dedicate more time to meteorological and climatic research to obtain the best schedules to share with engineering and computing and the optimal months to observe, prioritizing the times of lower water vapor and wind for high frequency and long baseline observations.

- For this, it is also recommended to dedicate more time to work on weather forecasts dedicated to ALMA, based on specific forecasting models such as Weather Research & Forecasting Model (WRF) or machine learning algorithms, especially for Phase RMS.
- It is proposed to train AoDs, operators, and safety to instruct them on recurrent atmospheric events at the AOS, seeking to improve problem-solving, both during the observation and in the field.

7.2 Technical downtime characterization

A technical downtime is recorded in the Shift log Tool and declared as an entry every time we have a technical issue in the system that does not allow us to continue with PI science observations in a given array family (12m, 7m and/or Total Power) during science operations. This includes:

- Activities are suspended or failed by technical issues
- Activities are suspended to investigate or solve technical issues

Currently, and for allowing technical downtime analysis based on the ALMA KPI Dashboard by Engineering ([AD03]), it is necessary that each technical downtime includes a PRTSPR jira ticket associated with the corresponding SLT entry. If the issue requires an investigation, it should be linked to a new or existing PRTSIR jira ticket, where the Subsystem/HW component associated with the problem should be properly determined and recorded. In case a software component is associated with the cause of the issue, it should be linked to an ICT jira ticket.

If the issue reported by a PRTSPR ticket does not require an investigation or is not associated with any investigation, in some cases is declared "For Statistics", and is classified as an operational issue. One example is when the number of antennas is below the blocker number for PI science, another example is when we have a human error when the AoD runs a project SB in a band that was not turned on previously in any of the used antennas in the array.

7.2.1 Analysis

7.2.1.1 Preliminary analysis

We tried a preliminary characterization of the technical downtime by using keywords found in the sentences included in the "Subject" of the technical downtime entries in the SLT as well as the title of the JIRA tickets associated with those entries, in a similar way as it was done with the weather downtime in the previous chapter. The used tags associated with those specific keywords are: "power cut", (antenna) "below the blocker" (number), "correlator", "antenna issue", "AOS TB fire detection", "array recreation", "hilse", "cloud sat", "end of shift", "cai map setting", and "Other"

At the same time we used the classification used by engineering for the KPI dashboard to validate the previous characterization tags (obtained with specific keywords) and from this classification, we added those downtimes associated to correlator hardware component to the "correlator" tag; and also those component associated to the antenna hardware like Front End or Back End were added to the "antenna issue" tag.

Below in the Table 15, Table 16, and Table 17 we show the total time duration of each characterization tag component for the technical downtimes in the 12m array, 7m array and Total Power array, respectively. In the tables is also included the number of events (number of technical downtimes entries created).

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
12 [m]	Other	111.93	296
12 [m]	power cut	98.55	16
12 [m]	correlator	94.27	74
12 [m]	antenna issue	85.25	239
12 [m]	below the blocker	67.23	20
12 [m]	AOS TB fire detection	54.00	3
12 [m]	array recreation	9.63	46
12 [m]	hilse	8.65	9
12 [m]	cloudsat	3.68	7
12 [m]	end of shift	2.64	4

Table 15: Technical downtime characterization for the 12m array using keywords from the technical downtime entry summary and PRTSPR ticket title associated.

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
7 [m]	correlator	1086.25	388
7 [m]	antenna issue	167.45	40
7 [m]	Other	124.61	154
7 [m]	AOS TB fire detection	54.00	3
7 [m]	below the blocker	50.70	12
7 [m]	power cut	44.48	8
7 [m]	cai map setting	6.07	16
7 [m]	hilse	5.73	6
7 [m]	cloudsat	2.80	6
7 [m]	array recreation	1.07	8
7 [m]	end of shift	0.80	2

Table 16: Technical downtime characterization for the 7m array using keywords from the technical downtime entry summary and PRTSPR ticket title associated.

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
Total Power	correlator	1232.51	248
Total Power	Other	90.36	85
Total Power	antenna issue	56.61	20
Total Power	AOS TB fire detection	54.00	3
Total Power	power cut	15.16	4
Total Power	cai map setting	12.02	19
Total Power	cloudsat	1.72	4
Total Power	below the blocker	0.67	1
Total Power	array recreation	0.40	2

Table 17: Technical downtime characterization for the 12m array using keywords from the technical downtime entry summary and PRTSPR ticket title associated.

