International Civil Aviation Organization

Thirteenth Meeting of the Air Traffic Management Sub-Group (ATM/SG/13) of APANPIRG

Singapore, 25 – 29 August 2025

Agenda Item 3: Performance Frameworks and Metrics

PROGRESS OF THE APAC DATA ANALYTICS GROUP

(Presented by Singapore on behalf of Australia, China, Hong Kong China, India, Indonesia, Japan, Papua New Guinea, Philippines, Republic of Korea, Singapore, Sri Lanka, Thailand, United States and Viet Nam)

SUMMARY

This paper informs the Meeting on the progress made by the Data Analytics Group (DAG). To date, the DAG had commenced data sharing and analysis for eight Key Performance Indicators (KPIs) under the Global Air Navigation Plan (GANP). In this second report, DAG has progressed from an initial three-month interim analysis to a comprehensive one-year analysis, increased participation from States and improved data quality. Building on this foundation, DAG is now expanding its scope to include three additional GANP KPIs: Additional Time in Terminal Airspace (KPI08), Airport Throughput Efficiency (KPI11), and Additional Fuel Burn (KPI16). This progression demonstrates the region's growing capability in performance measurement and data analytics, and commitment to implementing more advanced performance metrics to have better insight of ATM performance to support management and operational decisions.

1. INTRODUCTION

1.1 The Global ATM Operational Concept (Doc 9854) envisaged a performance-based global air navigation system. Accordingly, ICAO published the Manual on Air Traffic Management System Requirements (Doc 9882) and the Manual on Global Performance of the Air Navigation System (Doc 9883). To complement the guidance in Doc 9883 on performance-based approach (PBA) to ATM, the Global Air Navigation Plan (GANP, Doc 9750) included a segment on key performance indicators (KPIs) for consideration by States to facilitate the PBA.

1.2 Using PBA for management and operational prioritisation in the implementation of ATM initiatives can provide States/Administrations a data-driven and scientific approach to achieve their performance objectives. To advance the adoption of PBA in the Asia/Pacific (APAC) Region, the Regional ATM Performance Measurement Framework Small Working Group (RAPMF/SWG) was established at the third meeting of the ATM Subgroup (ATM/SG/3) in 2015 to develop the APAC Air Traffic Management Performance Measurement Framework (ATM/PMF). In 2019, the Thirtieth Meeting of the Asia/Pacific Air Navigation Planning and Implementation Regional Group (APANPIRG/30) endorsed the ATM/PMF. The ATM/PMF provides the stages of implementation for KPIs identified under the KPAs in the GANP and prescribes a step-by-step PBA to ensure that the region will develop data and performance management capabilities in a harmonized manner.

1.3 The Data Analytics Group (DAG) was officially formed at ATM/SG/11 to continue building on this foundation to expand harmonized reporting across the region that each State can contribute according to their own capabilities. The DAG had since convened six meetings, four online and two physical, to agree on key matters to kickstart performance benchmarking and improve ATM performance in the region.

2. COMPREHENSIVE ONE-YEAR PERFORMANCE REVIEW OF 8 BASIC KPIS

2.1 Building on the analysis conducted in 2024, DAG members have completed a comprehensive analysis using one year of performance data. In 2024, the analysis was conducted using three-month data to allow States to familiarise themselves with the process and kickstart data collation at a manageable scale. Following this successful initial phase and increased familiarity with the data collection and measurement process, the analysis was conducted with one-year data. The analysis focused on eight KPIs, as listed in **Table 1**, which align with stage one of the APANPIRG-endorsed ATM/PMF. A data collection guide outlining the definitions and calculation methodologies for each KPI can be found in **Appendix A**.

Table 1: 8 KPIs Reported by DAG

KPA	KPI	Variant	GANP KPI Code
Capacity	Airport peak capacity	Departure	KPI09-D
		Arrival	KPI09-A
Capacity	Airport peak throughput	Departure	KPI10-1D
		Arrival	KPI10-1A
Efficiency	Additional taxi-out time	Advanced	KPI02-2
Efficiency	Additional taxi-in time	Advanced	KPI13-2
Predictability	Departure punctuality	± 15 mins	KPI01-2A
Predictability	Arrival punctuality	± 15 mins	KPI14-2A

2.2 For countries with many airports, only the major airports by traffic count were included. The airports participating in this exercise can be found in **Table 2**.

Table 2: Airports Participating in this Interim Data Analysis Exercise

State/Administrations	Participating Aerodromes
Australia	Brisbane Airport **(YBBN)** Melbourne Airport **(YMML)** Perth Airport **(YPPH)** Sydney Kingsford Smith Airport **(YSSY)**
China	Guangzhou Baiyun International Airport **(ZGGG)** Shanghai Pudong International Airport **(ZSPD)**
Hong Kong China	Hong Kong International Airport **(VHHH)**
Indonesia	Jakarta Soekarno–Hatta International Airport **(WIII)**
Philippines	Ninoy Aquino International Airport **(RPLL)**
Singapore	Singapore Changi Airport **(WSSS)**
Thailand	Bangkok Suvarnabhumi International Airport **(VTBS)**
United States	New York JFK Airport **(KJFK)** Chicago O'Hare International Airport **(KORD)** Dallas Fort Worth International Airport **(KDFW)** Houston George Bush Intercontinental Airport **(KIAH)** San Francisco International Airport **(KSFO)** Los Angeles International Airport **(KLAX)**

2.3 Further analysis of the one-year data gathered for the eight KPIs are elaborated below.

Capacity

2.4 **Figure 1** and **Figure 2** show the airport peak capacity and airport peak throughput for arrival and departure respectively.

