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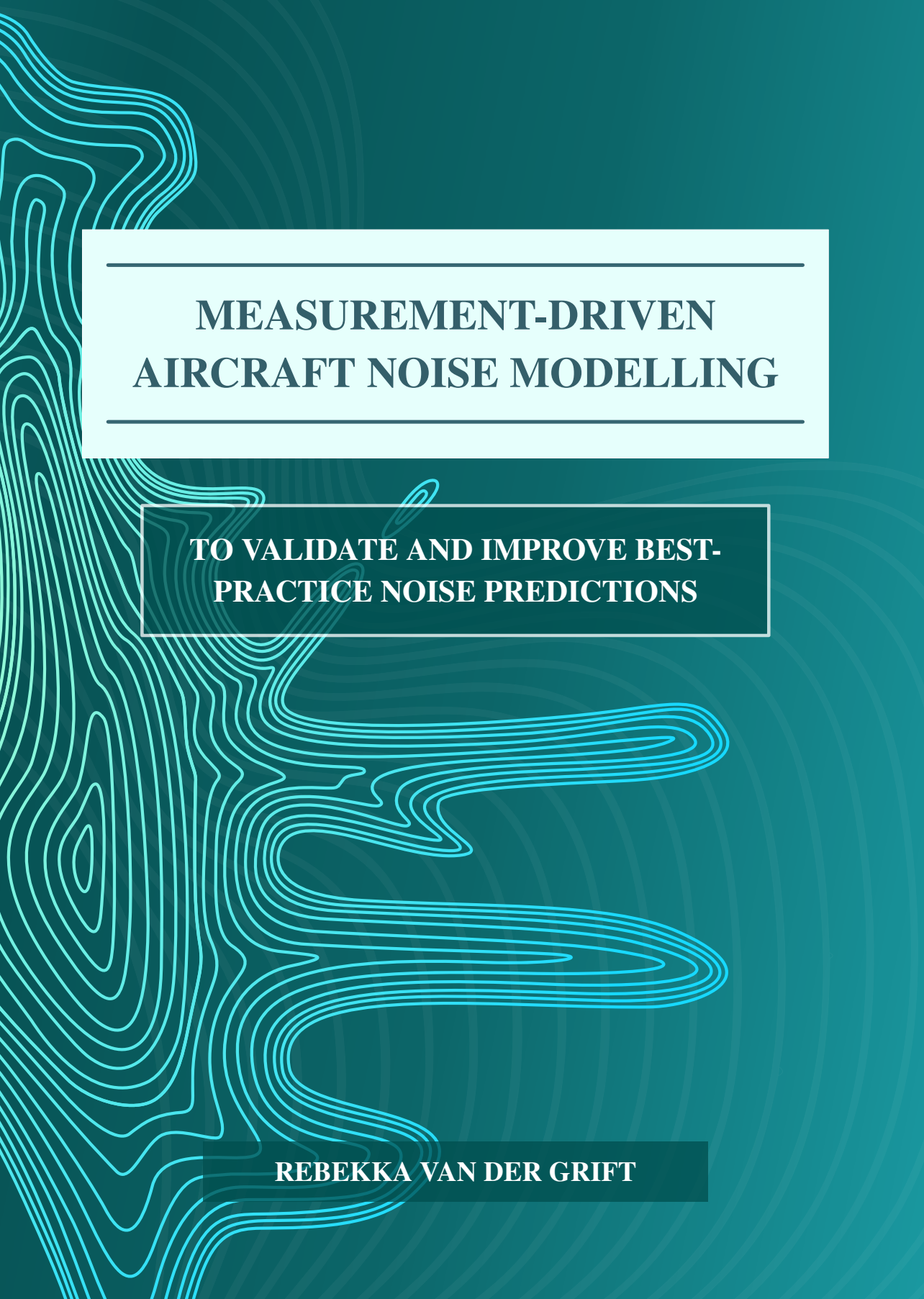
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MEASUREMENT-DRIVEN AIRCRAFT NOISE MODELLING

**TO VALIDATE AND IMPROVE BEST-
PRACTICE NOISE PREDICTIONS**

REBEKKA VAN DER GRIFT

MEASUREMENT-DRIVEN AIRCRAFT NOISE MODELLING

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PREDICTIONS

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TO VALIDATE AND IMPROVE BEST-PRACTICE NOISE
PREDICTIONS

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SUMMARY

Aviation continues to grow worldwide, bringing increasing challenges related to aircraft noise. Current noise assessments rely on best-practice models such as the European standard Document 29 (Doc 29) of the European Civil Aviation Conference, which is also used in the Netherlands. Given the strong dependence of airport policy and regulation on these models, their accuracy and reliability are essential. The objective of this thesis is therefore to improve the accuracy of the Doc 29 aircraft noise model using noise measurements collected around Amsterdam Airport Schiphol. The NOMOS monitoring network, consisting of 41 Noise Monitoring Terminals (NMTs), provides the measurement basis for several validation and model-improvement studies described in this thesis

Best-practice noise models use Noise-Power-Distance (NPD) tables, which provide noise levels as a function of engine power (thrust) and distance between aircraft and observer. Additional correction factors allow predictions under non-standard conditions. While computationally efficient, these methods rely on simplifying assumptions about aircraft operations, source noise characteristics, and propagation effects.

The first step of this research is to identify the challenges and limitations of current noise predictions and measurements. A comparison between annual noise metrics (L_{den} and L_{night}) from Doc 29 and NOMOS data reveals noteworthy trends: Doc 29 generally underestimates L_{den} , but overestimates L_{night} . Background noise and undetected flights were quantified and found to predominantly affect low-noise regions at greater distances from flight paths. This analysis also highlights the strong dependence of model accuracy on the correctness of aircraft performance input parameters.

To address this, a second research stage develops a method for accurately determining engine thrust for historic flights. Using either acoustically derived N1 values obtained from blade-passing frequencies or directly from onboard flight data, estimates of delivered thrust are reconstructed. Since Doc 29 requires corrected net thrust as input, conversion methods were evaluated. Simulations using the Gas turbine Simulation Program (GSP) provided the most accurate results. Based on these simulations, coefficients were derived and validated to reliably estimate thrust from N1 for use in standard best-practice formulas. Using this improved input, a validation study showed strong agreement between modelled and measured Sound Exposure Level (SEL) and $L_{A,max}$, though residual discrepancies remained.

To investigate the limitations of the NPD tables, back-propagated measurements were used to derive thrust-noise relations. Results indicate that for departures, the existing NPD tables overestimate the thrust-noise dependency. New NPD tables were therefore constructed directly from measurements, fully independent of the existing database. Applying these calibrated NPD tables improved departure noise prediction accuracy by approximately 25%, independently verified with measurements from Oslo Airport.

This thesis also assessed the use of standardised source spectra to calculate weather dependent corrections. Due to the simplified atmospheric assumptions, the absorption of sound during propagation is limitedly affected by the source spectra. The use of these source spectra are thus sufficient for this purpose.

A final step is to benchmark the Doc 29 model to an independent empirical model, sonAIR. With a more complex noise source modelling and propagation algorithms, sonAIR showed improvement compared to the measurements, specifically at lower elevation angles and in low-noise regions.

Overall, this thesis contributes to the validation and improvement of best-practice aircraft noise models through detailed analysis of noise measurements around Schiphol Airport. While Doc 29 performs well for estimating average noise exposure, its simplified assumptions about source noise and propagation limit its ability to represent the full complexity of aircraft noise. The improvements developed in this research contribute toward more reliable and transparent noise assessments.

SAMENVATTING

Luchtvaart blijft wereldwijd groeien, wat leidt tot toenemende uitdagingen rondom vliegtuiggeluid. Huidige geluidsbeoordelingen steunen op best-practice modellen zoals het Europese standaardmodel Document 29 (Doc 29) van de European Civil Aviation Conference, dat ook in Nederland wordt gebruikt. Omdat luchthavenbeleid en regelgeving sterk afhankelijk zijn van deze modellen, zijn hun nauwkeurigheid en betrouwbaarheid van groot belang. Het doel van dit proefschrift is daarom om de nauwkeurigheid van het Doc 29 vliegtuiggeluidsmodel te verbeteren met behulp van geluidsmetingen verzameld rond Amsterdam Airport Schiphol. Het NOMOS-monitoringsnetwerk, bestaande uit 41 Noise Monitoring Terminals (NMT's), vormt de basis voor verschillende validatie- en modelverbeteringsstudies die in dit proefschrift worden beschreven.

Best-practice geluidsmodellen maken gebruik van Noise-Power-Distance (NPD) tabellen, waarin geluidsniveaus worden gegeven als functie van motorvermogen (stuwkracht) en de afstand tussen vliegtuig en waarnemer. Met aanvullende correctiefactoren kunnen geluidsniveaus onder niet-standaard omstandigheden worden voorspeld. Hoewel deze methoden rekenkundig efficiënt zijn, steunen ze op vereenvoudigde aannames over vliegtuigoperaties, bronkarakteristieken en geluidspropagatie.

De eerste stap in dit onderzoek is het identificeren van de uitdagingen en beperkingen van de huidige geluidsvoorspellingen en metingen. Een vergelijking tussen jaarlijkse geluidsindicatoren (L_{den} en L_{night}) van Doc 29 en NOMOS-data laat duidelijke trends zien: Doc 29 onderschat over het algemeen L_{den} , maar overschat L_{night} . Achtergrondgeluid en niet-gedeteteerde vluchten werden gekwantificeerd en bleken vooral invloed te hebben in stille gebieden op grotere afstand van de vliegroute. Deze analyse benadrukt tevens de sterke afhankelijkheid van modelnauwkeurigheid van correcte invoergegevens voor vliegtuigprestaties.

Om dit te verbeteren, is in de tweede fase van het onderzoek een methode ontwikkeld om de motorstuwkracht van historische vluchten nauwkeurig te bepalen. Met behulp van akoestisch afgeleide N1-waarden uit bladpassagefrequenties of rechtstreeks uit vluchtdata wordt de geleverde stuwkracht gereconstrueerd. Omdat Doc 29 gecorrigeerde netto stuwkracht als invoer vereist, zijn verschillende omzettingmethoden onderzocht. Simulaties met het Gas turbine Simulation Program (GSP) leverden de meest accurate resultaten. Uit deze simulaties zijn coëfficiënten afgeleid en gevalideerd waarmee stuwkracht betrouwbaar kan worden geschat uit N1 in standaard best-practice formules. Met deze verbeterde invoer toonde een validatiestudie een goede overeenkomst tussen gemodelleerde en gemeten SEL en $L_{A,max}$, hoewel enkele afwijkingen bleven bestaan.

Om de beperkingen van de NPD-tabellen te onderzoeken, zijn teruggeprojecteerde metingen gebruikt om stuwkracht-geluidsrelaties af te leiden. De resultaten tonen aan dat voor starts de huidige NPD-tabellen de afhankelijkheid tussen stuwkracht en geluid overschatten. Daarom zijn nieuwe NPD-tabellen geconstrueerd die volledig zijn geba-

seerd op metingen, onafhankelijk van de bestaande database. Toepassing van deze gekalibreerde NPD-tabellen verbeterde de nauwkeurigheid van geluidvoorspellingen met ongeveer 25%, onafhankelijk bevestigd met metingen van Oslo Airport.

Dit proefschrift onderzocht ook het gebruik van gestandaardiseerde bronspectra voor het berekenen van weerafhankelijke correcties. Door de vereenvoudigde atmosferische aannames blijkt de absorptie van geluid tijdens propagatie slechts beperkt afhankelijk van het bronspectrum. De gebruikte gestandaardiseerde spectra zijn hiervoor dus voldoende.

Tot slot is het Doc 29 model vergeleken met een onafhankelijk empirisch model, sonAIR. Dankzij geavanceerdere bronmodellering en propagatie-algoritmen liet sonAIR betere overeenstemming met metingen zien, met name bij lage elevatiehoeken en in stille gebieden.

Alles bij elkaar genomen draagt dit proefschrift bij aan de validatie en verbetering van best-practice vliegtuiggeluidsmodellen door middel van gedetailleerde analyse van geluidsmetingen rond Schiphol. Hoewel Doc 29 goed presteert voor het inschatten van gemiddelde geluidsblootstelling, beperken de vereenvoudigde aannames over bronlawaai en geluidspropagatie het vermogen om de volledige complexiteit van vliegtuiggeluid te beschrijven. De in dit onderzoek ontwikkelde verbeteringen dragen bij aan betrouwbaardere en transparantere geluidsbeoordelingen.



1

INTRODUCTION

Global aviation continues to grow and is projected to reach 12.4 billion passengers annually by 2050 [1]. While technological advancements have led to quieter aircraft, communities around major airports are experiencing increasing levels of noise annoyance. High levels of environmental noise, particularly from aircraft, have been linked to adverse health effects, including cardiovascular diseases [2]. As a result, accurately assessing noise exposure in communities around the airport is essential for public health.

To evaluate and mitigate aircraft noise, predictive noise models are widely used. However, as noise pollution continues to rise, so does public scepticism toward these models. Communities increasingly advocate for the use of noise measurements, arguing that they provide a more transparent and trustworthy basis for assessing real-world noise exposure.

This thesis investigates the potential of noise measurements to validate and improve existing aircraft noise prediction models. This chapter consists of the following sections. Section 1.1 provides a background on aircraft noise modelling, section 1.2 outlines the current regulatory frameworks, and section 1.3 introduces the measurement system used in this research. Finally, the research objectives and structure of the thesis are presented in sections 1.4 and 1.5, respectively.

1.1. BACKGROUND ON AIRCRAFT NOISE MODELLING

With the rise of commercial aviation halfway through the 20th century, the effects of aircraft noise on the population became more apparent. The increasing number of people impacted led to growing public demands for regulation and mitigation efforts. Following this, numerous aircraft noise models have been developed over the decades with varying complexity. A distinction can be made between non-, semi- and fully empirical models. Each has its advantages and disadvantages.

Non-empirical, or physics-based, models focus on a mathematical representation of noise sources and propagation. This requires highly detailed simulations of airframe and engine components and their surrounding airflow, studied in the field of computational aeroacoustics. Non-empirical models are primarily used to study individual noise generation mechanisms at the component level, such as landing gear or wing configurations. Although they provide detailed physical insight, their high computational cost

limits their application.

As physics-based models are not practical for full aircraft predictions, semi-empirical modelling is often chosen instead. These model types combine empirical relations extracted from measurements with calculations of physical effects. The relations used in these models often flow from extensive measurement campaigns in wind tunnels and specially performed flyovers [3]. Well-known models are the Parametric Aircraft Noise Analysis Module (PANAM) [4], created by the German Aerospace Center (DLR) and the Aircraft Noise Prediction Program (ANoPP), developed by NASA [5]. Using a limited number of geometric inputs, the noise generated by different airframe components is calculated. Similar semi-empirical approaches exist for engine noise, modelling fan, jet, and core noise contributions using operational parameters such as thrust setting and engine rotational speed. The total aircraft noise is then obtained by combining the individual airframe and engine noise sources. The advantage of such models is the detailed source noise and frequency information for different operational flight phases, while having relatively fast computational times. Although semi-empirical models can use measured flight trajectories and operational data as input, their underlying source-noise relations are generally derived from controlled experiments and simplified operating conditions. Consequently, uncertainty remains when applying these relations to the broad range of operational conditions encountered in everyday airport operations. A recent development in semi-empirical noise modelling is the sonAIR noise model developed by Empa [6]. Created from an extensive measurement campaign around Geneva and Zurich airports, this model is less complex than ANoPP or PANAM while still able to split noise sources from the airframe and engines. Together with an advanced noise propagation model, sonX, noise exposure on the ground is calculated.

Although the models mentioned above serve their purpose, for noise management around airports, a large number of aircraft movements need to be analysed. This leads to the third type of models, called the empirical models. Historically, these calculations have been performed in a similar manner for decades. One important class of empirical models is the so-called best-practice methodology, which uses Noise-Power-Distance (NPD) tables derived from measurements. Here, for different combinations of power settings of the engines and distance from the aircraft to a point on the ground, a noise level is given. The methodology of best-practice noise modelling is further elaborated in chapter 2. Other empirical approaches also exist, including statistical and machine-learning-based models that derive noise directly from operational observations. Best-practice models remain the dominant approach for regulatory airport noise assessments and are therefore the primary focus of this thesis.

One of the main challenges of best-practice models lies in obtaining accurate input data, particularly the engine power or thrust used during flight. As open-source information on in-flight thrust is scarce, substantial assumptions about aircraft performance are required. Even though several studies have attempted to estimate thrust more reliably [7, 8, 9, 10], these approximations inevitably introduce uncertainty into the resulting noise predictions [11]. To successfully validate aircraft noise models, it is thus important to obtain reliable and accurate model input parameters. This forms an essential scientific gap addressed in this thesis.

One of the oldest documented models following the best-practice noise estimation

method is the Integrated Noise Model (INM), designed by the Federal Aviation Administration (FAA), and published in 1978 [12]. This model followed the guidelines from the SAE1845 [13] and ICAO Annex 16 [14]. The INM was replaced by the Aviation Environmental Design Tool (AEDT) in 2015 and is currently used worldwide [15]. In the Netherlands, the oldest recorded aircraft noise calculations for management stem from 1967. Later, the Dutch noise model ("Nederlands Rekenmodel" (NRM)) was introduced to calculate noise exposure [16]. This model has been revised multiple times to reflect evolving best practices, finally arriving at its current form in 2002 [17]. Although this model was validated with measurements [18], the need for a more harmonised approach to noise modelling surfaced. Following this demand, the European Civil Aviation Conference (ECAC) published the aircraft noise model Document 29 (Doc 29). Unlike the AEDT, Doc 29 is not a software tool but a guide for noise-contour modelling. The first version of Doc 29 was published in 1986, and similar to the INM and AEDT, it followed the guidelines from SAE [13] and ICAO Annex 16 [14]. Following revisions in 1997 and 2007, the fourth and most recent edition of Doc 29 was published in 2016. This latest edition is split into three volumes. Volume 1 [19] introduces the principles and applications of aircraft noise modelling. Volume 2 [20] expands on this by detailing the calculation methodology. Volume 3 [21] presents a verification methodology and accompanying data. Model verification ensures that all implementations of Doc 29 yield consistent results. Currently, both the Doc 29 model and the NRM are being used in the Netherlands to support a smooth transition before Doc 29 is fully established as the standard for aircraft noise modelling.