Regardless of its limitations, this preliminary analysis shows us clearly that the correlator issues in the ACA correlator dominates the technical downtimes affecting the 7m and Total Power array families. In order to improve the efficiency of these two arrays, it is clear that the efforts should be focused on solving or overcoming this limitation. For example, the ACASPEC in the future could help in some way with the Total Power observations, and the alternative of using the BLC for 7m observations could be also another way to overcome these limitations in the 7m array family.

In the case of the 12m array family, it seems to be that "power cut", "correlator", and "antenna issue" are more or less equally distributed and seem to be the more important components when ignoring the "Other" tag. This "Other" tag includes all the downtimes that could not be successfully associated to any of the other used tags, as the description in the "Subject" or associated jira ticket title is not including keywords covered in our analysis, as they do not show an usual pattern or is not clear at all. Additionally, these entries can be grouped in the following cases:

1. The downtime is not associated with any ticket, or investigation report or ICT.
2. Or the associated tickets are not linked to any specific component by engineering (by using the KPI dashboard characterization approach).
3. Or the associated component in the KPI dashboard characterization approach is not covered within our used tags: This case is dominated by the called "Operational" downtimes associated with the "For Statistics" jira tickets, and specifically the sub-classification "Other", that include several different reasons that are not really well characterized neither considered any accountability approach. Some examples here are: "SCO sanitization downtime", or "APE2: Trouble shootting of ACA specs issues" or "APE2: containers crashed by mistake".

In order of relevance points 1 and 2 together are dominant by far between those downtimes within the "Other" tag. Then, followed by point 3. This behavior is the same for the three array families.

7.2.1.2 Current limitations

The classification of the technical downtimes in the previous analysis show several limitations. In the current conditions, these limitations could affect in general any intent of trying a systematic classification that takes into account different levels of the required granularity. We will mention some of them here:

- Some of the used sentences in the subject of the downtime entries are not following any rule. Therefore, there is not a clear pattern in the used sentences, which result in the non-uniform use of words that could potentially be taken as keywords. At the end, this results in a non-clean neither optimal way to classify the different technical downtimes.
- The titles used for the PRTSPR jira tickets suffer the same problem.
- The engineering KPI dashboard approach for characterizing the technical downtime:
  - Is not always aligned with science operation needs of aiming to explain the reason why we are not running PI science; but it is more focused on a specific Hardware/Software component problem.
  - The operational downtimes (especially those "For Statistics"), are not clearly defined in terms of assigning accountability to a specific group or subsystem.
  - Some technical downtimes do not have any PRTSPR ticket associated or have several, making this difficult to discriminate by this system which supersede others to explain the declared technical downtime.
- The flag for Power Cut in a Technical Downtime associated with this issue is not consistently used.
- When comparing both classifications approaches, one using the keywords and the other using the engineering KPI dashboard based on affected components, it is clear that some used keywords could be misleading. For example for the correlator, when you could have in the first instance a correlator declared problem by the AoD, but later in a deeper investigation result in a problem associated with the backend in a given antenna, or something in the software, or other components that crashed; so, this is clear that an initial tag used for characterizing this downtime at lower metrics levels (where you have more granularity) could be misleading, to answer the question at higher level. However, in our analysis, this effect seems to be marginal at least in the dominant components tags of the technical downtimes for each array family.

7.2.1.3 Big downtime events

Taking the longer ("big") technical downtime events as those with time duration longer than 8 hours, we got the total time duration of each characterization tag component (already used in the preliminary analysis in subsection 7.2.1.1) with this subset of technical downtimes. These times are characterized in the Table 18, Table 19, and Table 20 for the 12m array, 7m array and Total Power array, respectively.

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
12 [m]	power cut	68.35	5
12 [m]	AOS TB fire detection	54.00	3
12 [m]	correlator	47.97	2
12 [m]	below the blocker	43.76	3
	TOTAL	214.08	13

Table 18: Technical downtime characterization for the 12m array using keywords from the technical downtime entry summary and PRTSPR ticket title associated, using only the "big" technical downtime events (longer than 8 hrs).

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
7 [m]	correlator	758.86	41
7 [m]	antenna issue	131.23	8
7 [m]	AOS TB fire detection	54.00	3
7 [m]	below the blocker	38.21	2
7 [m]	power cut	24.00	1
7 [m]	Other	16.82	1
	TOTAL	1023.12	56

Table 19: Technical downtime characterization for the 7m array using keywords from the technical downtime entry summary and PRTSPR ticket title associated, using only the "big" technical downtime events (longer than 8 hrs).