2.5 The airport peak throughput is calculated as the 95th percentile of the hourly number of operations recorded at an airport, while the airport peak capacity is determined based on various strategic and operational considerations. The arrival capacity of Hong Kong International Airport is determined by the required inter-arrival spacing under different modes of operation. By considering the aircraft fleet mix and the respective wake turbulence separation requirements, historic runway occupancy time of arrival and average approach speed, the hourly arrival capacity could be established.

2.6 It was observed that while majority of airports were operating below their peak capacities, Ninoy Aquino International Airport (RPLL) in Manila, Philippines was operating above the peak capacity. While the airport's official maximum throughput is set at 40 movements per hour—equally divided between 20 arrivals and 20 departures—actual aircraft movements have consistently exceeded this threshold. A 2016 study conducted by the University of the Philippines suggested the potential to increase capacity to 47-52 movements per hour, however, these recommendations were not implemented due to safety considerations. In response to this over-capacity situation, a joint memorandum between the Civil Aviation Authority of the Philippines (CAAP), Manila International Airport Authority (MIAA) and Civil Aeronautics Board (CAB) was issued to restrict general aviation and aerial works traffic at RPLL to manage the movement rates.

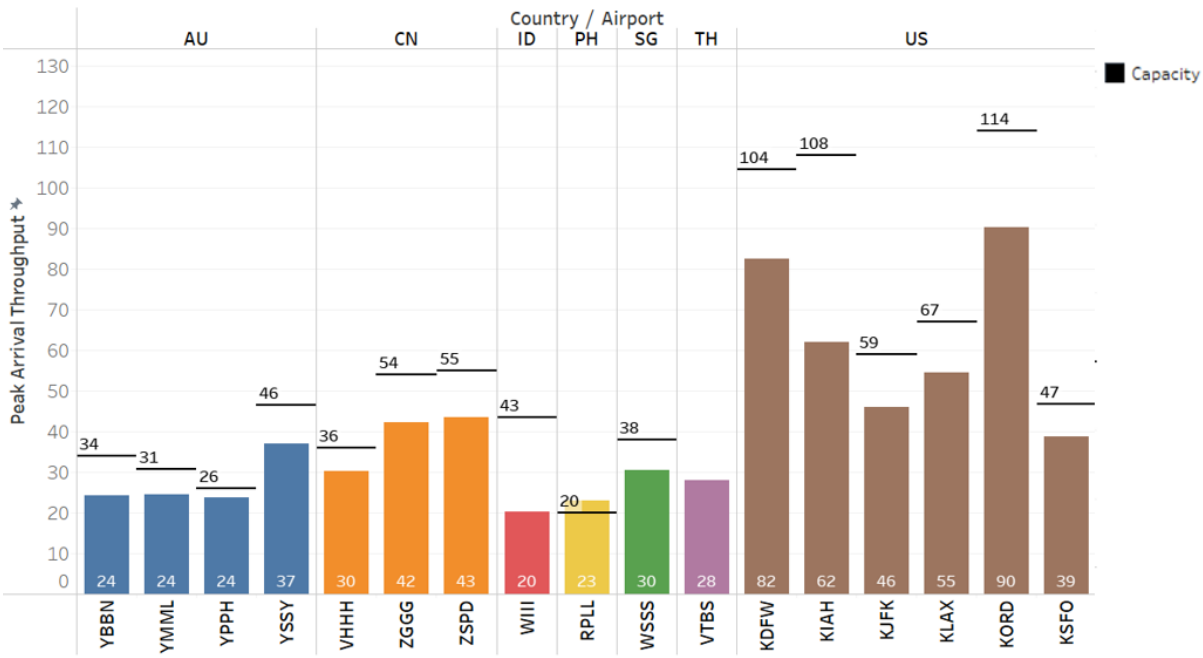

Figure 1: Arrival Capacities and Peak Arrival Throughputs (KPI09-A, KPI10-1A)