While Doc 29 offers a harmonised European methodology, some of its underlying assumptions originate from controlled measurements that differ from real-world airport operations. Although the Aircraft Noise and Performance (ANP) database [22] is continuously updated to include modern aircraft types and revised data sets, the applicability of the underlying best-practice assumptions to operational procedures remains an important topic for validation. The present work therefore critically examines how well the assumptions provided in Doc 29 remain valid.

1.2. AIRCRAFT NOISE REGULATIONS IN THE NETHERLANDS

Aircraft noise policy in the Netherlands is shaped by a combination of national legislation, international guidelines, and evolving public concerns. Central to this framework is the Airport Traffic Decree (Luchthavenverkeerbesluit (LVB)), which defines the legal boundaries for aircraft operations and noise exposure around major airports, particularly Amsterdam Airport Schiphol.

The LVB sets the official rules for air traffic at Schiphol, including the maximum number of flight movements and noise contour boundaries. In a recent update, a temporary LVB caps annual flight movements at 478,000, with a maximum of 27,000 night flights [23]. These limits are part of the Dutch government's commitment to reducing aircraft noise hindrance by 20% with respect to 2024 for the next year. The cap on flights is a result from a list of noise reduction measures and are found through a Balanced Approach (BA) procedure. In the new version of the LVB (potentially accepted into policy in November 2026) it is stated that with noise reduction above this target, controlled growth of the airport is again possible. All decisions from the LVB and BA are based on Doc 29

modelling results.

The LVB also defines noise enforcement points (Dutch: *handhavingspunten*) with set maximum values for noise exposure, which are used to monitor compliance. These thresholds are set in yearly Day-Evening-Night averages L_{den} . L_{den} is the primary metric used around the world to assess long-term exposure to aircraft noise. It is an energy-averaged sound level with penalties applied for evening (+5 dBA) and night-time (+10 dBA) noise events to reflect increased sensitivity during these periods. The LVB does not rely on direct measurements but on modelled noise contours, generated using the Doc 29 model. This reliance means that any systematic model bias directly affects legal compliance assessments and policy decisions. Although measurements could in principle offer an independent check on model results, their use in regulatory processes is complicated by, for example, uncertainties in event detection or variable background noise. These limitations have historically been a reason not to base legal noise contours on measurements and thus models are the standard.

Research has demonstrated a correlation between L_{den} levels and the percentage of people who report being highly annoyed by aircraft noise. Both the Environmental Noise Directive (END) and the World Health Organization (WHO) use dose-response relationships to estimate the proportion of highly annoyed individuals at different L_{den} levels. For example, at 55 dBA L_{den} , approximately 10–15% of people are expected to be highly annoyed, and this percentage increases significantly at higher levels [24, 25]. In the Netherlands, these relationships are used to quantify the health impact of aircraft noise and to inform policy decisions. The RIVM (Dutch National Institute for Public Health and the Environment) regularly investigates the number of highly annoyed people around Schiphol by performing surveys and comparing the results to the modelled L_{den} contours. Currently, the dose-response relation found in 2002 is used, although more recent research indicates that people experience greater annoyance at the same L_{den} [26, 27]. Possible causes for the increased annoyance are the growing number of aircraft flights at similar L_{den} due to quieter aircraft or non-acoustic factors such as a negative attitude towards aviation in general. The use of these dose-response relations with L_{den} is a debatable subject due to the generalised approach and lack of other annoyance metrics [28]. Further, dose-response relations differ greatly between airports [17, 29].

Nevertheless, the modelled L_{den} in combination with the dose-response curve and the current residential inventory around Schiphol are important for policy making. Next to the legal basis for monitoring the noise enforcement points, the model results are used to design noise-optimised flight routes, estimate the effects of newer aircraft, and drive the decision to reduce or increase flights at an airport. The accuracy and reliability of the Doc 29 model are thus crucial.

1.3. NOISE MONITORING SYSTEM

As early as 1993, Schiphol Airport became one of the first airports in the world with a permanent noise measurement system. Starting with only a few, the Noise Monitoring System (NOMOS) grew to 41 Noise Monitoring Terminals (NMT) placed at various distances from the airport. The current locations of these NMTs are illustrated in Figure 1.1. An NMT consists of a class-1 microphone placed on a 6 to 10 meter pole to

minimise ground reflections. NMTs can be placed on the ground or on roofs, depending on the location. Additional requirements for the placement and instrumentation are documented in ISO20906 [30].

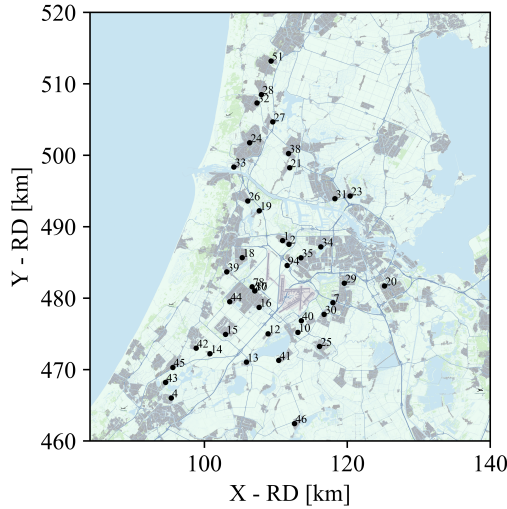


Figure 1.1: Locations of all NOMOS NMTs in Rijkdsdriehoek coordinate system.

NOMOS was originally installed to provide communities with information about aircraft noise and not necessarily to serve as a tool for model validation. An evaluation of the existing NMTs showed that not all NMTs adhere to these ISO requirements [31]. Some experience shielding, have close reflective surfaces, or are located in regions of high background noise. During the research in this thesis, only NMTs suitable for validation purposes are used. Next to location requirements, ISO20906 also recommends that reliable noise measurements should be taken under conditions where wind speed is lower than 10 m/s, and there is no precipitation [30].

NOMOS continuously and autonomously monitors environmental noise by detecting noise events. Each NMT records key acoustic parameters for every noise event, including the maximum A-weighted sound level ($L_{A,max}$) and the Sound Exposure Level (SEL), which quantifies the total energy of the event using the 10 dB-down method. In addition, Pressure Band Levels (PBLs) and downsampled MP3 recordings of the events are stored for further analysis. The definition of these metrics is further explained in chapter 2.

Each NMT is configured with a specific noise threshold, typically around 60 dBA, to trigger the recording of a noise event. However, background noise levels vary significantly by location, with averages between 35 and 50 dBA. ISO 20906 recommends a minimum difference of 10 dBA between the peak aircraft noise level and the ambient background to ensure reliable measurements [30].

When the sound level at an NMT exceeds its threshold, it is considered a noise event. The system then uses aircraft positional data to determine whether an aircraft was within

a defined proximity of the NMT at the time of the event. If a match is found, the event is classified as an aircraft noise event. If no aircraft are detected nearby, the event is likely attributed to another source. To improve the reliability of event classification, additional criteria can be applied, such as constraints on the rise and fall times (the time it takes for the noise level to increase or decrease by 10 dBA) and minimum or maximum event durations.

Although NOMOS provides an exceptionally large dataset, using it for scientific validation introduces several challenges. First, noise events may be missed when aircraft noise is masked by fluctuating background levels or when sound levels fall below the NMT threshold. Second, measurements are sensitive to contamination from non-aircraft noise, possibly leading to overestimation of event energy. Third, variations in microphone height, nearby reflective surfaces, and local shielding conditions introduce spatial biases that complicate direct comparison with modelled free-field levels. These challenges require careful data selection and pre-processing steps and are an essential part of this thesis, as they directly influence the reliability of the conclusions drawn.

Currently, the NOMOS measurements are purely informative to the community. They have no role in policy or regulations, despite the large availability of data. In this thesis, the full extent of the NOMOS network is utilised to support the assessment and validation of the Doc 29 noise model.

1.4. OBJECTIVES

The primary objective of this thesis is to improve the accuracy of aircraft noise models, specifically the Doc 29 model, using noise measurements collected around Amsterdam Airport Schiphol. Despite the widespread use of predictive models in aviation noise management, large-scale validation studies comparing model outputs with real-world measurements remain limited. This lack of validation is particularly concerning, given the increasing reliance on these models for regulatory decisions and the growing public concern over noise exposure. As aviation continues to expand, noise predictions must be both accurate and credible for protecting public health. The aim is to quantify where and why discrepancies arise and to develop practical methods that reduce these discrepancies at both event and annual scales. When comparing modelled and measured aircraft noise levels, discrepancies can originate from three distinct sources: model limitations, operational input data, and measurement limitations. Throughout this thesis, these sources are investigated separately whenever possible. To achieve the primary objective of improving aircraft noise predictions, three main sub-objectives are defined:

1. Validate standard Doc 29 model predictions at the single-event level and for yearly averages, and assess the causes of differences with measurements.
2. Obtain accurate model input based on historical operational data and validate it with flight data.
3. Identify the limitations of the model and estimate their effect by individually assessing model components against measurements.

In addition to improving model accuracy, this research contributes to enhancing transparency in the aircraft noise modelling process. By systematically comparing model predictions with spatially distributed noise measurements, the study provides insights into model performance and limitations. This approach supports more open and accountable noise assessments, addressing the needs and concerns expressed by communities living near airports.

1.5. THESIS STRUCTURE

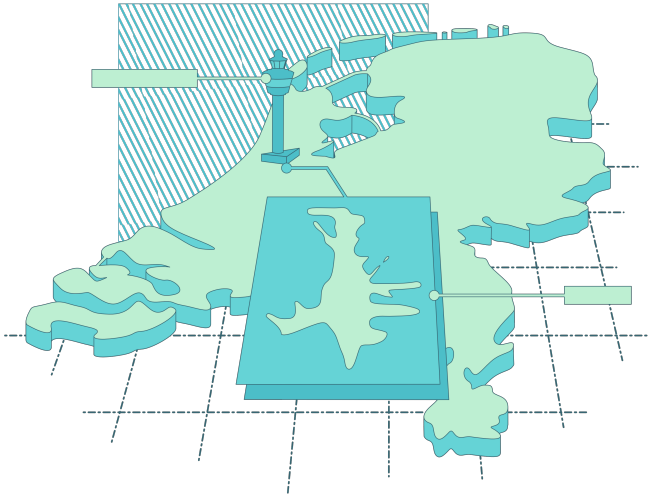
This thesis is organised into eight chapters, each contributing to the main research question concerning aircraft noise modelling improvement. The core content (Chapters 3 through 7) is based on peer-reviewed journal articles and conference papers, with modifications to reduce redundancy and ensure coherence.

First, **Chapter 2** presents the methodology underlying the Doc 29 noise model. It details the ANP database, outlines key assumptions and limitations, and describes the implementation and code structure developed for this research. This chapter sets the technical groundwork for the modelling efforts in this thesis. However, comparing these modelled noise levels to long-term measurements is not straightforward. **Chapter 3** analyses the challenges that emerge when comparing measured and modelled annual average noise levels such as L_{den} . This chapter quantifies the uncertainty of flight detection and background noise on the measurements. Analysis also indicates large assumptions in the modelling of aircraft performance. To address this operational uncertainty, **Chapter 4** focuses on obtaining accurate inputs to the noise model. A significant contribution of this chapter is the development and validation of novel techniques to estimate aircraft thrust using acoustic measurements and multiple conversion methods.

With a refined modelling baseline, **Chapters 5 and 6** focus on model improvement using the more accurate thrust estimation method by examining the ANP database and comparing its components to actual noise measurements. Chapter 5 focuses on the NPD tables, demonstrating how new insights into the relationship between thrust and noise can improve model accuracy and inform the calibration of these tables. Chapter 6 continues the validation and calibration of the ANP database by assessing the source spectra. The source spectra, used for modelling the atmospheric effect on noise, are analysed with measurements close-by and further away from the airport.

To broaden the perspective, **Chapter 7** introduces an alternative modelling approach: the sonAIR model. While the sonAIR model requires more extensive input, it demonstrates improved alignment with measurements around Schiphol Airport. This comparison highlights the trade-offs between model complexity and predictive accuracy.

Finally, **Chapter 8** provides comprehensive answers to the main research question. The chapter draws conclusions and offers future research directions on aircraft noise modelling and measuring.



2

BEST PRACTICE AIRCRAFT NOISE MODELLING

This chapter introduces the principles of best-practice aircraft noise modelling, with a particular focus on the European Doc 29 framework developed by the European Civil Aviation Conference (ECAC) [19, 20, 21]. As Doc 29 forms the basis for the analyses in this dissertation, this chapter establishes the foundation required for all subsequent chapters.

In section 2.1, an overview of the most commonly used noise metrics is given. Next, section 2.2 describes the Doc 29 modelling methodology in detail, including its underlying assumptions, computational structure, and known limitations. The practical use of the model, and how it is typically applied in operational and regulatory contexts, is discussed in section 2.3.

Despite its widespread adoption, existing implementations of Doc 29 tend to be rigid, offering limited flexibility for investigating individual components of the noise model (objective 3 of this thesis) or for incorporating improved and higher-resolution input data (objective 2). To address these gaps, a new and more adaptable Doc 29 implementation was developed specifically for this research. The design considerations and functionality of this new implementation are presented in section 2.4.

2.1. NOISE METRICS

Before we dive into aircraft noise modelling, it is important to clarify the different representations of noise. Sound is a fluctuation in air pressure, which can be captured using microphones. The measured data is a discrete time series of pressure signal, commonly sampled with 44,100 data points per second, defined as the sample frequency f_s in Hz. A typical noise measurement from an aircraft flyover is illustrated in Figure 2.1. On the left, the raw pressure disturbance is shown, which can be converted into an effective pressure amplitude, denoted as p_e .

A more commonly used representation of sound is the Sound Pressure Level (SPL), expressed in decibels (dB) [32]. SPL is a logarithmic measure of the effective pressure, relative to a reference pressure, and is defined as

$$SPL = 10 \log_{10} \left(\frac{p_e^2}{p_{e0}^2} \right). \quad (2.1)$$

where $p_{e0} = 2 \times 10^{-5} \text{ N/m}^2$ is the reference pressure.

The time-domain signal (sound) can be converted to the frequency domain using a Discrete Fourier Transform. This allows for the spectral analysis of all constituent frequencies in a noise measurement. The Overall Sound Pressure Level (OASPL) represents the total sound energy across all frequencies for a specific point in time and is shown in the upper part of Figure 2.1. An aircraft noise event is typically characterised by a gradual rise and fall in OASPL during a flyover.

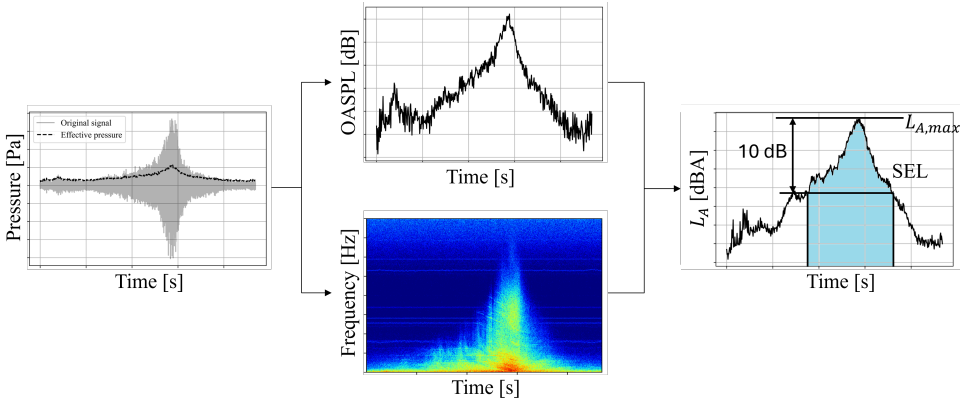


Figure 2.1: Visualisation of noise metrics used in aircraft noise modelling.

From the time-domain pressure signal, frequency content can also be extracted and visualised using a spectrogram, as shown in the bottom panel of Figure 2.1. Additionally, sound levels can be analysed in specific frequency bands, commonly 1/3-octave bands. For each band n , a Pressure Band Level (PBL), denoted as L_n , can be computed. In aviation, the A-weighting is commonly applied to the OASPL to account for the sensitivity of the human ear to certain frequencies [32]. The A-weighting correction is defined as

$$\Delta L_{A_n} = -145.528 + 98.262 \log_{10} f_n - 19.509 (\log_{10} f_n)^2 + 0.975 (\log_{10} f_n)^3 \quad (2.2)$$

where f_n is the centre frequency of the respective 1/3-octave band n . The A-weighted overall sound pressure level, denoted as L_A , can then be calculated by logarithmically summing the corrected PBLs:

$$L_A = 10 \log_{10} \left(\sum_{n=1}^N 10^{(L_n + \Delta L_{An})/10} \right). \quad (2.3)$$

This leads to the L_A curve as illustrated in Figure 2.1.