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
Total Power	correlator	972.21	56
Total Power	AOS TB fire detection	54.00	3
Total Power	antenna issue	31.98	3
Total Power	Other	20.14	2
	TOTAL	1078.33	64

Table 20: Technical downtime characterization for the Total Power array using keywords from the technical downtime entry summary and PRTSPR ticket title associated, using only the "big" technical downtime events (longer than 8 hrs).

We can see that consistently with the previous overall analysis, the big events in the 7m and Total Power arrays, are again dominated by the ACA correlator problems we had along the cycle 8. The 12m array is more homogeneously distributed between different components, and ordered by dominance they are: "power cut", "AOS TB fire detection", BL "correlator", and (antennas) "below the blocker" (number).

In the 7m, the only big event tagged as "Other" seems to correspond to a weather downtime (wrongly set as technical downtime) that triggers a Visual Inspection. As no ticket is associated with this downtime entry, the only useful sentence to characterize this downtime is appearing in the subject; that is: "VIR due to wind speed > 30 m/s".

In the Total Power array, the two big events tagged as "Other" seems to correspond to ACA Corr+TP issues associated with PRTSPR tickets, but they are not linked to any investigation ticket. Here are the title of the PRTSPR tickets associated:

- "APE2: ACA_TP: No coherence in ACA_TP Array"
- "APE2:HANDOVER:ACA TP array: no pointing results"

7.2.2 Discussion

Several of the limitations in the different characterization approach we tried to use here are probably due to pending (and also in progress in some way) work about establishing the granularity of the information we will need at the different levels in the observatory to get the different metrics and associated KPIs to be used on these different levels; starting from the higher level metrics/KPIs.

7.2.2.1 Discussion about the granularity at high level metrics

We need a clear and well organized procedure (and probably also the tools) to classify the different technical downtime issues from an operational perspective. That is, having an accountable and operational approach to classify the different downtimes; by answering the question about why we are not running PI science when we are affected by a technical downtime, and who are the accountable groups or subsystems (for example in terms of lack of resources, or inappropriate procedures, or user mistakes, or malfunction of key hardware or software subsystems). The answer to the question about why we are not running PI science during science operations, could be approached from different perspectives; but in order to be aligned with ALMA primary goals we should account first to the efficiency of the use of the different ALMA resources at higher level metrics from a science operational perspective. One typical example could be when we lost one antenna for a specific hardware component that is failing, and then we go below the blocker of antennas. The answer to the question about why we are not running PI science, at a higher level, is not because of the fail of the specific hardware antenna component, but is something broader about the availability of array elements (antenna resources). So, in this case, it is more appropriate at a higher level (from an operational perspective) to characterize this downtime as we are running with antennas "below the blocker" number. This approach needs to be widely discussed between different groups including DSO, Engineering, and Software, in order to converge in a common view about the needed granularity taking into account this operational perspective that should be aligned in an optimal mode with the higher level ALMA KPI of "ALMA resources-based KPI".

The alignment on this perspective is not a simple task, as a single event could involve and/or impact several different areas not necessarily directly related to the event in question. For example, a correlator problem could involve issues affecting the Technical Building that impact the correlator like the HVAC system or malfunction of sensors, or another example could be the malfunction of a hardware component that could involve problems with the power or cable connections. So, probably a good classification at high level, very often could require first a deep analysis at lower level to understand all the different components involved in a single event (like it is done by KPI dashboard initiative by engineering), and then by having a clear map of hierarchy of all these components allowing to organize them in terms of an operational perspective, a proper classification at a high level could be done.

This instance, plus other initiatives followed within engineering (like the KPI dashboard initiative), need to be recognized within a more global context and interest within ALMA in order to build a consistent and reasonable view of the different used metrics/KPIs/goals within the different levels (departments /subsystems /groups), and aligned with the ALMA Observatory primordial objectives. This task should involve all the different groups in ALMA. First, we should know clearly what questions we would like to answer as ALMA Observatory at the different levels.