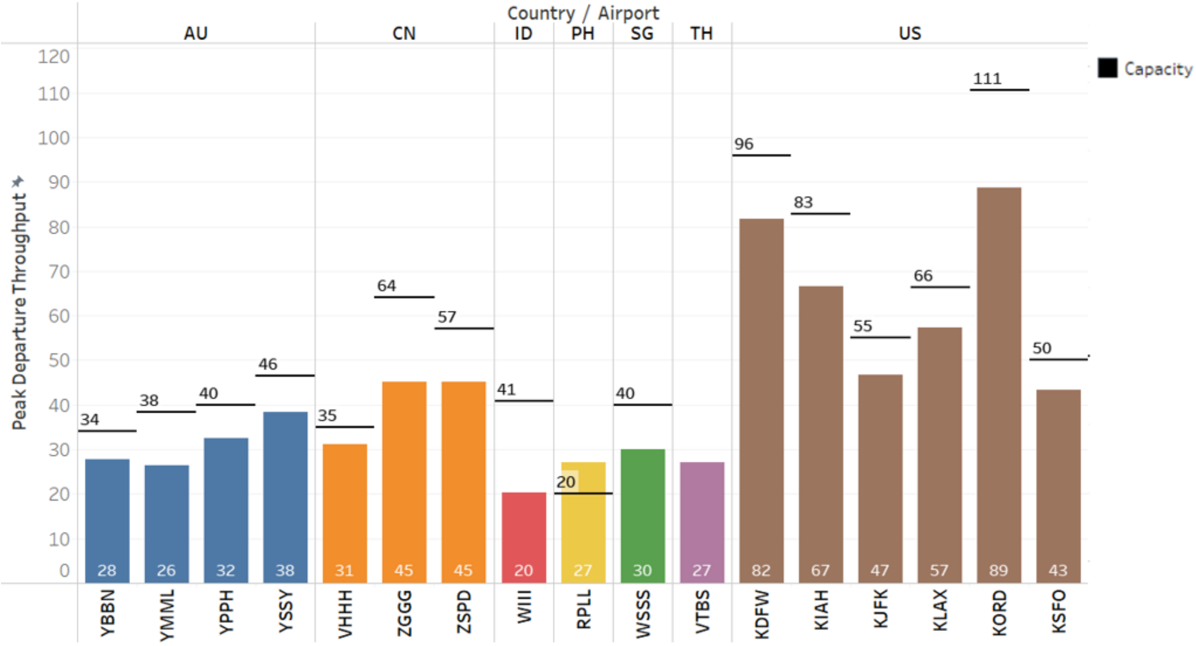

Figure 2: Departure Capacities and Peak Departure Throughputs (KPI09-D, KPI10-1D)

<u>Efficiency</u>

2.7 **Figure 3** and **Figure 4** show the average additional taxi time taken for arrival and departure respectively.

2.8 The charts include additional taxi time for both the advanced and basic variant. Basic variant assumes the same reference time for all flights, regardless of their gate and runway. Advanced variant, on the other hand, assumes that reference time is unique to each flight's gate and runway allocation. The DAG concurred on a preference to adopt the advanced variant for this KPI, as it provides more accurate assessment that accounts for varying distances between runway and gates and allows for a fairer comparison of additional taxi time taken for flights located at different gates.

2.9 The relationship between basic and advanced taxi time variants is complex and airport-specific. While the advanced variant offers more precise identification of surface constraints by considering specific gate-runway combinations, it can sometimes yield higher additional taxi times than the basic variant. This occurs when a significant proportion of flights have lower unimpeded taxi times based on gate-runway pairings than on the airport-wide averages. At Shanghai Pudong Airport, 66% of flights belonged to gate-runway pairings with unimpeded taxi times below the airport-wide unimpeded time. Since the advanced variant calculates additional time using these lower gate-runway unimpeded times rather than the higher airport-wide unimpeded time, it results in larger additional taxi times. This shows that the relationship between basic and advanced variants can vary depending on the airport's operational group distribution and their respective unimpeded taxi times.

2.10 Analysis of the data also shows that taxi-out times are generally longer than taxi-in times across all airports. This difference can be primarily attributed to departure queue management at runway holding points. During taxi-out, aircraft often need to join a sequence of departing traffic and may experience additional waiting time at holding points to maintain safe separation between successive departures. This queuing effect is less pronounced during taxi-in operations, where arriving aircraft typically proceed directly to their assigned gates with minimal holding, notwithstanding any gate availability issues. The additional buffer in taxi-out times also accounts for engine warm-up requirements and pre-departure checks that airlines need to perform before take-off.

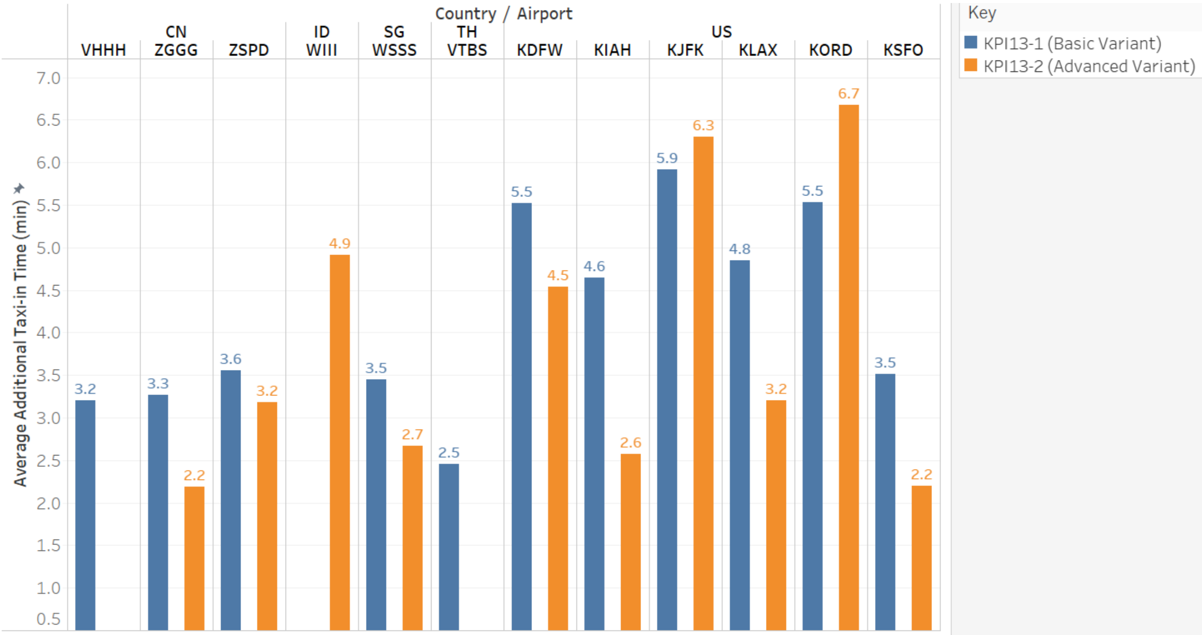

Figure 3: Additional Taxi-In Time for Basic and Advanced Variants (KPI13-1, KPI13-2)