The most relevant metrics used in aircraft noise modelling are the peak noise level or the maximum A-weighted sound pressure $L_{A,max}$, and the Sound Exposure Level (SEL). While $L_{A,max}$ is the peak level in a flyover, SEL accounts for both the intensity and duration of the noise event. It represents the total sound energy normalised to a reference period of one second. SEL is calculated by integrating the A-weighted SPL over the duration of the event, typically from the points where the level drops 10 dB below the peak. This is illustrated by the shaded area on the right panel of Figure 2.1 and is calculated by

$$SEL = L_{AE} = 10 \log_{10} \left[\int_0^T 10^{\frac{L_A(t)}{10}} dt \right] \quad (2.4)$$

where T is the integration time and $L_A(t)$ is the A-weighted noise level over time. SEL is commonly used to calculate long-term exposure metrics, as later explained in section 2.3.

Lastly, the Effective Perceived Noise Level (EPNL) is a standardised metric used primarily for aircraft noise certification. Expressed in EPNLdB, it reflects not only the physical sound pressure level but also how humans perceive and judge aircraft noise. EPNL builds on the Perceived Noise Level (PNL), which converts octave-band sound pressure levels into a single value using a linear annoyance scale of noisiness curves that accounts for the human ear's varying sensitivity across frequencies [32]. To capture the full noise event, the PNL time history is integrated into the Perceived Noise Level Tone-corrected (PNLT) curve, which adds penalties for tonal components, such as engine fan tones. The EPNL metric is then calculated by integrating PNLT values over the duration of the flyover, in a manner similar to SEL. Because EPNL is the regulatory metric used in ICAO Annex 16 [14] and FAA Part 36 certification procedures [33], it plays a central role in airport noise policy. However, since its primary purpose is certification rather than community noise exposure assessment, it is not used further in the research presented in this dissertation. The focus is put on the SEL and $L_{A,max}$ metrics, in line with airport environmental assessments and regulatory frameworks.

2.2. METHODOLOGY OF AIRCRAFT NOISE MODELLING

Aircraft noise modelling is a critical component of environmental impact assessments around airports. The European Civil Aviation Conference (ECAC) Document 29 (Doc 29) provides the internationally recognised best-practice methodology for predicting aircraft noise exposure. This section outlines the methodology and key assumptions embedded in the Doc 29 approach.

2.2.1. OVERVIEW OF THE MODELLING FRAMEWORK

The Doc 29 methodology is designed to estimate noise levels at ground receivers resulting from aircraft operations. It is based on an empirical model that combines measured noise data with simplified representations of aircraft flight paths and environmental conditions. The model is built to balance computational efficiency with sufficient accuracy for regulatory purposes. Its simplified structure is shown in Figure 2.2. The modelling process consists of four core components:

1. Flight path segmentation,
2. Noise-Power-Distance (NPD) lookup tables,
3. Application of correction factors,
4. Summation of segment contributions and calculation of noise metrics.

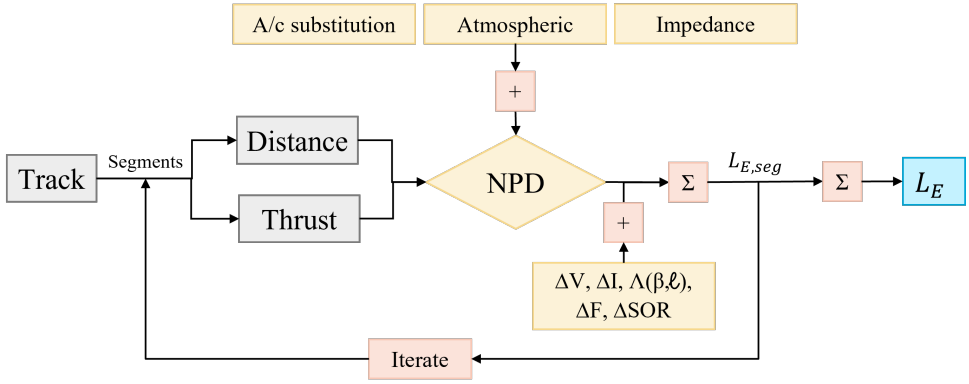


Figure 2.2: Methodology of the Doc 29 best-practice noise model.

2.2.2. FLIGHT PATH REPRESENTATION AND SEGMENTATION

Flight path representation in a noise model can be defined in one of three categories [19]. The simplest method is the Closest Point of Approach (CPA) method, suitable for instantaneous noise metrics such as $L_{A,max}$. In this method, the noise level is calculated for a single point in time and space.

For exposure-based metrics like L_E or specifically SEL, the approach is expanded into a segmentation modelling method. Aircraft flight paths are represented as a series of continuous straight-line segments. Each segment is characterised by a fixed aircraft configuration (e.g., speed, thrust, altitude), and treated as a finite portion of an idealised infinite flight path. The assumption is that, within each segment, the aircraft's noise emission characteristics remain constant. This segmentation allows the model to approximate the continuously varying aircraft trajectory using discrete elements. For the exposure noise metrics, the segments are summed according to the energy fraction (section 2.2.5), and the maximum level is simply the largest of the individual segments. The segmentation method assumes each segment is represented by an acoustic monopole

source, while directional effects are introduced separately through correction factors. Further, the flight path within each segment is assumed sufficiently straight. Curved trajectories are modelled using multiple smaller segments, which increases the computational time.

A more advanced modelling approach is to consider a higher density of points along a flight path. At each point, the sound radiating from the aircraft is calculated. Examples of such models include the sonAIR model (chapter 7), which requires detailed 3D spectral characteristics of aircraft noise. They can be computationally intensive, and therefore less suited for most modelling practices at airports. The segmentation method is thus the considered best practice.

2.2.3. NOISE-POWER-DISTANCE (NPD) TABLES

NPD tables are the empirical core of the Doc 29 model. They provide noise levels of four different metrics (SEL , $L_{A,max}$, $EPNL$ and $PNTL_{max}$) as a function of engine power setting and slant distance to the receiver for specific aircraft types and configurations (departure or arrival). These tables are documented in the Aircraft Noise and Performance (ANP) database [22]. Figure 2.3 illustrates the SEL curves for a B737-800 departure for five different engine power settings at the ten specified distances in the NPD table. The noise level decreases logarithmically with increasing distance, while it increases linearly with increasing power setting. Interpolation and extrapolation are used to estimate noise levels for intermediate power settings and distances not explicitly listed in the tables.

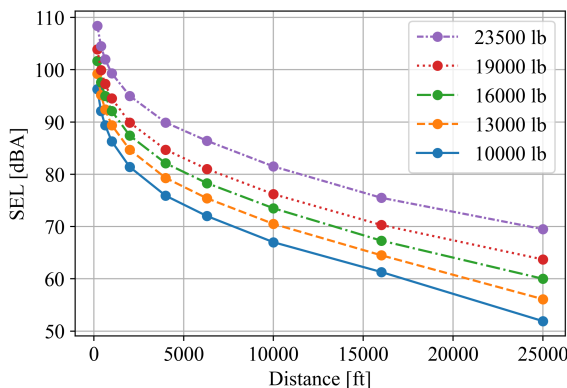


Figure 2.3: Values of SEL in the NPD table for the B737NG.

NPD data represent average conditions and are applicable across a range of operational scenarios (e.g. different flap settings). It also assumes that aircraft of the same type exhibit similar noise characteristics. For example, aircraft types such as the B737-700 and B737-800 use the same NPD table for noise modelling. Correction factors per subtype are applied as described in section 2.2.4. NPD tables are valid under a set of reference conditions. It assumes the noise emission is omnidirectional in the horizontal plane, the aircraft flies a standard 160 knots ground speed, and the atmosphere is homogeneous and standard (roughly ISA conditions). Any deviations from these conditions

require a correction factor.

The distance parameter is defined as the distance between the aircraft and a position of 1.2 m above ground. The local terrain is assumed to be flat with soft ground and free of reflecting objects within several kilometres of the aircraft's ground track. Although the NOMOS system used in this dissertation employs microphones on higher poles, Doc 29 states that modelled and measured A-weighted sound exposure levels are relatively insensitive to receiver height [20]. This is also confirmed in a recent measurement campaign around Rotterdam-The Hague Airport [34].

The NPD values and other ANP data are derived from a limited set of controlled noise measurements. Since these measurements cover only specific operating conditions and source–receiver geometries, additional corrections, interpolation and extrapolation procedures are applied to obtain the complete NPD dataset under ANP reference conditions. When an aircraft manufacturer submits new ANP data, it is reviewed by the European Union Aviation Safety Agency (EASA). EASA checks the feasibility of the new ANP data and compares the model outcomes (using EUROCONTROL's IMPACT model [35]) to the certification measurement data obtained through methods described in ICAO Doc 9501 [36]. Measurement locations and conditions for aircraft noise certification are described in Code of Federal Regulations [33].

Although NPD values are derived from real measurements, the database relies on a series of processing steps, including corrections and extrapolations. This introduces uncertainty in the data for operational conditions not specifically measured when the dataset was created.

2.2.4. CORRECTION FACTORS

To adapt the reference NPD data to real-world conditions, a set of correction factors is applied. These corrections are typically empirical and are designed to maintain model simplicity while improving accuracy.

AIRCRAFT SUBSTITUTION CORRECTION

Whenever a specific aircraft type is not available in the ANP database, a substitution, also called a 'proxy', aircraft with similar noise and performance characteristics is used. Such a substitution can be selected based on a list of criteria such as engine category (jet, turboprop, piston), engine installation (wing or fuselage), aircraft maximum take-off weight (MTOW) or certified noise levels. The substitution method is described in detail in Doc 29 Volume 1 [19]. A table of best substitutions is published alongside the ANP database [22]. Two different substitution tables exist.

The first table includes all certified aircraft configurations as known in ICAO Annex 16 Volume I Chapter 1 [14] sorted by noise record number. These numbers represent a certain airframe-engine combination for a specified MTOW. For each certified configuration, corrections in decibels (ΔdB) or number of equivalent flight movements (N) are provided separately for departure and arrival operations. The equivalent flight movements correction is used when modelling a high number of flights, for example, a yearly averaged L_{den} . For this research, a single decibel correction is used for each flight departure (Δdep) or arrival (Δarr). A positive ΔdB means that the aircraft to be modelled has higher certified noise levels than the proposed ANP proxy.

The second table is a condensed version of the first table and provides ANP proxies for each ICAO aircraft code. This substitution is used when only the ICAO code is available to describe the aircraft. The corrections ΔdB in this table represent the noisiest aircraft configuration for a given ICAO code / ANP proxy pair.

During this research, the Aircraft Noise Certificate (ANC) database of EASA was used to obtain noise record numbers of each specific tail number in the data sets. This allows for the more detailed aircraft substitution correction to be applied.

ATMOSPHERIC CORRECTION

Doc 29 is developed to predict aircraft noise propagation under a wide range of environmental conditions. Changing atmosphere influences acoustic energy through mechanisms such as molecular absorption, refraction due to temperature and wind gradients, scattering from turbulence, and ground interaction. Although all these phenomena affect noise predictions, they require extensive models to estimate them [37]. Testing these advanced noise propagation methods on multi-event calculations resulted in limited differences [38]. As a trade-off for computational efficiency, Doc 29 therefore only corrects for the absorption using an NPD adjustment.

Standard NPD tables are normalised to attenuation rates defined in SAE AIR-1845 [13]. The absorption coefficients in AIR-1845 are not derived from a specific physical atmospheric state. Instead, they represent arithmetic averages of empirical data collected during aircraft certification tests conducted in Europe and the United States. As such, they serve as a standardised reference baseline rather than a physically modelled atmosphere.

To account for deviations from this reference baseline, an atmospheric correction method is applied as described in Appendix D of Doc 29 Volume 2 [20]. This correction adjusts the atmospheric absorption component of sound propagation based on actual local meteorological conditions. The correction is implemented by computing a correction factor $\Delta L_A(T, p_a, h_{rel}, d_i)$ for each distance d_i in the NPD table. This factor represents the difference in atmospheric absorption between the actual local atmosphere, i.e. temperature T , pressure p_a , and relative humidity h_{rel} , and the reference atmosphere. The correction is frequency dependent and accounts for the spectral shape of the aircraft noise source. It is calculated by

$$\begin{aligned} \Delta L_A(T, p_a, h_{rel}, d_i) &= L_{A,atm}(T, p_a, h_{rel}, d_i) - L_{A,ref}(d_i) \\ &= 10 \log_{10} \sum_{n=17}^{40} 10^{(L_{n,ref} + \alpha_{n,ref} d_{ref} - \alpha_n d_i - A_n)/10} \\ &\quad - 10 \log_{10} \sum_{n=17}^{40} 10^{(L_{n,ref} + \alpha_{n,ref} d_{ref} - \alpha_{n,ref} d_i - A_n)/10} \end{aligned} \quad (2.5)$$

where $L_{n,ref}$ is the so-called spectral class, a reference sound level in the n -th 1/3-octave band at $d_{ref} = 1000$ ft, obtained from the ANP database. Each aircraft type is assigned a general spectral class. Further, α_n is the absorption coefficient for the actual atmosphere, calculated using SAE ARP5534 [39]. $\alpha_{n,ref}$ is the absorption coefficient for the reference atmosphere. Finally, A_n is the A-weighting factor for the n -th frequency band.

The spectral classes and thus the atmospheric correction contain 24 1/3-octave bands, with centre frequencies ranging from 50 Hz to 10,000 Hz, corresponding to band

numbers 17 through 40. Since the spectral classes are expressed in dB and the NPD tables in dBA, the spectra are A-weighted using A_n before summation. The use of the spectral classes is examined in detail in chapter 6.

IMPEDANCE ADJUSTMENT

In addition to changes in absorption, atmospheric conditions affect the acoustic impedance of air, thereby altering the relationship between sound pressure and intensity. The impedance correction adjusts NPD levels for deviations in temperature and pressure from reference conditions by

$$\Delta_{\text{impedance}} = 10 \cdot \log_{10} \left(\frac{\rho \cdot c}{\rho_0 \cdot c_0} \right), \quad (2.6)$$

where ρ and c are the local air density and speed of sound, and ρ_0, c_0 are the reference values. These values can be calculated from the ambient conditions of pressure and temperature at the airport. The impedance correction is generally very small.

DURATION CORRECTION

In Doc 29, the NPD data are referenced to a standard flyover speed of typically 160 knots. When an aircraft flies a trajectory segment at a different speed, the SEL must be adjusted to account for the fact that the noise event becomes longer or shorter. This adjustment is called the duration correction. Because SEL is an energy-integrated metric, a slower aircraft (lower segment speed V_{seg}) stays within the observer's vicinity for a longer time, increasing the received sound energy. The duration correction modifies SEL according to

$$\Delta V = 10 \cdot \log_{10} \left(\frac{V_{\text{seg}}}{V_{\text{ref}}} \right). \quad (2.7)$$

This correction only compensates for the change in event duration, ensuring that SEL reflects the correct time-integrated noise exposure at the receiver. It is thus not a speed correction. The adjustment does not account for any changes in the aircraft's instantaneous source noise that may occur due to flying faster or slower. The produced noise of components like the airframe noise during approach, are partly dependent on operational speed. As shown in Snellen et al. [40], airframe noise can increase significantly with higher flown speed, meaning that ignoring speed-dependent source noise can lead to discrepancies between predicted and actual noise levels. At present, Doc 29 does not include a correction for these speed-related noise emission changes. Only SEL is modified through the duration effect, while instantaneous noise metrics remain uncorrected for speed changes.

ENGINE INSTALLATION EFFECTS

Aircraft engines are mounted in various configurations, such as under the wing or on the fuselage, which influences the directionality of noise radiation. The installation correction accounts for shielding, reflection, and refraction effects caused by the airframe and flow fields. It is a function of the depression angle between the wing plane and the observer:

$$\Delta_I(\phi) = 10 \cdot \log_{10} \left(\frac{(a \cdot \cos^2(\phi) + \sin^2(\phi))^b}{c \cdot \sin^2(2\phi) + \cos^2(2\phi)} \right) \quad (2.8)$$

where empirical coefficients a, b, c vary by engine placement and are derived from experimental measurements. ϕ is the depression angle as visualised in Figure 2.4. This correction is a simplified directional component which is not dependent on the operation and aircraft type. Large-scale measurement campaigns showed significant differences between aircraft types and operating procedures [6], showing that the Doc 29 correction factor is limited in its use.

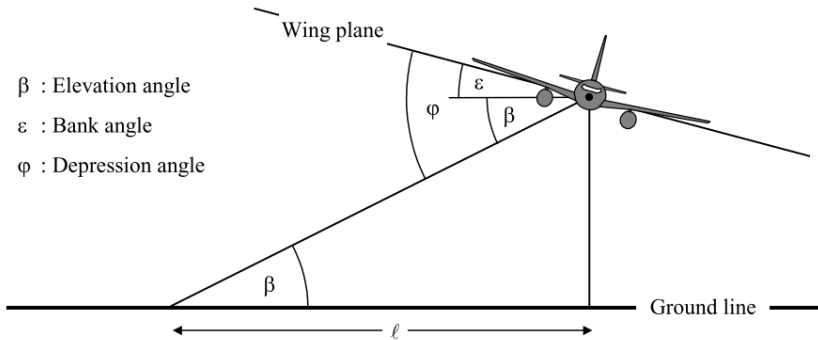


Figure 2.4: Aircraft-observer angles in plane normal to flight path (adapted from [20])

LATERAL ATTENUATION

Sound propagating at low elevation angles over the ground experiences excess attenuation due to interference between direct and reflected waves, as well as atmospheric refraction. To account for these effects, the lateral attenuation correction $\Lambda(\beta, \ell)$ is applied to both maximum and exposure metrics. The correction depends on the elevation angle β and lateral displacement ℓ from the flight path. This attenuation is calculated using the standard AIR-5662 [41], based on empirical data. The attenuation effect is illustrated in Figure 2.5. The attenuation remains constant for lateral displacement distances above 3000 ft (≈ 914 meters) and is 0 for elevation angles above 50° . This lateral attenuation correction is a highly simplified estimation of multiple complex characteristics of aircraft noise. A recent study compared the accuracy of lateral attenuation corrections of current best-practice models with those from the sonAIR model for grazing sound incidence angles [42]. The measurements indicated that the sonAIR model outperformed the predictions made by the Aircraft Environmental Design Tool (AEDT), a standard best-practice model similar to Doc 29. In chapter 7, a comparison with NOMOS measurements shows that sonAIR also outperforms Doc 29 for lower elevation angles and larger distances.