7.2.2.2 Other recommendations

In terms of technical downtime mitigation strategy, this may include the evaluation of the technical downtime from a science operation perspective, aligned with high level ALMA goals. And, starting from that analysis where the priorities are well established, each group and subsystem involved in the different aspects of these priorities, should evaluate possible actions to mitigate the number of hours of PI science lost by technical downtimes. This should not be the mandate of this instance to establish any specific mitigation action, but maybe this could be an instance to motivate a longer-term work involving different groups in ALMA to establish high level priorities in the observatory aligned with the observatory goals to increase the efficiency.

7.3 Scheduling downtime characterization

A scheduling downtime is recorded in the Shift log Tool and declared as an entry every time we do not have any PI science SB execution available to be executed in a given array family (12m, 7m and/or Total Power) during science operations, even when the current weather and technical conditions allow band 3 or higher frequency bands executions. So, this situation is declared due to a lack of available activity. This includes the following cases:

1. Although the array family is not set to weather/technical downtime, no PI projects appear on the scheduler even the current sky condition is suitable (in good, but not marginal conditions) for any Band 3 frequency (30 rms frequency > 120 GHz in the DSA) or higher Bands. Also, any EOC, calibration, or antenna integration activities are unavailable.
2. Idle time is required to optimize the scheduling of science operations, e.g., waiting to start a time-constrained project or waiting while the polarization calibrator and/or the target source goes through zenith in a polarization project running in session.
3. If we have idle time at the end of a shift, as we do not have time enough to complete any observation, we need to set scheduling downtime for that.
4. We are waiting for resources from another array that is currently in use to continue with the observations, e.g., 7m array is waiting for Total Power antennas to be available and currently used in observations, required as support for HF observations in the 7m array.

7.3.1 Analysis

7.3.1.1 Preliminary results

We tried a preliminary characterization of the scheduling downtime by using keywords found in the sentences included in the "Subject" of the scheduling downtime entries in the SLT as well as the title of the JIRA tickets associated with those entries, in a similar way as it was done with the weather and technical downtimes in the previous chapters. The used tags associated with those specific keywords are: "no projects", "no project for b3", "end of shift", "waiting", "antenna issue", "pwv", "phase", and "Other".

Below in Table 21, Table 22, and Table 23 we show the total time duration of each characterization tag component for the scheduling downtimes in the 12m array, 7m array and Total Power array, respectively. In the tables is also included the number of events (number of scheduling downtimes entries created).

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
12 [m]	no project	124.98	138
12 [m]	end of shift	9.90	33
12 [m]	no project for b3	6.80	5
12 [m]	Other	5.77	9
12 [m]	waiting	2.66	8
12 [m]	antenna issue	0.36	2
12 [m]	phase	0.21	1

Table 21: Scheduling downtime characterization for the 12m array using keywords from the scheduling downtime entry summary and PRTSPR ticket title associated.

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
7 [m]	no project	92.02	60
7 [m]	end of shift	7.22	28
7 [m]	Other	4.21	2
7 [m]	antenna issue	2.39	4
7 [m]	waiting	1.69	4
7 [m]	pwv	0.32	1

Table 22: Scheduling downtime characterization for the 7m array using keywords from the scheduling downtime entry summary and PRTSPR ticket title associated.

FAMILY AFFECTED	TAG	TIME DURATION [hrs]	Number of events
Total Power	no project	194.39	91
Total Power	Other	8.33	7
Total Power	end of shift	3.92	14
Total Power	antenna issue	1.59	2

Table 23: Scheduling downtime characterization for the Total Power array using keywords from the scheduling downtime entry summary and PRTSPR ticket title associated.

From the previous results we can see that the tag called "no project" is the one that dominate by far in three the array families. In principle, this tag should correspond to the first case pointed before (1.) to declare scheduling downtime; this is a lack of SB projects in that period of time available in the DSA scheduler gui to be executed even in the lower frequency bands. In marginal weather conditions for band 3 observations, this could be confusing to distinguish between scheduling downtime and weather downtime; that is why the criteria of scheduling downtime should be based in the information given by the DSA scheduling gui; that is not only based on the SB project availability but also in the weather conditions stated as a recommendation by the DSA scheduling gui in terms of the maximum limit of the observing frequency limit allowed to run PI science projects. At this time, the procedure of declaring scheduling downtime is manual, and depend on the AoD/AO on shift. And by the moment this have not been possible to validate the declared entries with the information displayed by the DSA scheduler gui, at the time the downtime was declared. A future validation procedure would be desirable, to avoid misinterpretation of the conditions to declare scheduling downtime, specially when we are running in marginal weather conditions.