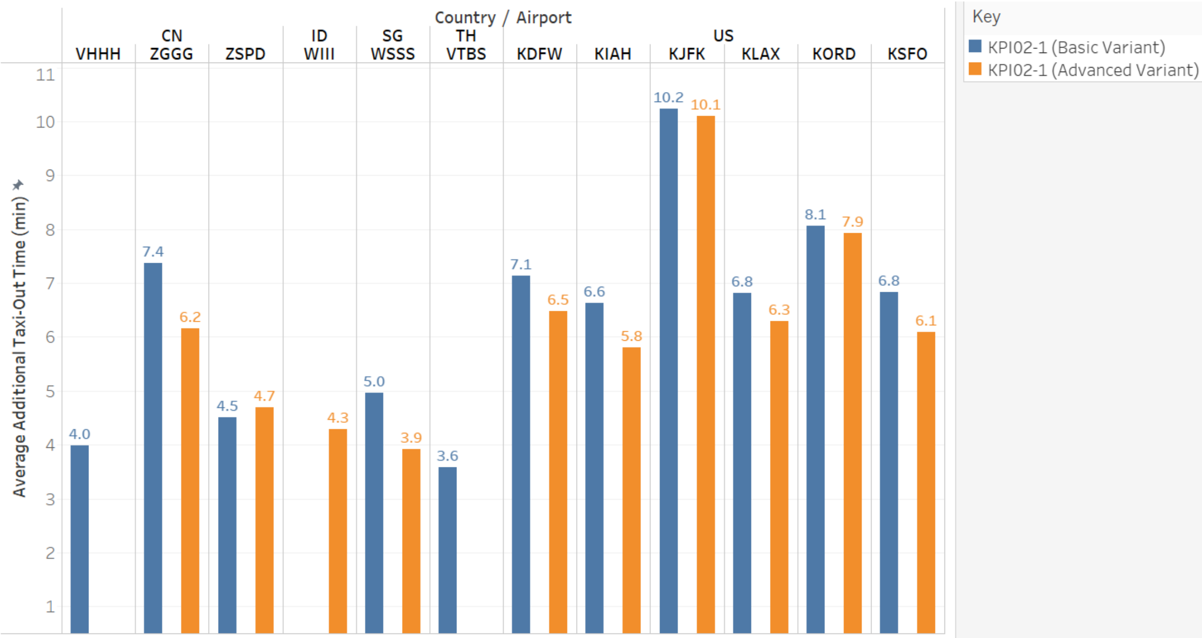

Figure 4: Additional Taxi-Out Time for Basic and Advanced Variants (KPI02-1, KPI02-2)

Predictability

2.11 **Figure 5** shows the arrival and departure punctuality distribution binned by its deviation from the respective scheduled arrival and departure time.

2.12 Across all airports, we observe that arrival on-time performance (OTP) is poorer as compared to departures. This is due to observed higher occurrences of both early and late arrivals; departures on the other hand are rarely early. Having more arrivals falling out of the +/- 15 min on-time bin indicates poor adherence to slot schedules which may lead to demand-capacity imbalance. Such observation offers motivation to analyse delays from unexpected developments that impact individual flights, along with the buffers built into the ATM system, to identify areas where greater efficiency can be realized.

2.13 States have implemented various initiatives to improve OTP. Hong Kong China employs a positive reinforcement strategy through incentives such as preferential aircraft stand allocation for airlines with good OTP, while Thailand implements certain penalties for slot timing violations. To enhance stakeholder coordination, Singapore has an OTP Taskforce in place, comprising of the airport operator, ground handlers and airlines, to study and drive improvement in OTP for Singapore Changi Airport; Hong Kong China conducts regular bi-monthly meetings between airport operators, airlines, and ATC focusing on A-CDM operations. These varied approaches demonstrate the region's commitment to improving predictability while highlighting opportunities for greater harmonisation of OTP management strategies. US Department of Transportation requires airlines to submit OTP which is similar to the percentages coloured in (grey + blue) below for arriving flights. (https://www.transtats.bts.gov/ot_delay/ot_delaycause1.asp).