FINITE SEGMENT CORRECTION

NPD data represent noise from an infinite flight path, whereas real aircraft movements are segmented. The finite segment correction adjusts the exposure level to reflect the limited contribution of each segment. It is based on the energy fraction F , which quan-

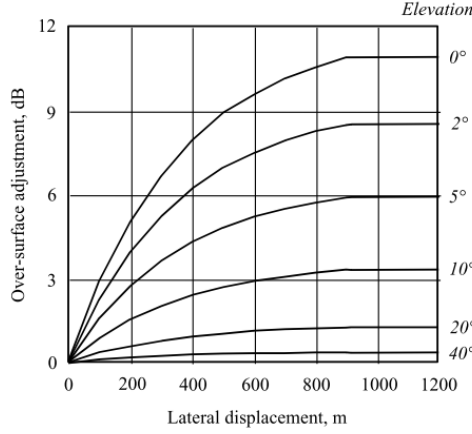


Figure 2.5: Variation of lateral attenuation with elevation angle and lateral distance [20]

tifies the proportion of total noise energy received from a segment:

$$\Delta_F = 10 \cdot \log_{10}(F). \quad (2.9)$$

The energy fraction originates from expressing the noise exposure of a finite path segment in terms of the exposure E_∞ from an idealised infinite straight flyby. For a 90° dipole source, the instantaneous mean-square sound pressure varies approximately as d^{-4} , where d is the slant distance to the aircraft. This fourth-power behaviour arises from a combination of spherical spreading (d^{-2}) and a directivity term $\sin^2 \psi$ representing all remaining physical effects such as source directivity, finite sound speed, atmospheric absorption, and Doppler shift. Here ψ is the angle between the flight path and aircraft-observer vector. The energy fraction thus depends on the segment geometry and observer position. The resulting fourth-power dipole has directional characteristics which approximate those of jet aircraft sound. This incorporates the longitudinal directivity of aircraft noise and the angular extent of the segment as seen from the observer's position. While the physical mechanisms behind aircraft noise directivity are complex, studies have shown that the resulting noise contours are relatively insensitive to the exact directional model used [20]. Therefore, a simplified expression for F is sufficient for accurate modelling. This is expressed as

$$F = \frac{1}{\pi} \left(\frac{\alpha_2}{1 + \alpha_2} + \arctan \alpha_2 - \frac{\alpha_1}{1 + \alpha_1} - \arctan \alpha_1 \right), \quad (2.10)$$

where α is the relative distance q to the point of closest approach divided by the scaled distance d_λ of the beginning (1) and end (2) of the segment. The exact derivation of this equation is given in Appendix E of Volume 2 of Doc 29 [20].

This correction factor is only applied to integrated noise metrics, such as SEL. If you produce a L_A versus time curve using the $L_{A,max}$ metric, and subsequently calculate SEL from this, it will differ from the SEL resulting from the above described procedure.

START-OF-ROLL DIRECTIVITY

During takeoff, jet engines produce a pronounced rearward noise lobe. For observers located behind the start-of-roll (SOR) point, a directivity correction is applied to capture this effect. The correction Δ_{SOR} quantifies how the total noise measured behind the SOR differs from the total noise measured laterally to the SOR position. Δ_{SOR} is a function of the azimuth angle ψ between the aircraft axis and the observer, where the nose is 0° and the tail at 180° . The directionality is based on empirical functions for jet and turboprop aircraft, obtained from an extensive measurement campaign [43]. The correction is then scaled based on the distance d_{SOR} between the observer and the aircraft at the start of the ground roll segment. The shape of the corrections can be seen in Figure 2.6, where the correction is 0 for angles between 0° and 90° .

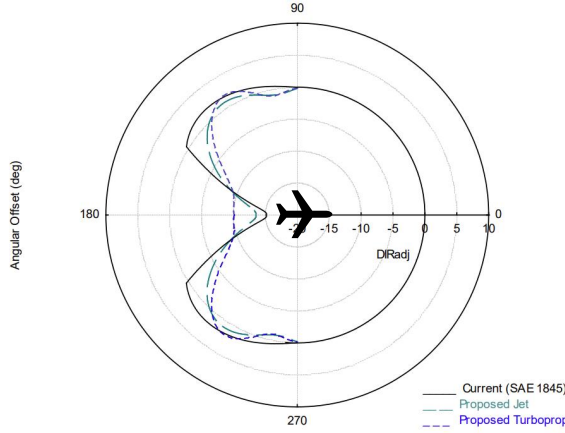


Figure 2.6: Take-off-roll directivity adjustments based on measurements. Adapted from [43].

SUMMATION OF CORRECTIONS

The atmospheric correction and the aircraft substitution correction are applied to the NPD table before the segmentation. All other correction factors are applied for each segment in the flight path. It is assumed that all corrections are additive in the logarithmic domain and the influence of each factor is independent of the others. The segment noise levels are defined as

$$L_{\max, \text{seg}} = L_{\max}(P, d) + \Delta_I - \Lambda(\beta, \ell) + \Delta_{\text{SOR}} \quad (2.11)$$

and

$$L_{E, \text{seg}} = L_{E\infty}(P, d) + \Delta_V + \Delta_I - \Lambda(\beta, \ell) + \Delta_F + \Delta_{\text{SOR}} \quad (2.12)$$

for the maximum noise level and the exposure-based metrics, respectively.

2.2.5. SEGMENT CONTRIBUTION AND NOISE SUMMATION

Once all flight path segments have been computed, the final noise metric estimates can be derived. These estimates differ depending on whether the metric is instantaneous or time-integrated.

Instantaneous metrics, such as $L_{A,max}$, are determined by identifying the point on each segment that is closest to the observer. For segments preceding the observer, this is typically the segment's endpoint. For segments directly overhead, the closest point may lie anywhere along the segment. The model iterates through all segments, calculating the noise level at the closest point for each, and retains the maximum value. This approach ensures that the highest instantaneous noise level experienced by the observer is captured.

Time-integrated metrics, such as the SEL, require summing the contributions from all segments. Each segment contributes a portion of the total noise energy, with segments nearer to the observer generally contributing more. The final exposure noise metrics are calculated by logarithmically summing all segment contributions according to

$$L_E = SEL = 10 \log_{10} \sum_{i=1}^N 10^{L_{E,seg_i}/10} \quad (2.13)$$

where i is the number of the segment in the flight path of N segments.

This use of finite segments and logarithmic summation in calculating SEL introduces inherent uncertainty in the noise prediction. The modelled segment energy cannot be precisely matched to measured noise levels. Using the model, the SEL is constructed as the energetic sum of contributions from all discrete segments along the trajectory. In contrast, the measured SEL at a fixed monitoring station may only consider the dominant contribution of a single segment, or a limited number of consecutive segments. As a result, it becomes unclear which part of the flight contributes to an individual measurement. This complicates the back-propagation of measured levels in chapter 5 and limits the precision with which measurements can be related to the underlying source data.

2.2.6. SUMMARY

The Doc 29 methodology provides an empirical approach to aircraft noise modelling. It combines standardised data with simplified flight path representations and correction factors, which enable consistent and reproducible noise calculations. The model is optimised for large-scale airport noise calculations, not for detailed acoustic simulations as the model contains a number of simplifications and assumptions. The accuracy of the Doc 29 model is highly dependent on the empirical ANP data used as input. The research in chapters 5 and 6 of this dissertation is focused on this empirical data.

2.3. APPLICATION OF THE MODEL

The model can be applied to calculate the noise metrics at a specific location, for example, a NOMOS NMT. While it can be applied to analyse individual flyovers, Doc 29 is intended primarily for evaluating large volumes of aircraft movements over designated time intervals. The most common metrics are the L_{den} and the L_{Night} . The L_{den} , a Day-Evening-Night average, is used to assess the cumulative noise impact around an airport. The L_{Night} is to specifically assess the noise impact during night hours between 23:00

and 7:00. L_{den} is defined by

$$L_{den} = 10 \log \left(\sum_{i=1}^N 10^{(SEL_i + W_i)/10} \right) - 10 \log(T) \quad (2.14)$$

where N is the total number of events in a year, SEL_i are the SEL values per aircraft event (measured or modelled) at specific locations, and W_i are the assigned penalties for day (0 dBA), evening (5 dBA) or night (10 dBA) flights. The T is the total reference time (in seconds) over which the period is averaged. This results in a factor of 75 for all seconds within a year. For the night-time metric L_{night} , an eight-hour period (23:00 to 07:00) is used, resulting in a normalisation factor of 70.2.

To prevent the model from having to calculate noise levels of 500,000 flights, flights with similar aircraft types, weights and routes can be clustered. For instance, in 2024, approximately 1,400 B737-800 aircraft executed a Continuous Descent Approach (CDA) to runway 18R via waypoint SUGOL. Simulating this group collectively significantly reduces processing time, but it adds an assumption about the average track and thus the expected noise on the ground. In general, this clustering is applied when looking at future scenarios. When evaluating historical flights, the actual flown track is taken. This dissertation focuses on historical flights and measurements, thus clustering is not applied and individual flights are calculated.

To assess the overall community noise exposure, noise levels are computed on a pre-defined spatial grid around the airport. At Schiphol, the standard grid spans approximately 80 km × 80 km, with grid points spaced every 250 meters. Noise levels between grid points are interpolated to form noise contours as depicted in Figure 2.7. At Schiphol Airport, the 58 and 48 dBA L_{den} contours and the 48 and 40 dBA L_{night} contours were reported yearly. The World Health Organisation (WHO) marks the 45 dBA contour as a lower bound for noise hindrance [24]. Due to recent changes in policy, Schiphol now includes noise calculations up to this 45 dBA mark, following the WHO guidelines. This increases the noise contour area significantly as seen in Figure 2.7.

An important final step is estimating the number of highly annoyed (HA) residents within the L_{den} contour areas. Residential housing data is used to identify the population exposed to various noise levels. These houses are visible in Figure 2.7 in pink and blue for the 45 and 48 L_{den} contour, respectively. To quantify annoyance, a dose–response relationship is applied, based on survey responses that capture perceived noise disturbance. While the most detailed local study at Schiphol was conducted in 2002, the Dutch National Institute for Public Health and the Environment (RIVM) includes relevant aircraft noise questions in its health monitoring surveys every four years. Recent results suggest that the correlation between L_{den} and the percentage HA is evolving and varies between airports [29]. The use of L_{den} as the only predictor for annoyance remains debated. Critics argue that it inadequately reflects chronic noise exposure and its health consequences. Nevertheless, the combination of Doc 29 and dose–response modelling remains the main method for policy making.

2.4. MODEL IMPLEMENTATION

The research performed in this thesis requires a suitable Doc 29 model. Although multiple Doc 29 implementations are available, such as the IMPACT model from EUROCON-

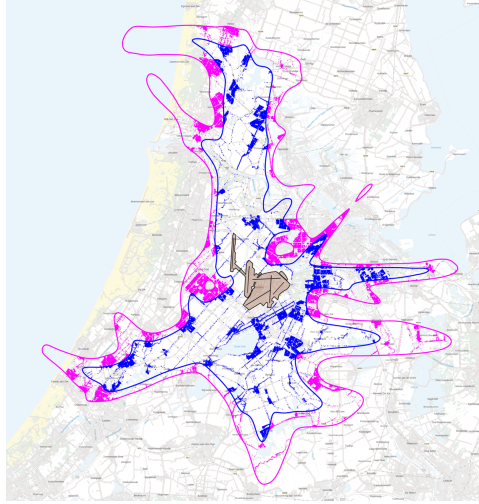


Figure 2.7: The 45 (pink) and 48 (blue) L_{den} noise contour around Schiphol Airport for the year 2023.

TROL [35], these models are limited in their use. First, their reliance on standardised input procedures results in a generic representation of actual flight paths, as further discussed in chapter 3. To insert accurate flight input, as developed in chapter 4, it is necessary to alter the segmentation method and data formats. Second, the standard Doc 29 implementations offer little to no flexibility in altering model components. This is an essential requirement for the objective of this dissertation, which investigates and tests potential improvements to noise modelling frameworks.

This section describes the data used for this implementation in section 2.4.1, including potential open source alternatives. Further, it will shortly describe certain implementation choices based on this data in section 2.4.2, and finally, in section 2.4.3, the model is verified with Doc 29 Volume 3 [21].

2.4.1. DATA SOURCES

The data required for accurate aircraft noise modelling is categorised into four groups.

AIRCRAFT NOISE AND PERFORMANCE (ANP)

The first and foremost is the data from the ANP database [22]. This is an aircraft specific database that includes the NPD tables and spectral classes as discussed in section 2.2. Next to that, it includes a set of performance characteristics such as MTOW, maximum thrust, aerodynamic and jet coefficients. Finally, each aircraft has a set of standard procedural steps or fixed point profiles. These will be elaborated on in chapter 3.

The legacy ANP v2.3 database is publicly accessible via the EASA website, whereas newer versions, including v2.8 used in this research, are available upon request. Both are considered open-source under EASA's licensing framework.

AIRCRAFT NOISE CERTIFICATION (ANC)

In cases where aircraft are not covered in the ANP dataset, substitution corrections are applied using data from the ANC database. This database is maintained by EASA and accessible to competent authorities, air navigation service providers, and EU/EEA airport operators via the EASA environmental portal. It contains certified noise data submitted by all airlines operating in Europe.

Noise certificate data is often also openly available, although not always easily accessible. National databases such as the Dutch Aircraft register¹ also contain similar information, including noise record numbers for all aircraft registered in the Netherlands. These registries must be supplemented with similar databases from other nations to ensure full coverage of aircraft operating at Schiphol Airport.

METEOROLOGICAL DATA

The third data set needed for accurate modelling is local weather data at the airport. While Meteorological Aerodrome Report (METAR) data is commonly used operationally, this research utilises hourly weather observations from the Royal Netherlands Meteorological Institute (KNMI) station at Schiphol Airport. The dataset, available in ASCII format from the KNMI website[44], spans over six decades. Next to temperature, pressure and relative humidity needed for the atmospheric correction, the data also contains information about windspeed and direction and the presence of rain. This is needed to check for suitable conditions for measurements. The weather is assumed uniform across the area around Schiphol.

OPERATIONAL FLIGHT DATA

Operational data represents one of the most critical inputs, capturing actual aircraft movements and characteristics. This includes a range of details about the aircraft, such as operation type (arrival or departure), timestamp, aircraft type, callsign, tail number, runway, pathname, origin/destination airport and stage length. In addition to flight lists, trajectory data is required to model the noise. For this research, high-resolution radar data provided by Dutch Air Traffic Control (LVNL) is used, comprising positional updates (latitude, longitude, altitude) every four seconds along with aircraft speed. Although radar data is not open source, comparable data can be obtained from ADS-B feeds, such as those provided by the OpenSky Network [45]. It is important to note that thrust and weight of the aircraft is not included in this trajectory data and thus needs to be estimated using ANP data or through methods as described in chapter 4

2.4.2. MODEL SET-UP

For this research, a Doc 29 model is developed in Python (v3.13) with a simple code architecture. The main script handles dataset selection, followed by the loading and preprocessing of all relevant data sources as outlined previously. The formatted data is then passed through the model following the flow outlined in Figure 2.2. The model supports two distinct modes of output:

¹<https://www.ilent.nl/onderwerpen/luchtwaardigheid/eigenaren/luchtvaartuigregister>

- Grid output: generates noise contours across a predefined grid for single or cumulative flights. This mode is useful for visualising the impact of model improvements or input variations.
- NMT output: computes noise levels specifically at NMT locations and compares the results with corresponding empirical measurements. This is suitable for validation studies.

The model was specifically implemented for Amsterdam Schiphol Airport, Rotterdam-The Hague Airport and Oslo Gardermoen Airport.

The biggest difference compared to standard implementations of the Doc 29 model is the segmentation strategy. Traditional Doc 29 models segment flight paths in the spatial domain, assuming large, linear segments aligned with standard procedures. However, when taking actual flight tracks with more irregular altitude and thrust profiles, smaller segmentation steps are necessary. Secondly, when segmenting in the spatial domain, it is difficult to synchronise exact segments to the timestamps of the receivers on the ground. This is necessary to link noise predictions to measurements at the NMT locations. Therefore, the implementation in this dissertation segments the track in the time domain, based on the track points.

2.4.3. MODEL VERIFICATION

To ensure all implementations of Doc 29 produce the same output, ECAC Doc 29 Volume 3 provides a framework to verify the model output with given inputs [21]. This volume defines a comprehensive set of reference scenarios with benchmark output data for verifying model fidelity. The reference set includes three hypothetical aircraft types and four trajectory configurations (approach and departure, both curved and straight). These scenarios are designed to isolate and test distinct components of the noise model, including geometric processing, source modelling, directivity, propagation effects, and cumulative time-integration logic. Figure 2.8 visualises the fictive verification layout, illustrating the 18 receptor grid placements for both arrival (left) and departure (right) operations. All four reference trajectories were processed through the Doc 29 implementation developed in this research, and the resulting noise levels were compared point-by-point with the benchmark values provided in the verification dataset.