7.3.1.2 Current limitations and scheduling downtime entry validation

The characterization of the scheduling downtime at this time is also done manually by including a comment in the "Subject" of the downtime entry, and/or linking to a "For Statistics" PRTSPR jira ticket. So, this is sensible to any misinterpretation about the reason to declare a scheduling downtime, or suitable to be affected by mistyping error at the time of including comments, or by the use of random sentences in the "Subject" or title of the jira tickets associated to the downtime. We can see in this characterization analysis some used tags that do not correspond to scheduling downtimes, like "antenna issue", "pwv", or "phase". Although those tags are not significant in the statistics for scheduling downtimes, the fact they are there, shows us how the scheduling downtime characterization procedure is not mature enough and is susceptible to errors, in a similar way as it is also for the other downtimes.

The "Other" tag, include scheduling downtime entries that do not include any useful information to be characterized or again include mistyping in the used words or unclear/misleading sentences. Some example are: "No project to observe", "Weather Down time", "DV13 failed", "Scheduling", etc…

Considering these limitations it could desirable an improved procedure how are declared and characterized these downtime entries, and if possible to include validation tools within the procedure such as the involvement the DSA scheduling gui.

7.3.2 Discussion

7.3.2.1 DSA scheduling monitoring for scheduling downtime validation

In general, it seems to be that at this time the DSA scheduling gui is the more reliable tools to be used for monitoring and validation of the scheduling downtimes, as includes most (or all) of the information required for the more relevant component of the declared scheduling downtimes, corresponding to the lack of SB projects in that period of time available in this tool to be executed even in the lower frequency bands. So, by having a record of the DSA scheduling gui searches results, collecting all the relevant information, would be a great opportunity to contrast this information with the scheduling downtime entries declared by this reason. Also, the DSA scheduling gui, could be useful directly to suggest a scheduling downtime when it is required, as well as, go/nogo observations for monitoring the weather conditions, information that is key to declare and discriminate between the scheduling and weather downtimes, specially in the case of marginal weather conditions.

7.3.2.2 Other recommendations

At the level of SLT record it is also needed to organize in a better way the classification of the scheduling downtimes by including a limited number of tags to be used for the characterization; in the same way it was suggested for the weather downtime. This basically should include the cases described at the beginning of this section:

- No projects available even under good band 3 weather conditions
- Waiting to optimize the scheduling of a science projects
- Idle time at the end of a shift, as we do not have enough time to run any science project.
- Waiting for resources from another array that is currently in use

In terms of scheduling downtime mitigation strategy, this will require by sure a more deeper investigation and control of the declared events in order to establish if there is any fine tuning needed on the queue building process, or if really this is an issue that by construction is affecting the scheduling of projects; for example when we have too low amount of project applying for ALMA time at some specific LST range. However, this is part of each group and subsystem related to scheduling of PI science project to evaluate this situation and found the best solution taking into account many several details that are not in the scope and purpose of this investigation.

8 Final discussion and conclusions

8.1 General recommendations

To promote this long-term pending work we recommend creating a longer-term working group in order to get basic definitions on the different downtimes, as well as procedures and high level granularity characterization. This consequently could lead to sub-system requirements for different tools (like SLT, KPI dashboard initiative, etc…) as well as new policies for operations. The future development of these related tools should primary be oriented to respond to the higher-level ALMA KPIs perspective.

Additionally, from this analysis, it is clear that, this is very important to give some priority to work on consolidating the different data sources used in the different aspects to characterize the downtimes. This work could require establishing the ownership on the data sources where it is not clear yet, as well as the automation, and refinement on the procedures to increase the quality of the collected data to characterize the different downtimes entries. This could be also a coordinated work within a second group within a longer-term initiative, including different stakeholder in order to build database oriented within the data science initiative, to produce useful and centralized data sources that will respond to all the requirements of the different groups, but also organized and aligned with the higher level ALMA objectives and KPIs, like the resource-based KPI metrics.

In terms of mitigation strategy, this should include a previous work to improve the classification schema of the different downtimes. Starting from this improved schema where the priorities are well established, this should be part of each group and subsystem related to evaluate possible actions to mitigate the number of hours of PI science lost by the different downtimes already well characterized. This should not be the mandate of this work to establish any specific mitigation action, but maybe this could be an instance to motivate a longer-term work involving different groups in ALMA to establish high level priorities in the observatory aligned with the observatory goals to increase the efficiency. In the next subsection we explore some possible actions just to inspire a future work on this.