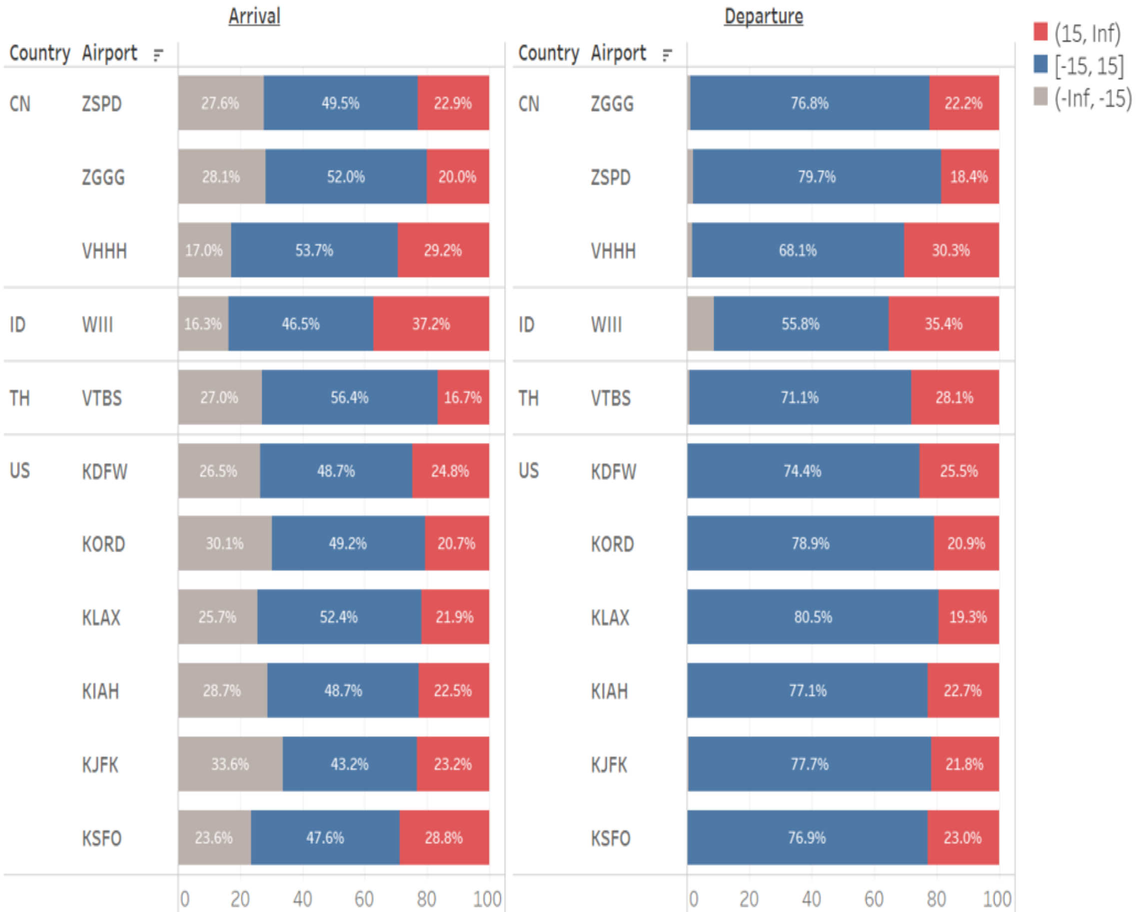

Figure 5: Range of Arrival and Departure Punctuality Across Airports (KPI14, KPI01)

Overall Analysis

2.14 To provide meaningful interpretation of findings for individual airports, it is essential to consider the operational context of each airport. Airports vary significantly in their infrastructure and operational characteristics. Major hubs like Hong Kong International Airport and Singapore Changi Airport operate multiple runways with 2024 annual traffic volumes of 364,000 and 370,000 movements respectively. The terminal infrastructure also varies considerably, from airports with multiple terminals for international flights connected by automated people movers like Bangkok Suvarnabhumi International Airport to those with single-terminal setups like Hong Kong International Airport. Gate configurations also vary significantly - from facilities like Australia's major airports which have between 33 to 70 gates, to larger airports like Hong Kong International Airport which operates approximately 180 gates. These fundamental differences in airport configuration and capacity influence how each facility manages its operations.

2.15 Performance variations across States reflect the diverse operating environments in the region. Several key factors contribute to these differences. Traffic composition plays a major role, with airports handling predominantly international flights facing distinct challenges in predictability due to the complexity of long-haul operations and network effects, compared to those managing mainly domestic operations. Infrastructure configuration also plays a significant role - multi-runway airports typically demonstrate different efficiency patterns in their taxi times compared to single-runway facilities. Weather patterns introduce further variability, with airports in tropical regions contending with seasonal monsoons and visibility constraints. Additionally, the ratio of passenger to cargo operations and the distribution of traffic throughout the day influence both capacity utilisation and predictability metrics. These operational contexts, combined with local airspace characteristics and ground movement constraints, collectively shape the performance profiles observed across airports in the region.

2.16 Analysis across the three Key Performance Areas reveals notable patterns and interdependencies. A consistent correlation exists between capacity and predictability, where airports operating closer to their declared capacity generally demonstrate lower OTP. This suggests that high-capacity utilization may compromise schedule reliability. The relationship between efficiency and predictability is equally apparent, with data showing that airports experiencing longer additional taxi-in times typically record poorer arrival punctuality. These relationships suggest that capacity constraints and ground movement efficiency have direct implications for schedule adherence. Taken together, the findings underscores the need for a balanced optimization approach, where improvements in one performance area are aligned with and support outcomes in others.