Across all scenarios, the model reproduced the published reference values with negligible differences. The maximum deviation observed was 0.01 dBA at receptor point R05 during the arrival case. Although small, the difference is explained by the modelling of the ground roll segments during landing. [20] assumes a linear deceleration of velocity and a corresponding linear drop in engine power, with a distinct kink at the touchdown point plus 10% of the stopping distance. However, comparison with verification datasets revealed discrepancies when these assumptions were applied. To achieve closer alignment with the reference data, the velocity profile during landing was modelled using an exponential decay function, while preserving the linear power drop. This modification reduced the error in engine thrust predictions to approximately 100 lbs for the final segment.

In summary, the verification demonstrates that the model implementation developed for this thesis conforms to Doc 29 best-practice standards and reproduces refer-

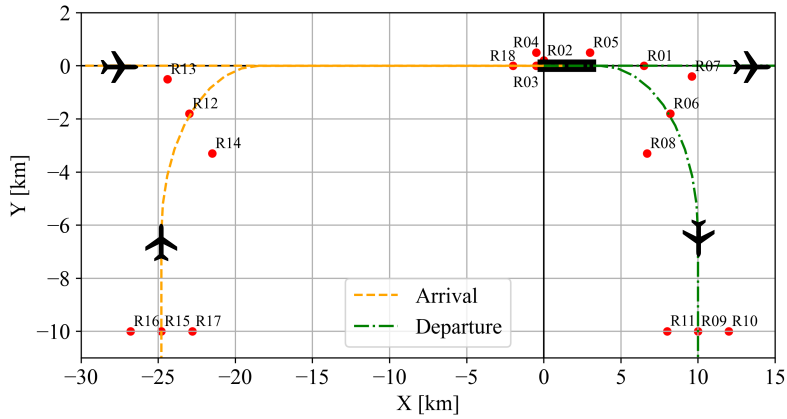


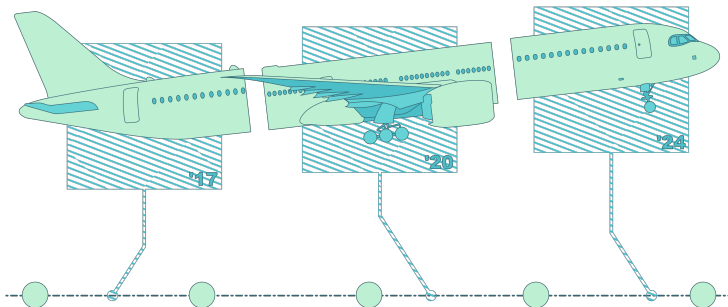
Figure 2.8: Top view geometry of the verification scenario: two arrival routes on the left of the runway, right for departures

ence results with high accuracy. Moreover, the flexible architecture of the implementation enables more detailed input handling and facilitates targeted analysis of individual model components, supporting the broader research objectives of this study.

3

CHALLENGES OF COMPARING MEASURED AND MODELLED ANNUAL AVERAGE NOISE LEVELS

When trying to validate the annual average noise levels predicted by the Doc 29 model as described in chapter 2, multiple challenges arise. This study compares the modelling result with measurements from noise monitoring terminals around Amsterdam Airport Schiphol from 2017 to 2024. This data is further described in section 3.2. In section 3.3 an initial comparison between the measured and modelled noise levels is given. While strong correlations confirm Doc 29's suitability for system-level assessments, systematic biases persist, with nighttime levels L_{night} generally overestimated and L_{den} underestimated. Three dominant uncertainties were identified: operational variability between modelled procedures and flown tracks (section 3.4), background noise effects influencing measured levels (section 3.5), and undetected flights leading to systematic underestimation in measurements, particularly for quieter aircraft and in low-noise regions (section 3.6). Accounting for these factors improves correlation and reduces deviation between measurements and predictions as shown in section 3.7. These results demonstrate promising methods for enabling noise model validation near airports.



3.1. INTRODUCTION

A growing aviation industry is causing increased annoyance in the communities around large airports [46, 26]. Noise policies are developed to address these concerns and to find a balance between aviation activities and noise pollution. Beyond annoyance, research has demonstrated that aircraft noise exposure can lead to adverse health effects, including sleep disturbance and cardiovascular impacts [47]. In particular, nighttime aircraft noise has been shown to trigger acute cardiovascular responses and is associated with increased risks of cardiovascular mortality [48]. These findings underline the societal relevance of aircraft noise and the importance of accurately quantifying noise exposure.

To address these impacts, noise policies are developed to balance aviation activity with environmental and community constraints. These policies are often based on noise modelling, using best-practice models, such as the Aviation Environmental Design Tool [15] or the European Civil Aviation Conference (ECAC) Document 29 methodology [19], short Doc 29. With these models, the noise impact of different aircraft and flight routes can be evaluated. This evaluation is performed through calculations of yearly average Day-Evening-Night noise levels L_{den} , expressed as noise contours. This metric represents the noise experienced on the ground due to all flight movements over a full year. The models are generally accurate within 1-2 dBA [13] and are widely used for route optimisation, environmental impact assessments, and even regulatory decisions such as flight limitations. Given their influence on policy, it is essential that these noise predictions are both accurate and robust. Therefore, validation through direct measurements is a topic of interest.

Dedicated measurement campaigns can be deployed to gain insight into the characteristics of aircraft noise. For example, aircraft noise measurements can be used to investigate the source noise of aircraft as a function of different flight parameters [40, 49, 50]. At larger measurement distances, the effects of noise propagation and incidence angles also become increasingly important. These effects can also be investigated using such measurements [51, 42]. Measurement campaigns are also often used to investigate the effectiveness of specific noise reduction measures [52].

Studies that use noise measurements to validate best-practice noise models often rely on existing noise measurement systems around airports. A common method is to compare the single-flight noise levels of a specific aircraft type with measurements [53, 54]. In general, good agreement has been reported, with deviations within 3 dBA. However, such validation efforts are inherently selective. Measurements are usually taken from large aircraft operating close to airports, where noise levels are high, and data quality is more reliable. This introduces a measurement bias, as only certain flight phases and propagation distances are captured [55]. Consequently, these studies may not fully represent the diverse noise exposure scenarios that support policy decisions. Validating annual average noise levels, such as L_{den} , is therefore essential, yet remains challenging.

Next to this measurement bias, an additional challenge arises from the difficulty of detecting and isolating aircraft noise events in real-world measurement environments. Noise monitoring systems are frequently affected by background noise, which complicates the identification and classification of aircraft-related sound events. Recent studies have therefore explored the integration of surveillance data, such as Automatic Dependent Surveillance–Broadcast (ADS-B), to support the identification and attribution

of noise events [56]. These approaches have demonstrated improved detection performance compared to traditional radar-based methods, but they also highlight the complexity of linking acoustic measurements to individual flights.

Moreover, the increasing availability of flight trajectory data has revealed significant discrepancies between prescribed flight procedures and actual operations. Analyses based on ADS-B data show substantial variability in aircraft trajectories and flight profiles, even for standardised procedures such as noise abatement departures [57]. Such variability can lead to differences in predicted noise levels and spatial exposure patterns, particularly when simplified or representative trajectories are used in modelling frameworks. Incorporating real-world trajectories into noise modelling has been shown to improve the representation of operational variability and improved comparison with noise measurements [58].

These challenges become particularly relevant when considering cumulative noise metrics such as L_{den} . Unlike single-event comparisons, the validation of annual average noise levels requires a comprehensive representation of all contributing flights, including those with low sound exposure levels that may not be detected by measurement systems. Previous work has shown that measurement systems can miss a substantial number of low-level events, especially at larger distances from the airport, leading to potential biases in estimated annual averages [59]. Consequently, validating cumulative noise metrics remains an open challenge, despite its importance for policy applications [60].

The objective of this research is to identify and quantify the challenges that arise when comparing measured and modelled aircraft noise levels when the focus is on annual average indicators such as L_{den} . These challenges originate from three main sources: i) the modelling framework, where often a mismatch exists between the assumed and actual flown track and used thrust, ii) the measurements, for example, due to background noise, and iii) dataset selection or incomplete detection of flights. Differences between measured and modelled noise levels cannot be attributed to only a single source. This study dives into the three sources by addressing them and estimating how these influence measured annual average noise levels. Finally, it provides a structured interpretation of discrepancies between models and measurements in the context of policy-relevant noise metrics. By addressing these objectives, this research contributes to a clearer understanding of the reliability of annual noise predictions. It also supports the development of validation strategies that can strengthen confidence in noise modelling for both regulatory and community applications.

For the above aims, this research considers the averaged aircraft noise level as predicted by the Doc 29 model with measurements around Amsterdam Airport Schiphol. Section 3.2 describes the model and measurement data used for this research. In section 3.3, an initial comparison between modelled and measured noise levels is presented. Based on these results, several observations are highlighted and investigated in the subsequent sections. In section 3.4, the uncertainty introduced by the model input assumptions is discussed by comparing standard procedures to proprietary onboard flight data. Section 3.5 analyses the effect of background noise on measuring in an uncontrolled environment by quantifying the differences between daytime and nighttime measurements. Lastly, section 3.6 addresses the dataset bias by analysing the flights that are not

detected by the measurement system and consequently investigates their effect on total annual noise levels. In section 3.7, above effects are combined to give a good estimate of the comparison of modelled and measured annual noise levels. Finally, section 3.8 summarises the main findings and their implications for future noise modelling and validation efforts.

3.2. NOISE MODEL AND NOISE MEASUREMENTS

3

3.2.1. NOISE METRICS

As described in chapter 2, aircraft noise quantification can be performed using a variety of noise metrics. Most commonly, instantaneous metrics such as the maximum A-weighted noise level $L_{A,max}$, or time-integrated metrics such as the Sound Exposure Level (SEL), are used. These metrics describe the noise intensity of individual aircraft flyovers. For the research in this chapter, the noise exposure for a full year is quantified. This is done using a Day-Evening-Night average indicator L_{den} and its nighttime equivalent L_{night} .

3.2.2. NOISE MODEL

The model used in this research is the European standard Doc 29 aircraft noise model [19]. The reference [20] describes the calculation methodology in detail. The Doc 29 methodology utilises the Aircraft Noise and Performance (ANP) database [22] and works in a manner similar to the Aviation Environmental Design Tool (AEDT) [15]. Both models are denoted as best-practice noise models. The ANP database contains so-called Noise-Power-Distance (NPD) tables for different aircraft types. These tables provide the expected noise level (e.g. SEL) on the ground, as a function of the engine thrust setting and distance from the aircraft.

Often, the most challenging part of best-practice noise modelling is the availability of accurate operational input parameters. For this research, the methodology developed by the Royal Netherlands Aerospace Centre (NLR) is used. References [61, 62] describe how airport-specific operational procedures are developed for Amsterdam Airport Schiphol. This methodology is a trade-off between accuracy and computational demands.

The model output consists of L_{night} and L_{den} predictions on a spatial grid around the airport, roughly 80×80 km. These noise contours include all flights of commercial traffic and general aviation. Helicopter noise is outside the scope of this research. Commercial traffic refers to flights operated by airlines that are available for individual bookings of passengers, cargo, and/or mail transport. These aircraft movements can be subdivided into scheduled flights, which follow fixed routes according to published timetables, and non-scheduled flights, which include charter services with a non-regular operational character. General aviation traffic comprises all other traffic that does not fall under commercial traffic and is independent of aircraft size. This category includes, for example, small business aviation, technical flights following maintenance, and public service operations.

Aviation policy in the Netherlands is based on operational years, which run from

November 1st to October 31st.¹ This research utilises the data from 2017 to 2024.² In Table 3.1, the number of flights operated at the airport of each operational year is given with its corresponding number of nighttime flights. A clear effect of the COVID-19 pandemic is visible in the years 2020 and 2021.

Table 3.1: Number of flights performed in each operational year at Schiphol Airport, rounded off.

Year	Night $N_{flights}$	Total $N_{flights}$
2017	32,300	495,000
2018	31,200	497,400
2019	30,100	497,300
2020	16,100	272,600
2021	16,500	238,700
2022	23,900	395,100
2023	24,500	430,800
2024	24,900	473,800

3.2.3. NOISE MEASUREMENTS

Schiphol Airport is equipped with the Noise Monitoring System NOMOS, consisting of 41 Noise Monitoring Terminals (NMTs), placed at different distances from the runways as illustrated in Figure 3.1. These NMTs are often installed in and around residential areas as their primary goal is to inform the public about aircraft noise exposure. A Dutch national research campaign has investigated the suitability of these NMTs for aircraft noise model validation purposes [31]. Each NMT was given a quality score based on criteria such as location, background noise, and the potential for reflection and obstruction. These criteria match the ones outlined in ISO20906 [30]. Only the NMTs considered suitable for noise model validation are used for the research presented in this contribution. The NMTs deemed not suitable are depicted in red in Figure 3.1. For example, NMT 33 (marked as red) is mounted on a pole approximately one meter above a roof surface and located near a large air-conditioning unit. This causes a high measured background noise and reflections.

The NMTs are placed on high poles 6 to 10 meters tall to minimise ground reflections. A recent study measured differences up to 2 dBA depending on the elevation angle of the aircraft when compared to measurements without ground effect [34]. The Doc 29 model predicts noise levels for a height of 1.2 m above the ground, but states that *"Comparison of measurements at 1.2 m and 10 m and theoretical calculation of ground effects show that variations of the A-weighted sound exposure level are relatively insensitive to receiver height."* [20]. [34] confirmed this result by showing minimal differences for measurements at 1.75 m and 4.5 m.

In addition to the noise metrics $L_{A,max}$ and SEL for each noise event, NOMOS gathers operational characteristics such as radar tracks, aircraft type, operation type, tail num-

¹Detailed noise contour assessments are available in the usage forecast evaluation reports: <https://www.schiphol.nl/nl/jij-en-schiphol/gebruiksprognose-alles-wat-je-maar-wilt-weten/>.

²For example, the operational year 2017 spans from 1st November 2016 to 31st October 2017.

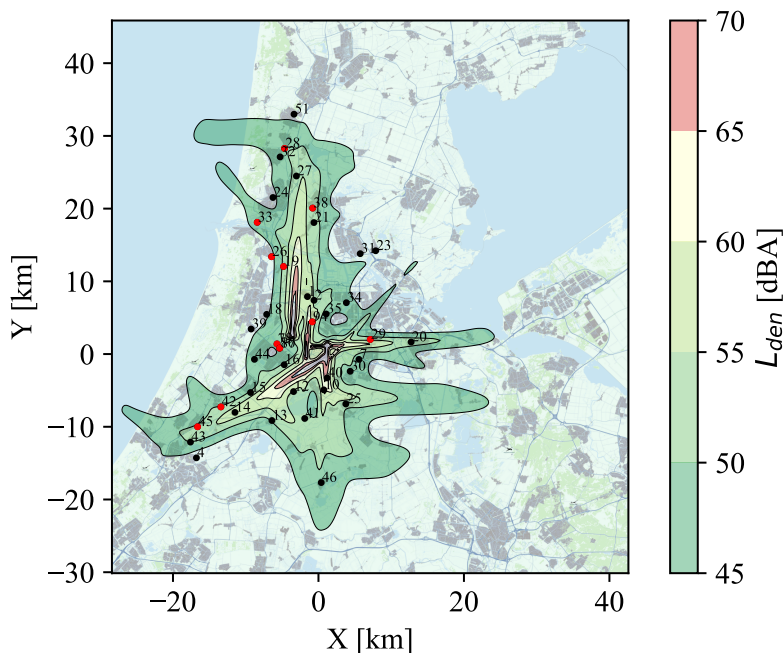


Figure 3.1: Locations of the 41 NOMOS NMTs around Schiphol Airport with respect to the modelled L_{den} of 2023. Red NMTs are not used for validation purposes.

ber, and departure/arrival time. An important parameter used in this study is the Point of Closest Approach (PCA). For each flight-NMT combination, the system calculates the slant distance r , elevation angle β , and altitude h at the moment the aircraft passes closest to the NMT, as visualised in Figure 3.2. Each flight thus results in 41 PCAs, one for each NMT. For NMTs where increased noise levels are detected, the corresponding PCA is coupled to the specific measured noise event. At Schiphol, previous years had a capacity of up to 500,000 flights per year, which results in a large dataset. The availability of PCA data for all NMTs enables the identification of flights with no corresponding noise measurements.

NOISE MEASURING THRESHOLDS

NMTs register aircraft noise by identifying increased noise levels, while accompanying software simultaneously uses radar data to check for aircraft nearby. To prevent non-aircraft events such as road traffic, dogs, or alarms from being falsely detected as aircraft noise, NMTs are equipped with thresholds. These thresholds are often defined relative to the local background noise level and defined as the noise value in dBA that the peak of the noise of the event $L_{A,max}$ must surpass. A 10 dBA difference with $L_{A,max}$ is the standard to adequately remove background noise levels [30]. Around Schiphol, background noise levels are often around 45 dBA. This results in thresholds ranging from approximately 58 to 65 dBA, depending on location and time of the day. For some NMTs, night-

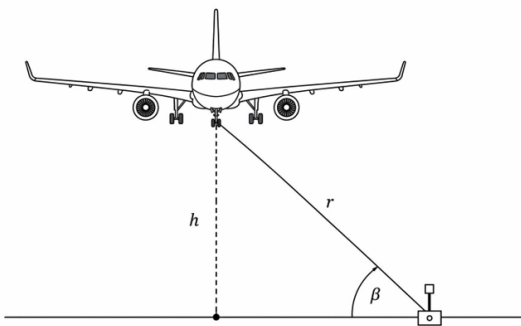


Figure 3.2: Visualisation of aircraft-observer geometry.

time thresholds are set 2-5 dBA lower due to less background noise. Average background noise levels can be estimated using an L90 metric, the noise level exceeded during 90% of the measurement period. A boxplot of daily L90 values and their daytime thresholds for each NMT is presented in Figure 3.3. The circles outside the boxplot represent outlier days. The figure illustrates the variability in background noise conditions at each NMT throughout the year 2023. This highlights the importance of selecting a high-enough threshold to exclude background noise from real aircraft noise events.