8.2 More specific conclusion and recommendations

Below we summarize the different conclusions and recommendations from the more detailed analysis followed along each section:

8.2.1 QA0 Pass target critical analysis

- QA0 Pass target should be taken more like a desirable goal approach but not as part of a high-level KPI, as it involves some elements that are out of our control and predictability like weather conditions and social disruptions events like pandemia or social outburst.
- As a high-level metric within the ALMA resource-based KPI, we should try to use something like TEA corrected by weather downtime. And at low-level the percentage of some components of the operations with respect to the total time, and some other components of the science operations with respect to the total allocated time minus weather downtimes.
- This group recommends a new QA0 Pass target goal of 4000 hrs, with 4300 hrs as a stretch goal.
- The recommended level 0 ALMA resource-base KPI should be the TEA corrected by weather downtime with a target of 53%.
- The main reasons preventing us to reach the 4300 hrs target were the weather conditions, the resource availability due to technical time, and engineering technical downtimes.

8.2.2 Weather downtime

- High wind speed conditions were a very relevant component of the weather downtime during Cycle 8. This is especially important for the Total Power array. In this context, the adapted policy that increases the wind speed limit from 15 m/s to 16 m/s in the Total Power array could have a relevant impact on the amount of weather downtime in the Total Power array, increasing the overall efficiency in this array.
- The precipitation as liquid and solid was the dominant weather downtime component in the 12m and 7m array, with a significant part corresponding to big weather downtimes events with a duration longer than 12 hours. These downtimes duration are suitable to be affected by triggering of Visual Inspections.
- The fact, that we do not have reliable measurements for these events, makes the current procedure to declare these weather downtimes and establish the trigger for Visual Inspection susceptible to big uncertainties.
- We recommend the use of instruments to collect measurements for the precipitation, and snow accumulation since they allow us to implement new policies for weather downtime declaration, allowing a better tunning in the procedures to determine, for example, when it really needed to trigger a visual inspection.
- In the short term, we recommend implementing the new policies based on the proposed granularity (Subsection 7.1.2.1) for the logging of the weather downtime to improve its characterization. This will help to improve the uncertainties coming from the current logging procedure that is neither systematic nor well organized.
- We recommend developing a weather station service that centralize all the weather monitoring points and activates/deactivates the alarms for weather conditions-related protocols that affect the use of the different observatory resources.
- This weather station service would have a key role in automating the weather downtime characterization, overcoming several of the difficulties we have now in getting the granularity required for these events.

8.2.3 Technical downtime

- Technical downtime suffer seriously of a problem of lack of information, and a systematic structure in order to be characterized in terms of the effect on the availavility of the main resources during science operations.
- We recommend a working group for "operational technical downtime characterization with accountability", including different stakeholders, to start with a first approach based on the ALMA resource-based KPI perspective.
- This working group should converge in a clear and well structured operational characterization flow, opening the way to answer the question about why we are not running PI science during these downtimes, who they are the related accountable groups or subsystems.
- Regardless of the current limitations, the analysis on technical downtime shows clearly how the ACA correlator was the dominant component of technical downtime affecting the 7m and Total Power arrays during cycle 8.
- In the 12m array, there seems to be several components affecting in similar way in term of significance. Therefore the "power cut" do not seems to be a dominant component, but a relevant one between others like "correlator", or "antenna issues".

- Big (long duration) events are mainly associated to "power cut", BL "correlator" issues, and "Technical Building at AOS issues" components. They have a relevant incidence in the total downtime, so this is desirable to minimize these big (long duration) events.

8.2.4 Scheduling downtime

- The scheduling downtime seems to be dominated by far with the case when we lack of available projects even under good band 3 weather conditions.
- The current procedure for the scheduling downtime characterization suffers of similar limitations as others downtimes, so it is needed to define a better procedure.
- We recommend a well delimited use of fixed tags (or keywords) for each specific case of scheduling downtime.
- Also we recommend the use of tools like the DSA scheduling GUI to suggest and discriminate scheduling downtimes due to lack of available projects to be observed in a given period from weather downtimes due to marginal weather conditions for band 3.
- Additionally we recommend to use the DSA scheduling gui for monitoring the scheduling conditions in order to evaluate and validate declared scheduling downtime entries.