2.17 Regional trends indicate that major hub airports share common characteristics. One notable pattern is that departure punctuality generally exceeds arrival punctuality, likely reflecting the greater control that airports and airlines have over departure processes compared to arrivals, which are more susceptible to upstream variability. Additionally, the consistent observation that additional taxi-out times exceed taxi-in times across all airports points to a common regional characteristic in departure management, possibly linked to common practices in runway sequencing and departure queue management.

3. NEXT STEPS

3.1 To further advance data analysis and performance measurement in the region, the DAG will be looking to expand data collection scope to include three additional GANP KPIs:

a) KPI08 – Additional Time in Terminal Airspace;

b) KPI11 – Airport Throughput Efficiency; and

c) KPI16 – Additional Fuel Burn.

3.2 These three additional KPIs were selected for their strategic importance in measuring advanced aspects of ATM performance. KPI08 (Additional Time in Terminal Airspace) is crucial for identifying inefficiencies in terminal operations and approach sequencing. KPI11 (Airport Throughput Efficiency) provides insights into how effectively the runway is being used, helping airports optimize their operations. KPI16 (Additional Fuel Burn) is crucial to measure fuel burn and carbon emissions to help member States plot its trajectory towards ICAO Long Term Aspirational Goal (LTAG). These metrics align with stage two of the ATM/PMF endorsed by APANPIRG and represent a progression beyond the initial eight basic KPIs. The DAG will further discuss and refine the methodology for these three KPIs before kickstarting data collection in 2026.

3.3 The expansion of performance measurement capabilities is a critical step towards establishing a harmonised framework for performance evaluation to enable States to benchmark against their own historical performance and contribute to a broader understanding of regional trends and opportunities for improvement. The DAG will continue to adopt a phased and inclusive approach, taking into account the varying data capabilities and operational contexts of participating States.

3.4 Beyond analysis of GANP KPIs, the DAG will expand its analytical scope to encompass cross-boundary issues that affect multiple States and regional operational challenges. The DAG will also incorporate root cause analysis to better understand the underlying drivers of observed performance variations and enable more targeted improvements. These shifts will enable the DAG to adopt a more integrated approach that identifies emerging issues, shares best practices, and proposes data-driven solutions to enhance overall ATM performance in the Asia Pacific region.

4. ACTION BY THE MEETING

4.1 The meeting is invited to

a) note the information contained in this paper;

b) encourage States who are not currently members to join the DAG; and

c) encourage States to participate in the ICAO Asia/Pacific Data Analytics Group to share best practices and solve common problems.

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DATA COLLECTION GUIDE

1. INTRODUCTION

This document contains the definitions and calculation methodologies to be used for the Data Analytics Group’s (DAG's) performance management and data collection purposes. The data gathered will be studied and used to provide insights and illustrate the benefits of performance management.

2. PROTECTION AND USE OF DATA

a) All data provided and used shall be protected against public disclosure.

b) Data provided should only be used for the purposes of the DAG’s work as guided by the DAG’s Terms of Reference and Task List.

c) Written permission from the data provider shall be sought for the use of data for any purpose not provided for in (b).

d) Data quality and validation is the responsibility of the data provider.

3. GENERAL NOTES

The KPIs are based on GANP KPIs and organized by the GANP Performance Objectives (https://www4.icao.int/ganpportal/ASBU/KPI). Deviations from GANP definitions are italicized (if applicable). Only KPI variants considered by the DAG will have their definitions listed here. KPI variants will be identified by suffixing the main KPI identifier. For example, Variant 2A of KPI01 will be referred to as KPI01-2A. Data will be collected at a resolution of once a month. Cut-offs will be determined by Actual Take-off Time (ATOT) and Actual Landing Time (ALDT) in UTC.

States may choose their preferred reference year for calculating unimpeded or reference times.

4. PREDICTABILITY

For the predictability performance objective, the group will be collecting data to calculate KPI01 and KPI14. We will be calculating variants 2A and 2B of the KPIs, i.e. KPI01-2A, KPI01-2B, KPI14-2A, KPI14-2B.

4.1 DEFINITIONS

KPI Name	Departure Punctuality (KPI01)
Definition	Percentage of flights departing from the gate on-time (compared to schedule).
Measurement	% of scheduled flights
Variants	Variant 2A – % of departures delayed within ± 15 mins of scheduled time of departure Variant 2B – % of departures delayed <= 15 mins versus schedule
Parameters	On-time threshold (maximum positive or negative deviation from scheduled departure time) which defines whether a flight is counted as on-time or not. Recommended values: 5 minutes and 15 minutes.
Data Requirement	For each departing scheduled flight: • Scheduled time of departure (STD) • Actual off-block time (AOBT)
Formula	At the level of individual flights: • Exclude non-scheduled departures • Categorize each scheduled departure as on-time or not At aggregated level: • Compute the KPI: number of on-time departures divided by total number of scheduled departures

Table 1: Departure Punctuality Definition

KPI Name	Arrival Punctuality (KPI14)
Definition	Percentage of flights arriving at the gate on-time (compared to schedule).
Measurement	% of scheduled flights
Variants	Variant 2A – % of arrivals delayed within ± 15 mins of scheduled time of arrival Variant 2B – % of arrivals delayed <= 15 mins versus schedule
Parameters	On-time threshold (maximum positive or negative deviation from scheduled arrival time) which defines whether a flight is counted as on-time or not. Recommended values: 5 minutes and 15 minutes.
Data Requirement	For each arriving scheduled flight: • Scheduled time of arrival (STA) • Actual in-block time (AIBT)
Formula	At the level of individual flights: • Exclude non-scheduled arrivals • Categorize each scheduled departure as on-time or not At aggregated level: • Compute the KPI: number of on-time departures divided by total number of scheduled departures

Table 2: Arrival Punctuality Definition

4.2 DATA COLLECTION

To calculate the predictability KPIs, we would require the breakdown of flights by Arrival, Departure, and time buckets. There will be three time buckets and x = Actual – Scheduled for the below definitions:

- (-INF, -15) Flights arriving or departing when $x < -15$ minutes.
- [-15,15] Flights arriving or departing when $-15 \leq x \leq 15$ minutes.
- (15, INF) Flights arriving or departing when $x > 15$ minutes.