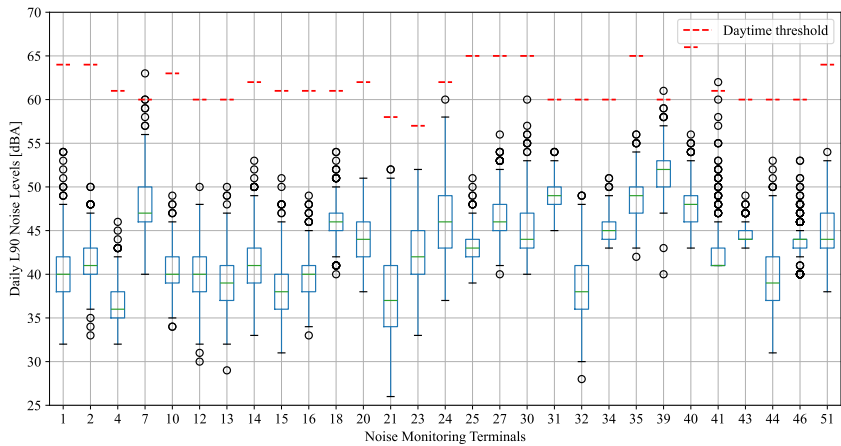


Figure 3.3: Boxplot of daily L90 background noise levels per NMT during the year 2023 and their corresponding daytime thresholds.

Although thresholds decrease the chance of contamination of aircraft noise events by other factors, they also prevent the detection of aircraft noise events that lie below the threshold. This mainly affects quieter aircraft like the A320-NEO (A20N), or flights at larger distances from NMTs. This effect is one of the challenges addressed in section 3.6. For some NMTs, like NMTs 10 and 25, the applied threshold is more than 10 dBA higher

than the highest recorded L90 values. This indicates that the threshold at these locations is likely set too high and should be readjusted in future monitoring efforts.

PRE-PROCESSING AND OUTLIER REMOVAL

Several pre-processing steps are required to ensure data quality before analysis. Because measurements have been taken in uncontrolled outdoor environments, disturbances or incorrect coupling to aircraft can occur. Aircraft at low elevation angles relative to an NMT are particularly problematic, as signals may be obstructed or reflected. In addition, unrelated noise sources such as road traffic may be incorrectly linked to an aircraft that is still on the runway at an elevation angle of 0° .

ISO 20906 recommends using only measurements at elevation angles above 60° to limit the effect of ground reflection and lateral attenuation. Applying this criterion, however, would discard a large portion of flights and hence would not provide a realistic image of the noise exposure at certain locations. Figure 3.4 shows the measured SEL for the B737-800 versus elevation angle and slant distance for arrivals and departures separately. It highlights increased variability at low elevation angles and indicates background noise influences beyond 10,000 ft. Based on data analysis, a more practical compromise was set in this study. Only events with elevation angles below 10° were excluded. This filter effectively removes the most unreliable measurements, where disturbances are most prevalent, while preserving a sufficiently large dataset for statistical analysis. Although the likelihood of disturbed measurements increases at the lower elevation angles (10 to 60°), these data are retained to ensure representativeness of real operational conditions.

It should be noted that lateral attenuation effects become more pronounced at low elevation angles, as described in Doc 29, where attenuation increases significantly as the elevation angle decreases. While this may influence the spread observed in the measurements by a given distance, the same effects are also inherently included in the Doc 29 modelling results used in this study. Therefore, both measured and modelled datasets are affected in a consistent manner, allowing for a fair comparison. Nevertheless, increased uncertainty in both measurement and modelling is expected in this angular range, which should be considered when interpreting the results.

Figure 3.4 also shows a clear cut-off in the measurements at 10,000 ft. This is due to a software constraint that limits the correlation of noise events with aircraft beyond this slant distance for all but a small number of NMTs.

ISO 20906 also recommends using only measurements recorded under wind speeds below 10 m/s and in the absence of precipitation [30]. For the Netherlands, this would result in a 24% reduction in the dataset. In this study, however, measurements under such less favourable weather conditions are retained, even though this would likely lead to somewhat elevated noise levels during these periods.

Further analysis revealed that some NMTs exhibited unexpected large noise levels. A small number of measurements exhibited physically unrealistic noise levels of approximately 120 dBA, most likely due software-related errors. These observations were removed during an initial quality-control step and are not included in the subsequent statistical analysis. To identify less obvious outliers, a w-test [63, 64] was applied to the residuals of a least-squares (LS) regression model. The data were first grouped by aircraft type and operation (arrival or departure), after which an LS model relating the measured

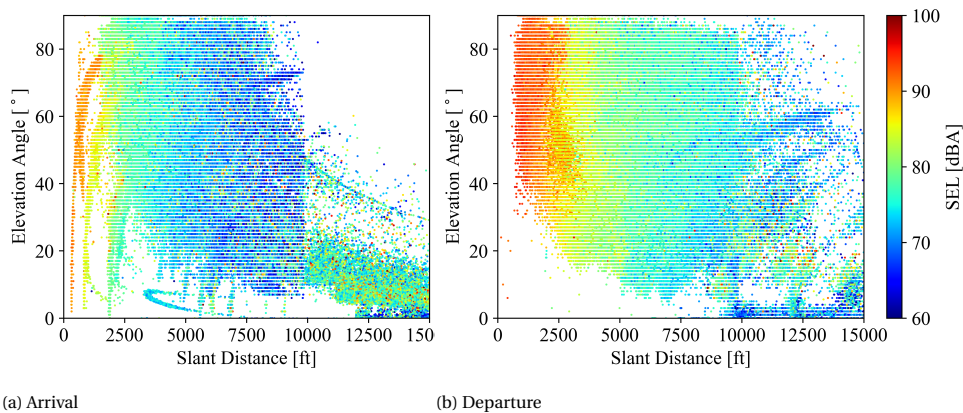


Figure 3.4: Complete eight operational years of measured B737-800 SEL levels across NMIs versus elevation angle and slant distance before outlier removal.

SEL to slant distance was fitted for each group. For every observation, the normalized residual was computed and tested using the w-test. The null hypothesis assumes that the observation is free from gross errors, whereas the alternative hypothesis assumes the presence of an outlier. Observations were flagged as outliers when the test statistic exceeded the critical value corresponding to the selected significance level. A significance level of $\alpha = 0.005$ was adopted. This value provides a balance between sensitivity to actual outliers and protection against falsely rejecting valid measurements. Figure 3.5 illustrates the procedure for arrival measurements of the A21N aircraft, where observations identified as outliers by the w-test are shown in red.

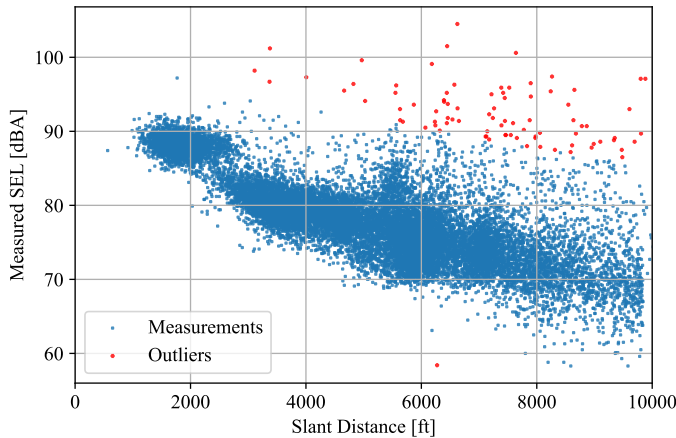


Figure 3.5: Complete eight years of arrival measurements of the A21N with respect to slant distance, where outliers are identified by the w-test.

Lastly, the NOMOS system occasionally experiences interruptions in data availabil-

ity. In twelve instances, gaps exceeding one week within a given year were identified. For a fair comparison of yearly average results, these specific NMTs and years are excluded from further analysis.

3.3. BASELINE MODELLED-MEASURED RESULTS

For each year, the L_{night} and L_{den} noise metrics were calculated from the available measurements and compared with their respective modelled values for all NMTs. The correlation coefficient (ρ) was calculated between the modelled noise levels L_{model} and the measured noise levels L_{meas} . Furthermore, the difference between model and measurement is defined as:

$$\Delta L = L_{\text{model}} - L_{\text{meas}} \quad (3.1)$$

where a negative ΔL indicates that the model underestimates noise relative to the measurements. For all NMTs, the median difference (μ) and standard deviation (σ) of ΔL were computed. Results are summarised in Table 3.2.

Table 3.2: Baseline results of comparing modelled L_{night} and L_{den} to measurements around Schiphol Airport. (The number of flights is rounded off.)

Year	N_{flights}	L_{night}			N_{flights}	L_{den}		
		μ [dBA]	σ [dBA]	ρ		μ [dBA]	σ [dBA]	ρ
2017	32,300	1.31	2.92	0.96	495,000	-0.68	1.53	0.96
2018	31,200	0.23	2.20	0.94	497,400	-0.99	1.76	0.94
2019	30,100	0.78	2.37	0.97	497,300	-0.63	1.86	0.95
2020	16,100	0.82	4.88	0.88	272,600	-1.39	2.42	0.92
2021	16,500	1.43	4.08	0.91	238,700	0.10	2.11	0.94
2022	23,900	1.90	3.67	0.93	395,100	-0.14	2.28	0.92
2023	24,500	1.68	3.54	0.94	430,800	-0.51	1.91	0.95
2024	24,900	0.23	3.25	0.92	473,800	-1.07	2.24	0.94
Average		1.05	3.36	0.93		-0.66	2.02	0.94

A strong correlation between modelled and measured noise levels is observed across all years, for both L_{night} and L_{den} . The correlation coefficients are slightly lower for the years 2020 and 2021. These two years coincide with a substantially reduced number of flights due to the COVID-19 pandemic. A clear difference emerges between ΔL_{night} and ΔL_{den} when analysing the μ . While the model generally overestimates nighttime noise levels, it tends to underestimate noise levels over the full day.

Another notable difference includes a larger standard deviation (σ) for ΔL_{night} compared to ΔL_{den} . Figure 3.6 illustrates these variations for 2023, showing measured and modelled noise levels per NMT. The correlation coefficient and its corresponding p-value are also given. A p-value smaller than 0.05 indicates statistical significance of the estimated correlation. As mentioned in section 3.2, NMTs deemed unsuitable for validation are indicated in red. These NMTs were excluded from the calculation of μ , σ , and ρ , but are shown for completeness.

When analysing the performance of individual NMTs, big differences were observed. Some NMTs, such as NMT 15, showed consistently lower measured noise than predicted

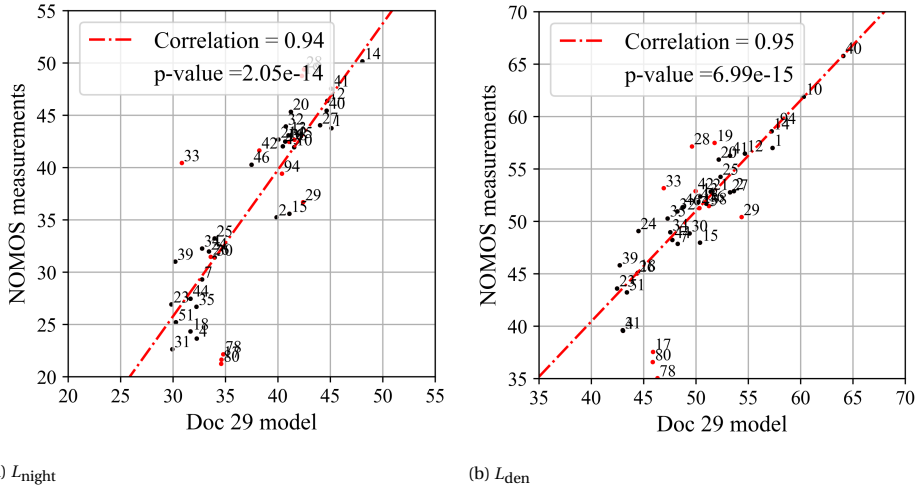


Figure 3.6: Measured and modelled L_{night} and L_{den} of all NMTs for the year 2023, including the correlation coefficient and p-value.

by the model. For L_{night} predictions, and to a lesser extent for L_{den} , the differences between measured and modelled noise levels increase in the so-called low-noise regions, defined, for example, as $L_{\text{den}} < 50$. Measurements further from the airport have lower signal-to-noise ratios, making it more difficult to accurately isolate aircraft noise from background noise. As a result, noise measurements may be overestimated due to the presence of background noise, or aircraft noise events may not be detected at all. In the latter case, the noise contribution of some of the flights is entirely omitted from the measurements, leading to the underestimation of L_{den} or L_{night} .

In the next three sections, the main identified causes that challenge this comparison of measured and modelled L_{den} are addressed. Starting with the potential mismatch between the actual track and thrust and the assumed model input in section 3.4. After, in section 3.5, the influence of ambient noise on the noise measurements is discussed. Finally, in section 3.6, the effect of missing flights, due the fact that they have not been detected by the NOMOS system, on the comparison is quantified.

3.4. MODEL INPUT DISCREPANCIES

The first challenge in comparing measured and modelled aircraft noise levels lies in the discrepancies between the assumed operational procedures in the noise model and the actual flight operations. This section provides a preliminary analysis of these operational differences and their potential impact on noise modelling.

When comparing measured and modelled aircraft noise, it is essential to assess how the modelled flight inputs differ from the actual flown tracks. In best-practice noise modelling, so-called *procedures* are used. These procedures consist of consecutive segments with changing altitude, speed, flap settings, and thrust. The procedures are defined as the distance from the start-of-roll (SOR) for departures and the distance to the

landing threshold for arrivals. The ANP database provides default departure and arrival procedures for most aircraft types [22]. As each airport often has its own operational preferences, Schiphol has developed a procedure database specific to the airport in the form of Fixed Point Profiles (FPP) [61]. To evaluate the discrepancy between these procedures and actual operations, an analysis is performed. The results presented in this section are based on Van Pijlen [65], who examined four aircraft types (A330-300, B737-800, B777-300 and A321neo) using proprietary airline data, consisting of 100 departure and 100 arrival flights per type. The dataset includes flight parameters such as calculated net corrected thrust F_n/δ .

3.4.1. DEPARTURES

Departure procedures typically include acceleration on the runway, an initial climb, a second acceleration, and a subsequent climb. Above an altitude of 10,000 ft, altitude, speed, and thrust profiles are extrapolated for simplicity. FPPs vary based on the aircraft take-off weight, which is estimated from trip length and fuel load. In addition to weight and aircraft type, the specific procedure can differ. The most common departure procedure is the Noise Abatement Departure Procedure 2 (NADP2), which includes an acceleration step at 800 ft. Variants with acceleration at 1000 or 1500 ft are also used. For modelling purposes, the departure procedure for a flight is assigned based on airline questionnaires. This introduces uncertainty because weather conditions or operational restrictions can cause deviations from the selected FPP.

Figure 3.7 illustrates example A330-300 departure profiles using airline flight data. The graphs show the lower and upper bounds of the FPP as a function of the aircraft weight. The upper bound of the altitude profile in Figure 3.7a represents the lowest aircraft take-off weights, while in the FPP thrust profile (Figure 3.7b), it represents the highest aircraft take-off weights. It is evident that the flown altitudes are significantly lower than those prescribed by the FPP. Additionally, the corresponding thrust settings are also reduced compared to the model assumptions. To assess the effect of these discrepancies on the noise, the summed SEL (not normalised to L_{den}) was calculated for a spatial grid around Schiphol, using both the airline data and the FPPs, respectively. Figure 3.8 shows that noise levels are estimated to be lower when actual aircraft performance is used instead of the standard NADP2 procedure. This effect can be significant, depending on NMT location, up to -3 dBA. For this aircraft type, reduced thrust has a larger impact on noise levels than the lower flown altitudes. However, few definitive conclusions can be drawn because performance differences vary among aircraft types. In addition, proprietary flight data listing the thrust is not available for all aircraft types, which restricts a more comprehensive analysis.

3.4.2. ARRIVALS

Arrival procedures at Schiphol are classified as Continuous Descent Approach (CDA) or stepped approaches. In stepped approaches, aircraft maintain level flight segments at altitudes such as 2000 or 3000 ft. Such procedures are often used at congested airports to facilitate traffic sequencing. Schiphol's arrival FPP includes both reduced- and full-flap variants for the CDA and stepped approaches. The stepped approach has variants starting the level segment at 5 to 40 km before the runway. For modelling noise at

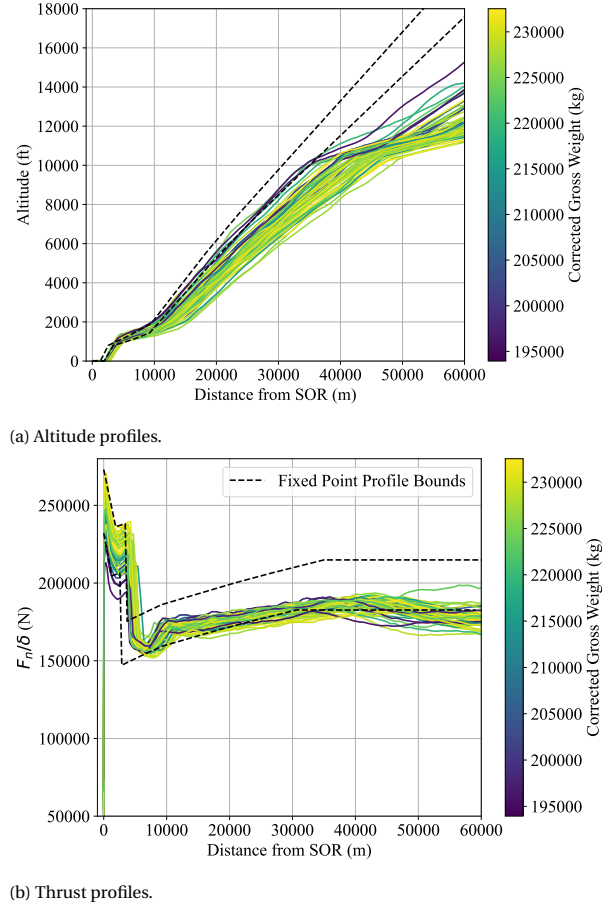


Figure 3.7: Example departure profiles and take-off weights of the A330 compared to the FPPs. Modified from [65].