Table 3 shows a sample of the data collection template with dummy data for illustration.

Airport	Date	Phase	No. of Flights	(-INF, -15)	[-15,15]	(15, INF)
ZZZZ	2022-11	DEP	12,345	190	8,386	3,769
ZZZZ	2022-12	DEP	12,346	114	8,064	4,168
ZZZZ	2023-01	DEP	12,347	137	8,886	3,324
ZZZZ	2022-11	ARR	12,348	2,203	6,887	3,258
ZZZZ	2022-12	ARR	12,349	2,038	6,237	4,074
ZZZZ	2023-01	ARR	12,350	2,347	6,619	3,384

Table 3: Data Collection Template for Predictability with Dummy Data

4.3 CALCULATION METHODOLOGY

For departures,

1. Exclude non-scheduled flights and cancelled flights.
2. Calculate the time difference AOBT – STD.
3. Categorize each flight into the 3 buckets of (-INF, -15), [-15,15], (15, INF).
4. Sum up the number of flights in each bucket for every month.

For arrivals,

1. Exclude non-scheduled flights and cancelled flights.
2. Calculate the time difference AIBT – STA.
3. Categorize each flight into the 3 buckets of (-INF, -15), [-15,15], (15, INF).
4. Sum up the number of flights in each bucket for every month.

5. EFFICIENCY

For the basic efficiency performance objective, the group will be collecting data to calculate KPI02 and 13. We will be calculating both the basic and advanced variants of the KPIs. i.e. KPI02-1, KPI02-2, KPI13-1, KPI13-2.

5.1 DEFINITIONS

KPI Name	**Additional taxi-out time (KPI02)**
Definition	Actual taxi-out time compared to an unimpeded/reference taxi-out time.
Measurement	Minutes/flight
Variants	Variant 1 – Basic (computed without departure gate and runway data) Variant 2 – Advanced (computed with departure gate and runway data)
Parameters	Unimpeded/reference taxi-out time: • Recommended approach for the basic variant of the KPI: A single value at airport level, e.g. the 20th percentile of actual taxi times recorded at an airport, sorted from the shortest to the longest. *[For basic variant, reporting can be done at runway level if data is available]* • Recommended approach for the advanced variant of the KPI: A separate value for each runway/gate combination, e.g. the average actual taxi-out time recorded during periods of non-congestion (needs to be periodically reassessed). *[For advanced variant, the reference taxi-out time will be set at 20th percentile of actual taxi times recorded. To prevent issues with low sample sizes, data may be reported at runway and gate cluster level instead of at the individual gate level.]*
Data Requirement	For each departing flight: • Actual off-block time (AOBT) • Actual take-off time (ATOT) In addition, for the advanced variant: • Departure gate ID • Take-off runway ID
Formula	At the level of individual flights: 1. Select departing flights, exclude helicopters 2. Compute actual taxi-out duration: ATOT minus AOBT 3. Compute additional taxi-out time: actual taxi-out duration minus unimpeded taxi-out time At aggregated level: 4. Compute the KPI: sum of additional taxi-out times divided by number of IFR departures

Table 4: Additional Taxi-Out Time Definition

KPI Name	**Additional taxi-in time (KPI13)**
Definition	Actual taxi-in time compared to an unimpeded/reference taxi-in time.
Measurement	Minutes/flight
Variants	Variant 1 – Basic (computed without landing runway and arrival gate data) Variant 2 – Advanced (computed with landing runway and arrival gate data)
Parameters	Unimpeded/reference taxi-in time: • Recommended approach for the basic variant of the KPI: A single value at airport level, e.g. the 20th percentile of actual taxi times recorded at an airport, sorted from the shortest to the longest. *[For basic variant, reporting can be done at runway level if data is available]* • Recommended approach for the advanced variant of the KPI: A separate value for each runway/gate combination, e.g. the average actual taxi-in time recorded during periods of non-congestion (needs to be periodically reassessed). *[For advanced variant, the reference taxi-in time will be set at 20th percentile of actual taxi times recorded. To prevent issues with low sample sizes, data may be reported at runway and gate cluster level instead of at the individual gate level.]*
Data Requirement	For each arriving flight: • Actual in-block time (AIBT) • Actual landing time (ALDT) In addition, for the advanced variant: • Arrival gate ID • Landing runway ID
Formula	At the level of individual flights: 1. Select arriving flights, exclude helicopters 2. Compute actual taxi-in duration: AIBT minus ALDT 3. Compute additional taxi-in time: actual taxi-in duration minus unimpeded taxi-in time At aggregated level: 4. Compute the KPI: sum of additional taxi-in times divided by number of IFR arrivals

Table 5: Additional Taxi-In Time Definition

5.2 DATA COLLECTION

The Basic Efficiency KPIs will be collected with the following data collection template.