Schiphol, arrival FPPs are matched to flown vertical flight profiles (from radar data) using a weighted least-squares error metric, reducing mismatches between modelled and flown trajectories. However, deviations in the start location and extent of the stepped approach remain. For example, in Figure 3.9a, stepped approaches starting at 50 km or even 85 km before the runway are visible. Thrust prediction during arrivals is challenging because small deviations in altitude or speed require short thrust increases, as shown in Figure 3.9b.

A similar analysis as for departures was performed for arrivals, producing the SEL grid illustrated in Figure 3.10. In contrast to departures, using actual flight data results in higher modelled noise levels. This is mainly due to lower flown altitudes and intermittent thrust increases during the approach operations. Because thrust patterns during arrivals are highly irregular, predicting their effect on total L_{night} and L_{den} remains difficult.

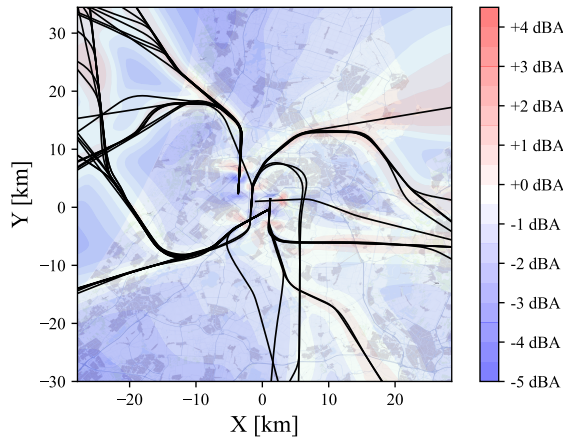


Figure 3.8: Effect on summed SEL of actual A330 departure performance compared to standard FPP. Modified from [65].

Finally, atmospheric conditions introduce additional variation in the noise model input. Doc 29 provides a methodology to account for impedance and atmospheric absorption, but temperature variations also affect aircraft performance. For example, colder conditions or nighttime operations generally require less thrust for similar altitude and speed changes, while hot conditions typically lead to increased thrust requirements. Although average meteorological conditions in the Netherlands are close to ISA, these variations can still significantly influence aircraft performance. For example, in van der Grift et al. [66], it is found that the thrust of an aircraft can be reduced by roughly 5% for a 10 C° colder day. This would consequently correspond to a 1 dBA noise decrease for a B738. Quantifying this effect for the annual averages is outside the scope of this research.

3.5. OFFSET IN MEASURED NOISE LEVELS DUE TO AMBIENT NOISE

The second challenge in comparing modelled and measured aircraft noise levels arises from the presence of ambient noise, affecting the measurements of the continuous noise measurement system. In contrast to measurement campaigns with more controlled conditions, NMTs are placed in an uncontrolled environment with background noise. This background noise can cause higher measured noise levels in SEL and thus higher measured L_{den} noise values. Background noise levels differ per NMT and time of day. Analysis showed lower L90 background noise levels during night hours (23:00-7:00) than during day hours (7:00-19:00). This systematic difference between day and night can help analyse the effect of background noise on the measured SEL of the aircraft noise events. In section 3.5.1, the differences between measured noise during day and night are quantified. Section 3.5.2 tries to extract the effect of background noise on the measured SEL and calculate the effect on the total measured L_{den} .

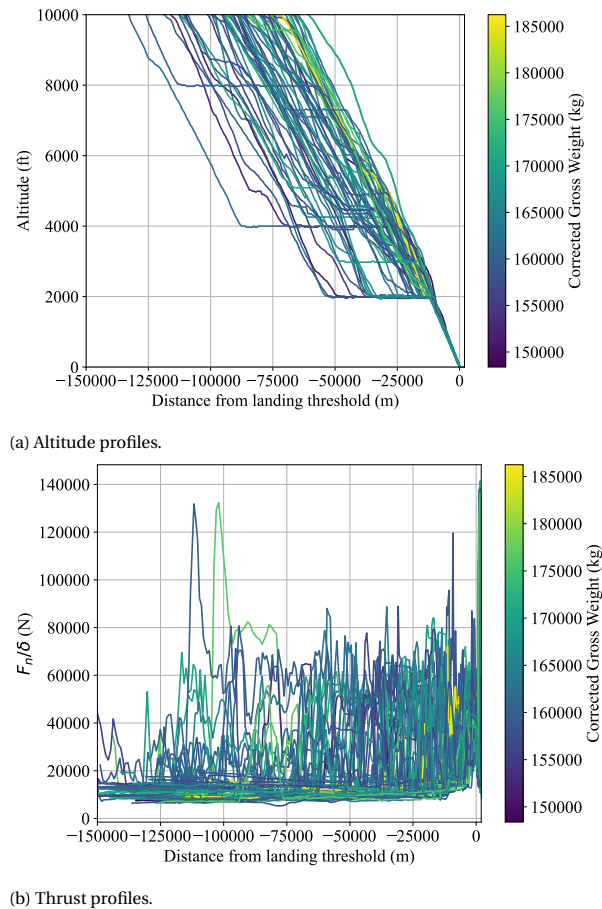


Figure 3.9: Example arrival profiles and landing weights of the A330 relative to runway threshold. Modified from [65].

3.5.1. QUANTIFICATION OF DIFFERENCES IN MEASURED DAY AND NIGHT NOISE LEVELS

To quantify the day-night differences, the average measured SEL per NMT were calculated separately for day and night. The resulting differences between SEL_{day} and SEL_{night} are illustrated in Figure 3.11 for the year 2024. Most NMTs show lower measured nighttime noise levels. The average difference is approximately 0.9 dBA. However, this result alone does not confirm a causal relationship between time of day and measured noise levels. Operational differences between daytime and nighttime traffic may also contribute. For example, lower nighttime temperatures can result in higher air density, allowing aircraft to achieve the required performance with reduced engine thrust during take-off. In addition, operational procedures differ between day and night. For example, 72% of nighttime arrivals use CDA, compared to only 38% during the day. CDA

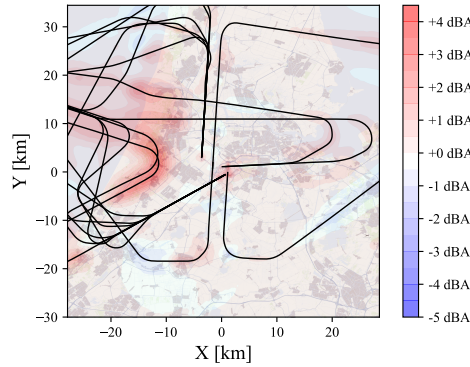


Figure 3.10: Effect on summed SEL of actual A330 arrival performance compared to standard FPP. Modified from [65].

procedures maintain higher aircraft altitudes for a longer period. This increases the average PCA distance at night, lowering SEL_{night} compared to SEL_{day} . Further analysis

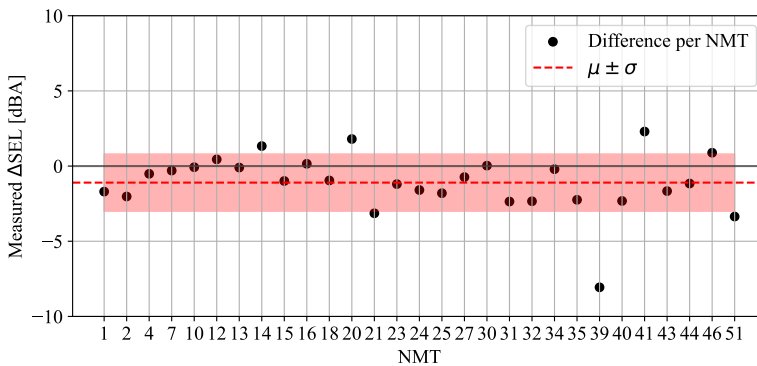


Figure 3.11: Mean difference between measured SEL (night - day) per NMT for the operational year 2023.

of average PCA during arrivals revealed substantial differences at NMTs located farther from the arrival paths, such as NMT 39. This can explain the large difference in measured SEL in Figure 3.11 for this NMT, as an average altitude difference of approximately 1,500 ft was observed between day and night operations. This difference can correspond to noise level differences of up to 3 dBA. Differences in PCA were negligible for NMTs directly under fixed arrival routes (e.g., NMTs 1, 10, and 14). Aircraft over these latter NMTs typically follow the Instrument Landing System (ILS), maintaining similar altitude profiles during day and night.

Additional operational differences between day and night are observed in fleet composition. Smaller aircraft types, such as the E190, fly less frequently during the night. Conversely, a higher proportion of large (cargo) aircraft, such as the B747-400, fly during the night. This change in fleet mix would be expected to increase the measured night-

time noise levels, which does not seem to be the case. To find the effect of the different ambient noise levels between day and night on the measured SEL, the uncertainties within operational differences need to be removed.

To isolate the effect of background noise, SEL values were analysed across fixed PCA distance bins. Measurements were grouped into bins of 1000 ft. For each aircraft type and operation, median SEL values were calculated separately for day and night. The Mann-Whitney U test was applied to assess statistical significance between these non-normally distributed, unpaired datasets [67]. Only bins with more than 20 measurements and statistically significant differences were considered. To avoid location bias, comparisons were restricted to measurements from the same NMTs with sufficient night-time data. The results, averaged across NMTs per distance bin, are shown in Figure 3.12 for three different aircraft type groups. For most aircraft, like the B737NG series depicted in Figure 3.12a, the measured differences increase with the PCA distance. This effect is more pronounced for arrivals than departures, which is expected given the lower source noise levels of arriving aircraft. The day-night SEL differences (ΔSEL_{DN}) were fitted using second-order polynomial curves (see Figure 3.12). The fitted curve through the bins is constrained to start at 0 dBA at the 0 ft bin.

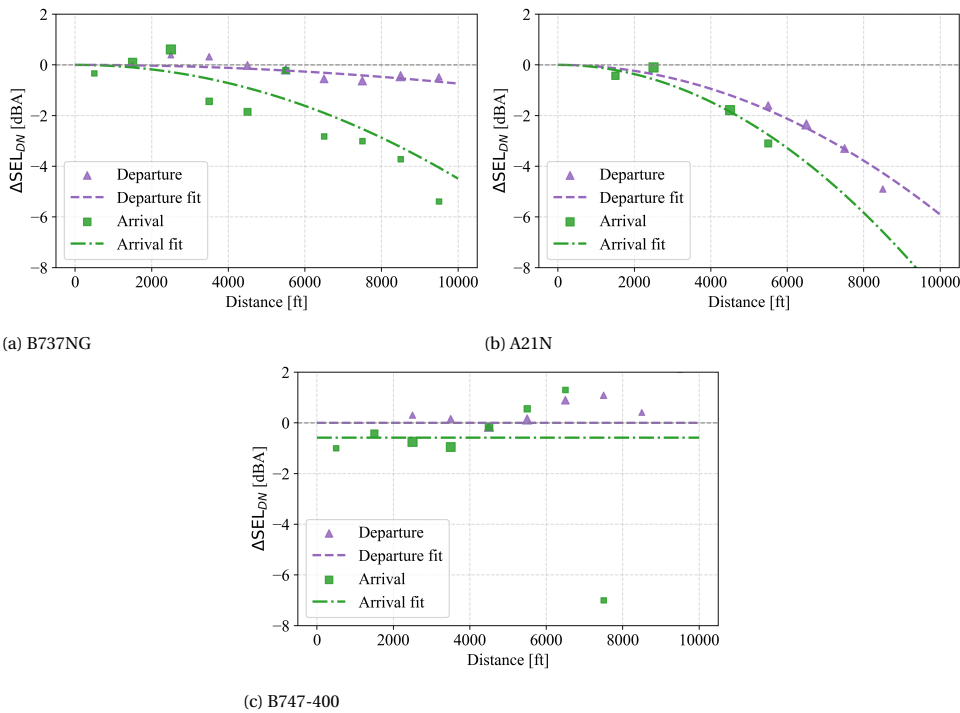


Figure 3.12: Weighted average differences in measured SEL between day and night for three aircraft groups for arrival and departure operations with a fitted curve. This includes measurements for all eight operational years. The area size of the points indicates the relative number of measurements in the respective bins.

Note that most aircraft types lack sufficient data at either close or far distances. For

example, few close-range departure measurements in the 0-1000 ft bin exist due to rapid climb rates and NMT placement away from runways. Similarly, quieter aircraft, such as the A21N or regional jets, often lack long-distance data. This limits the ability to detect statistically significant day-night differences. For the available measurements of the A21N in Figure 3.12b, larger differences in measured SEL between the daytime and nighttime measurements are found due to the lower source noise level of this aircraft type. In contrast, larger aircraft like the B747, shown in Figure 3.12c, show smaller or insignificant differences. This is likely due to their higher source noise levels, which reduce the relative impact of background noise.

From the above results,

- almost always higher levels per event during daytime compared to nighttime
- consistently smaller differences for aircraft with high source noise levels
- consistently larger differences for aircraft with low noise levels, such as the A21N
- increasing effect with distance

demonstrated that the ambient noise has a significant impact on the measurements during daytime (increased noise levels).

3.5.2. EFFECT OF BACKGROUND NOISE

The obtained polynomial curves for ΔSEL_{DN} were used to estimate the effect of background noise on individual daytime measurements by subtracting the ΔSEL_{DN} from the measured levels. This results in the values in Figure 3.13 where the effect is averaged over the eight years of measurements. For most NMTs, the effect of background noise is modest, limited to 1 dBA and similar for all evaluated years. For the NMTs further away from the flight path, such as NMTs 4 and 24, the estimated effect is almost twice as large.

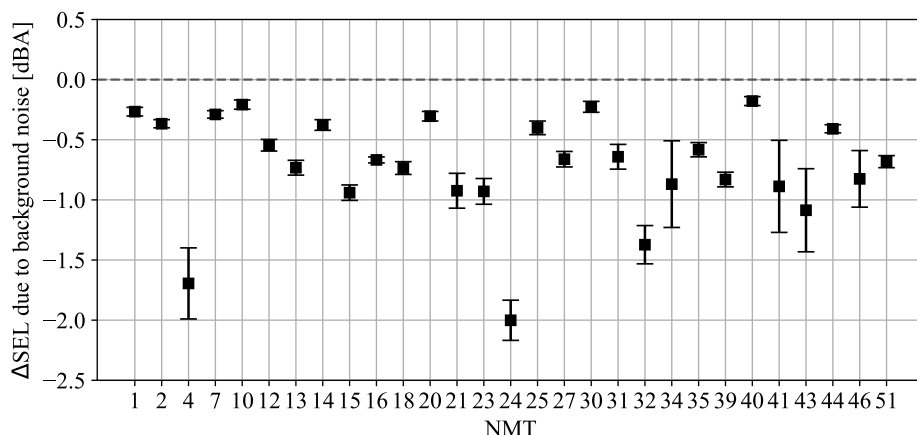


Figure 3.13: Estimated effect of background noise on the measured SEL per NMT (arrivals and departures combined), averaged over 8 operational years and the standard deviation between the years.

The last step is to implement these newfound background noise corrections on all daytime measurements of the total measured L_{den} and compare this to the modelled values at each NMT. The results presented in section 3.3 are updated, and the new figures of the year 2023 are visible in Figure 3.14b. The effect on L_{night} is not calculated, as this methodology assumes that background noise at night is already limited. In comparison to Figure 3.14a, the overall impact of the background noise correction on L_{den} is modest, despite larger corrections at NMTs farther from the airport (i.e. > 1 dBA). The average correction across all NMTs is approximately 0.4 dBA. A summary of statistics across years is presented in Table 3.3, where the values in brackets are the results without the background noise correction. The median difference (μ) between modelled and measured L_{den} decreases after applying the correction, though not entirely eliminated. Standard deviation σ also improves slightly, while the correlation coefficient ρ remains the same for all years.

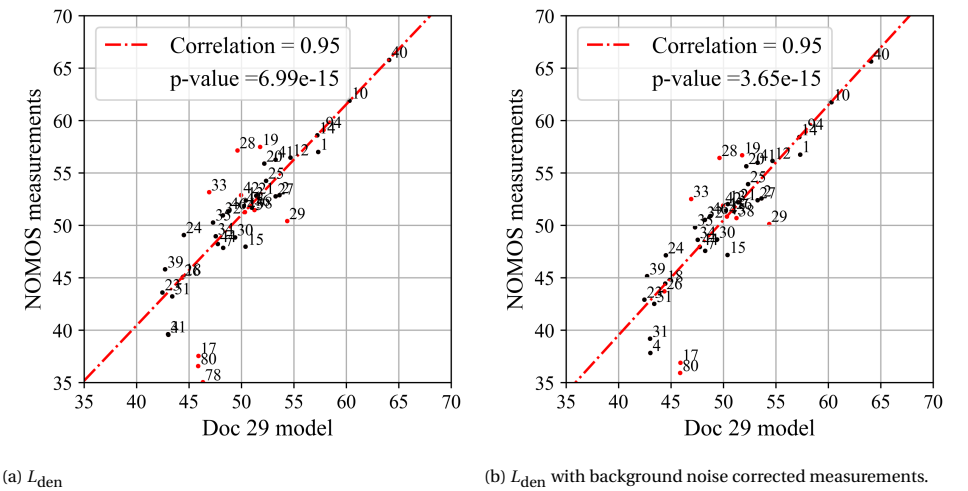


Figure 3.14: Measured and modelled L_{den} of all NMTs for the year 2023 with and without correction for background noise.