Airport	**Date**	**KPI02-1**	**KPI02-2**	**KPI13-1**	**KPI13-2**
ZZZZ	2022-11	10.03	4.85	2.07	1.75
ZZZZ	2022-12	11.71	5.27	2.34	1.83
ZZZZ	2023-01	11.89	5.32	2.40	1.90

Table 6: Data Collection Template for Efficiency (Basic) with Dummy Data

5.3 CALCULATION METHODOLOGY

Reference Time

1. Only include IFR flights.
2. Calculate actual taxi-out or taxi-in times for each flight: $\mathrm{ATOT} - \mathrm{AOBT}$ or $\mathrm{AIBT} - \mathrm{ALDT}$ respectively.
3. Group flights by runway and gate / gate clusters (e.g. $20L\_G$).
4. For each group, obtain the 20th percentile taxi-out or taxi-in time as the runway and gate / gate cluster combination's reference time.

Additional Taxi Time

1. Only include IFR flights.
2. Calculate actual taxi-out or taxi-in times for each flight: $\mathrm{ATOT} - \mathrm{AOBT}$ or $\mathrm{AIBT} - \mathrm{ALDT}$ respectively.
3. Group flights by runway and gate / gate clusters (e.g. $20L\_G$).
4. For each group, subtract the reference time from the actual times to obtain the additional taxi-out or taxi-in time, using a different reference time for each runway and gate / gate cluster combination.
5. Obtain the average additional taxi-out or taxi-in times for the month across all flights.

6. CAPACITY

For the basic capacity performance objective, the group will be collecting data to calculate all variants of KPI09, i.e. KPI09-A, KPI09-D, KPI09-AD. For KPI10, variant 1 on IFR operations will be calculated, i.e. KPI10-1A, KPI10-1D, KPI10-1AD

6.1 DEFINITIONS

KPI Name	Airport Peak Capacity (KPI09)
Definition	The highest number of operations an airport can accept in a one-hour time frame (also called declared capacity). Can be computed for arrivals, departures, or arrivals + departures.
Measurement	Number of departures / hour, Number of landings / hour, Number of (departures + landings) / hour
Variants	Variant A – Airport peak arrival capacity Variant D – Airport peak departure capacity Variant AD – Airport peak movement capacity (departures + arrivals)
Parameters	None
Data Requirement	Scheduling parameters for slot controlled airports Airport acceptance rates (AAR) Airport departure rates (ADR)
Formula	At the level of an individual airport: 1. Select highest value from the set of declared capacities 2. Compute the KPI: convert the value to an hourly rate, if the declaration is at smaller time intervals

Table 9: Airport Peak Capacity Definition

KPI Name	Airport Peak Throughout (KPI10)
Definition	The 95th percentile of the hourly number of operations recorded at an airport, in the “rolling” hours sorted from the least busy to the busiest hour. Can be computed for arrivals, departures, or arrivals + departures.
Measurement	Number of departures / hour, Number of landings / hour, Number of (departures + landings) / hour
Variants	Variant 1 – IFR operations only To be combined with: Variant A – Airport peak arrival capacity Variant D – Airport peak departure capacity Variant AD – Airport peak movement capacity (departures + arrivals)
Parameters	Time interval for “rolling” hours. Recommended value: 15 minutes The percentile chosen to exclude outliers. Recommended value: 95th percentile
Data Requirement	For each flight: Actual landing time (ALDT) Actual take-off time (ATOT)
Formula	At the level of an individual flights: 1. Select flights, exclude helicopters 2. Convert the set of landings to hourly landing / departure rates by “rolling” hour 3. Sort the “rolling” hours from the least busy to the busiest hour 4. Compute the KPI: it equals the landing rate value of the 95th percentile of the “rolling” hours

Table 10: Airport Peak Throughput Definition

6.2 DATA COLLECTION

Data will be collected for all variants of KPI09. For KPI10, data will be collected for KPI10-1A, KPI10-1D, and KPI10-1AD.

Airport	Date	KPI09-AD	KPI10-1AD	KPI09-A	KPI10-1A	KPI09-D	KPI10-1D
WSSS	2022-11	73	45	38	27	40	24
WSSS	2022-12	73	47	38	28	40	25
WSSS	2023-01	73	47	38	27	40	24

Table 11: Data Collection Template for Capacity with Sample Data

6.3 CALCULATION METHODOLOGY

This section will focus on KPI10 only as KPI09 consists of declared capacities.

Rolling Hours

The time interval for rolling hours will be set at 15 minutes. To illustrate rolling hours, consider the below example where we begin from 0900. Hourly peak throughputs will be calculated for the following time periods, where a new hourly period is considered every 15 minutes:

- 0900 – 1000
- 0915 – 1015
- 0930 – 1030

… and so on

Airport Peak Throughput

1. Restrict the hours considered to 0600 – 2259 local time for all airports.
2. For each month, calculate the number of flights per rolling hour for arrivals, departures, and arrivals + departures.
3. Arrange these rolling hours from the least number of flights to the greatest number of flights.
4. The 95th percentile rolling hour will be taken as the peak throughput.

— END —