In summary, background noise has a significant influence on aircraft noise measurements in uncontrolled environments. Lower nighttime background levels result in lower measured SEL values. These effects are larger for noise events with relatively low SEL values, such as for the quieter aircraft types. The resulting background noise corrections on SEL affect the measured L_{den} only to a small extent, resulting in a modest total correction.

3.6. ANALYSIS OF UNDETECTED FLIGHTS

The third challenge in comparing modelled and measured aircraft noise levels is the fact that not all flights are acoustically recorded by the monitoring system. The modelled noise contours are based on the summation of all flights departing from or arriving at Schiphol. The measured L_{night} and L_{den} , however, only consist of the noise levels of

Table 3.3: Comparison between modelled and measured L_{den} with estimated effect of ambient noise. Results without ambient noise incorporated are given within brackets.

Year	μ [dBA]	σ [dBA]	ρ
2017	-0.31 (-0.68)	1.55 (1.53)	0.96
2018	-0.57 (-0.99)	1.65 (1.76)	0.94
2019	-0.21 (-0.63)	1.85 (1.86)	0.95
2020	-0.91 (-1.39)	2.40 (2.42)	0.93
2021	0.48 (0.10)	2.07 (2.11)	0.94
2022	0.32 (-0.14)	2.30 (2.28)	0.93
2023	-0.01 (-0.51)	1.99 (1.91)	0.95
2024	-0.53 (-1.07)	2.22 (2.24)	0.94
Average	-0.22 (-0.66)	2.00 (2.02)	0.94

flights that surpass the detection threshold of the respective NMT. Flights that fly past NMTs without being detected are referred to as undetected flights.

3.6.1. PERCENTAGE OF UNDETECTED FLIGHTS

To determine the factors contributing to the non-detection of flights, the percentage of undetected flights is calculated with respect to the total number of flights with a PCA within 10,000 ft. The relationship between the percentage of undetected flights and the modelled noise levels L_{den} is shown in Figure 3.15. A weak but consistent negative relationship is observed, which can be described by an exponential decay function. To reduce the influence of data scatter, the analysis was performed with a binned representation of the results. In low-noise regions (i.e. lower L_{den} values), flights are more frequently undetected. This is likely because their noise levels remain below the ambient background noise and thus do not exceed the NMT threshold. Despite this trend, the moderate coefficient of determination ($R^2 = 0.59$) and the marginal statistical significance ($p = 5.05 \times 10^{-2}$) indicate that detection performance is also influenced by other factors such as measurement conditions and flight variability. A similar trend is observed for L_{night} .

Distance effect: At Schiphol Airport, arrival and departure routes are fixed. As a result, aircraft typically overfly the NMTs at similar slant distances. For NMT 18, located in a low-noise area, flyovers typically occur at a PCA of around 7,000 ft. While flights below this distance are often detected, detection rates drop substantially near 10,000 ft (≈ 3 km). Measurements associated with a PCA larger than 10,000 ft are deemed unreliable, as discussed in Figure 3.4 in section 3.2.3. Notably, several flyovers at smaller distances remain acoustically undetected. This is illustrated in Figure 3.16, showing that distance alone does not fully determine (un)detection.

Aircraft type: Detection, most likely, also depends on aircraft type. Table 3.4 lists the number and percentage of undetected flyovers for eleven aircraft types. While the B738 accounts for most undetected flights in absolute terms, the relative picture differs. The A20N family shows the highest proportion of undetected flyovers. More than 60% of A20N flyovers within 10,000 ft are not detected. The E295 follows closely with 59% of

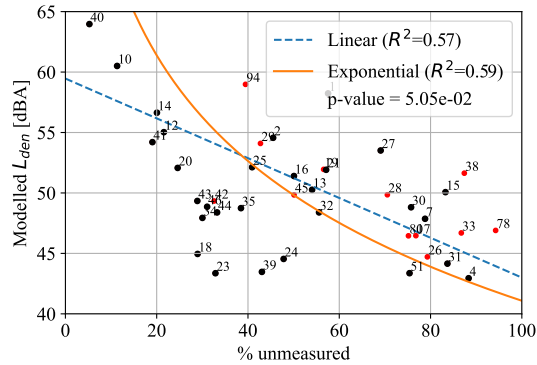


Figure 3.15: Percentage of undetected flights per NMT in comparison to the modelled L_{den} averaged over all eight operational years.

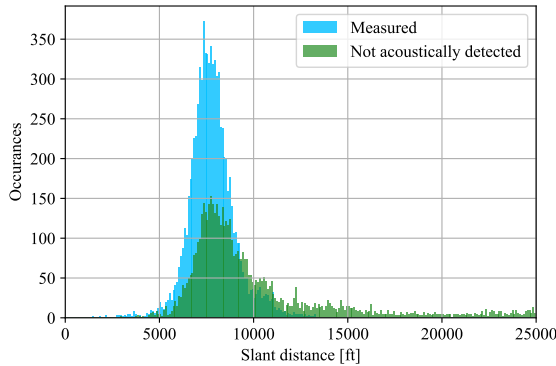


Figure 3.16: Slant distances of measured and unmeasured flights of all aircraft types over NMT 18 during the year 2023.

unrecorded flights. Both aircraft types are relatively newer and quieter.³ This suggests that their noise emissions often fall below the NMT thresholds. Note that the numbers in Table 3.4 refer to flyovers rather than flights. A single flight can be measured by an NMT close to the flight path, while it can remain undetected at more distant NMTs.

Operation type: Differences are also observed between the two operations: arrival and departure. When considering flights within a 10,000 ft PCA for all NMTs, 58% of arrival events are not measured on average. In contrast, only 45% of the departures are not recorded. This difference is likely due to the higher noise level of departure operations, which have a greater chance of exceeding the NMT detection thresholds. Analysis also shows a correlation between the difference in measured and modelled noise ΔL_{den} and the percentage of undetected flights at the individual NMTs. This correlation is 0.43 for arrivals and 0.54 for departures, with p-values of 4×10^{-7} and 7×10^{-14} , respectively. These findings highlight the limitations of acoustic monitoring systems in low-noise re-

³Quiet aircraft are defined as those certified under Chapter 14 of EASA noise standards.

Table 3.4: Number and percentage of undetected flyovers within 10,000 ft per aircraft type for the operational year 2024.

Aircraft type	$N_{\text{undetected}}$	$\%_{\text{undetected}}$
B738	183,653	41.4
E190	160,500	45.7
A320	99,749	48.5
E75L	88,979	51.6
E295	78,415	59.1
A20N	68,072	60.9
A319	53,681	50.8
B737	27,622	43.3
B772	27,215	37.2
A21N	25,026	51.6
A333	21,034	33.4

gions.

3.6.2. ASSESSING THE EFFECTS OF UNDETECTED FLIGHTS ON L_{NIGHT} AND L_{DEN}

The effect of undetected flights on the measured L_{night} and L_{den} can be investigated by estimating their noise contributions. In this contribution, this is fully based on measurements and performed using a weighted least-squares method, as described by [59]. The missed 'measurements' are predicted using operational data and the existing measurements.

This method groups flights based on key characteristics influencing noise emission, including aircraft type, operation type (arrival or departure), noise environment, and slant distance at the PCA. For each group, a logarithmic relationship between SEL and distance is fitted using measured data. To ensure reliable extrapolation at larger distances, this fit is regularised using Noise–Power–Distance (NPD) relations, which are incorporated as additional weighted observations in the least-squares formulation. As a result, measured data dominate the fit at short distances, while NPD-based observations constrain the behaviour at larger distances where measurements are sparse or unavailable.

The statistical analysis in [59] showed that noise levels of undetected flights could be estimated accurately for flights within a 10,000 ft PCA. Noise measurements beyond this distance are considered unreliable and are therefore ignored.

The effect on L_{den} is visualised in Figure 3.17 for all NMTs in the year 2023. A clear increase in the measured noise levels is evident for the NMTs in the low-noise regions, such as NMTs 4 and 31. For NMTs with already high measured and modelled L_{den} values, the inclusion of undetected flights has only a limited effect. The correlation between model and measurement also improves after accounting for undetected flights. The results for all operational years are summarised in Table 3.5.

The results are consistent over the different operational years. Slightly larger effects of undetected flights are observed in 2021 and 2022. For all years, the correlation coeffi-

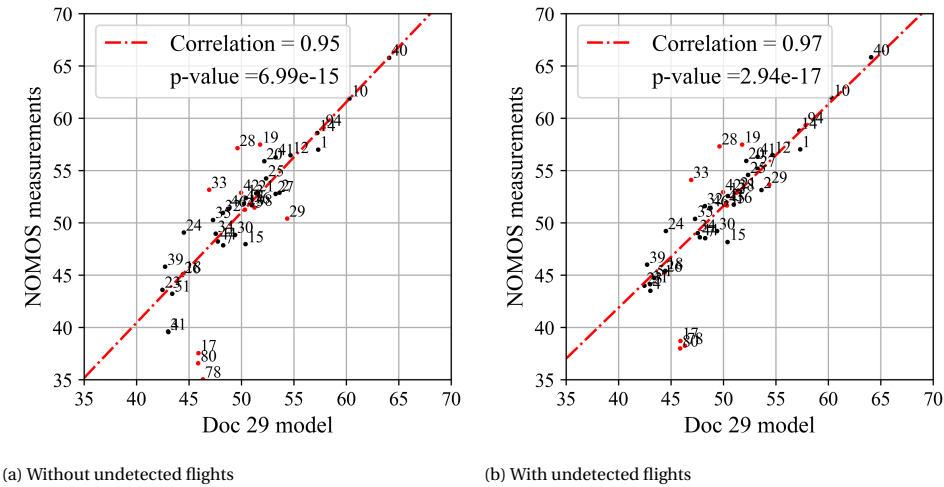


Figure 3.17: Measured and modelled L_{den} with and without the addition of undetected flights of all NMTs for the year 2023.

Table 3.5: Effect of undetected flights on the measured L_{den} and L_{night} and updated comparison between modelled and measured results. Results without undetected flights incorporated are given within brackets.

Year	ΔL_{night}			ΔL_{den}		
	μ [dBA]	σ [dBA]	ρ	μ [dBA]	σ [dBA]	ρ
2017	0.07 (1.31)	2.07 (2.92)	0.96	-1.18 (-0.68)	1.35 (1.53)	0.97
2018	-0.78 (0.23)	1.48 (2.20)	0.96	-1.48 (-0.99)	1.59 (1.76)	0.95
2019	-0.01 (0.78)	1.65 (2.37)	0.98	-1.17 (-0.63)	1.52 (1.86)	0.96
2020	-0.42 (0.82)	2.68 (4.88)	0.95	-1.86 (-1.39)	1.99 (2.42)	0.94
2021	-0.22 (1.43)	2.97 (4.08)	0.93	-0.72 (0.10)	1.60 (2.11)	0.95
2022	0.36 (1.90)	2.51 (3.67)	0.95	-0.87 (-0.14)	1.73 (2.28)	0.94
2023	0.34 (1.68)	2.62 (3.54)	0.96	-1.11 (-0.51)	1.41 (1.91)	0.97
2024	-1.10 (0.23)	1.79 (3.25)	0.97	-1.65 (-1.07)	1.71 (2.24)	0.98
Average	-0.22 (1.05)	2.22 (3.36)	0.96	-1.25 (-0.66)	1.61 (2.02)	0.96

cients improve after accounting for undetected flights. The standard deviation between measured and modelled noise levels is also reduced. This indicates a better agreement between the measured and modelled noise levels for both L_{night} and L_{den} . The updated yearly averages can therefore provide a more realistic representation of the noise exposure in the low-noise regions.

The effect of undetected flights is more pronounced for L_{night} than for L_{den} . On average, this effect is approximately doubled on $\Delta\mu$: 1.27 dBA for L_{night} and 0.59 dBA for L_{den} . This difference is primarily due to a higher percentage of undetected flights at night, particularly for NMTs located in low-noise areas. One possible explanation is that ambient sound during the day amplifies aircraft noise events, allowing them to exceed the NMT detection threshold more frequently. At night, lower ambient noise results in fewer noise

events exceeding the threshold. For most NMTs, the threshold is the same during the day and night. For a small number of NMTs (e.g. NMTs 25 and 41), where nighttime thresholds are set lower, similar percentages of undetected flights are observed during both day and night, supporting this hypothesis.

Including undetected flights reduces the model overestimation for L_{night} , while increasing the underestimation of L_{den} . The undetected flights are most prevalent in low-noise regions, where a relatively large proportion of events is initially missing from the measurement dataset. Adding these contributions increases the measured L_{den} values more strongly at these locations than at higher-noise sites, thereby altering the spatial distribution of measured noise levels. As a result, the comparison with the modelled results shifts, leading to a larger apparent underestimation by the model. At the same time, the correlation between modelled and measured levels improves significantly, indicating a more consistent representation of noise exposure across all NMTs. This behaviour is consistent with the previously observed relationship between low L_{den} values and a high percentage of undetected flights.

These findings highlight the importance of accounting for detection limitations when comparing measured and modelled noise levels, particularly for nighttime operations.

3.7. COMBINED RESULTS

The three main causes challenging the comparison of annual measured and modelled aircraft noise levels are identified in the previous sections. The model input discrepancies are difficult to quantify for the full year due to limited data availability. However, the effects of background noise and undetected flights are quantified and are combined in this section to give the most accurate result. For consistency, these results are plotted in Figure 3.18 for the year 2023. The results summarised for all years are presented in Table 3.6.

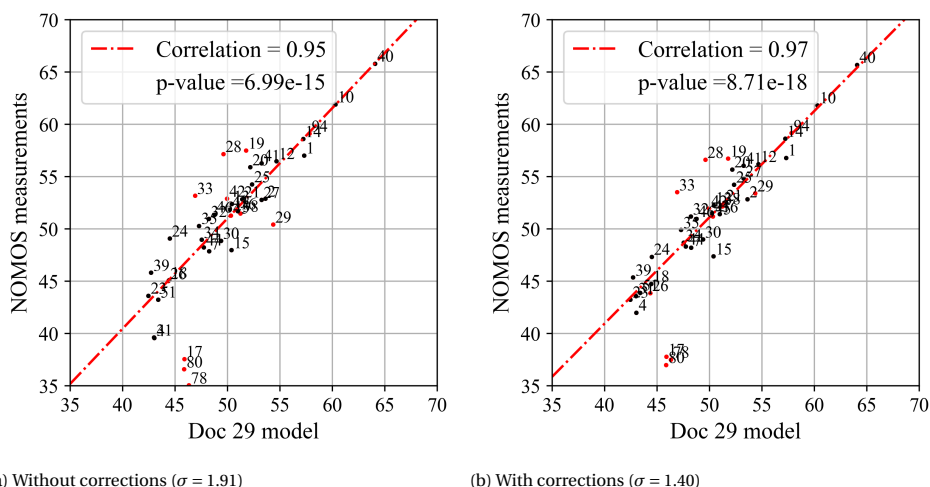


Figure 3.18: Measured and modelled L_{den} with and without the addition of undetected flights and the ambient noise correction of all NMTs for the year 2023.

Note that combining the corrections is not a simple addition of the two correction factors. As the background noise correction also influences the estimated SEL of the undetected flights, the combined effect is calculated by first incorporating the undetected flights to the measured L_{den} values and then applying the background-noise correction. Nevertheless, the effect of undetected flights is generally stronger than that of background noise. An effect of +0.14 dBA averaged over all NMTs over all eight years is found. These combined effects improve the correlation between measured and modelled noise levels, with an average correlation coefficient of 0.96. The average difference μ is slightly larger than the baseline levels depicted in Table 3.2. At the same time, the standard deviation σ is lowest compared to all previous results. This indicates that jointly accounting for undetected flights and background noise leads to a more consistent comparison between measured and modelled annual noise levels.

While the combined corrections improve consistency, a residual underestimation of L_{den} remains. This suggests that additional factors related to the modelling approach may contribute to the observed discrepancies, such as limitations in the representation of noise propagation, particularly at larger distances from the flight path.

Table 3.6: Estimated combined effect of background noise and undetected flights on L_{den} and updated comparison between modelled and measured results. Results without effects incorporated are given within brackets.

Year	μ [dBA]	σ [dBA]	ρ
2017	-0.79 (-0.68)	1.35 (1.53)	0.97 (0.96)
2018	-1.06 (-0.99)	1.46 (1.76)	0.96 (0.94)
2019	-0.72 (-0.63)	1.47 (1.86)	0.96 (0.95)
2020	-1.37 (-1.39)	1.91 (2.42)	0.95 (0.92)
2021	-0.32 (0.10)	1.55 (2.11)	0.96 (0.94)
2022	-0.39 (-0.14)	1.70 (2.28)	0.95 (0.92)
2023	-0.61 (-0.51)	1.40 (1.91)	0.97 (0.95)
2024	-1.10 (-1.07)	1.66 (2.24)	0.96 (0.94)
Average	-0.80 (-0.66)	1.56 (2.02)	0.96 (0.94)

3.8. CONCLUSIONS

This research investigated the challenges associated with comparing the annually averaged aircraft noise levels predicted by the Doc 29 model with measurements around Amsterdam Airport Schiphol. The analysis was performed through noise measurements from the Noise Monitoring System (NOMOS) from the operational years 2017 to 2024. The analysis revealed a strong overall correlation between modelled and measured results, confirming the robustness of Doc 29 as a best-practice tool. However, systematic discrepancies were identified: the model generally overestimates L_{night} while it underestimates L_{den} . To further investigate these discrepancies, this chapter investigated three main challenges influencing the comparison between modelled and measured noise levels.

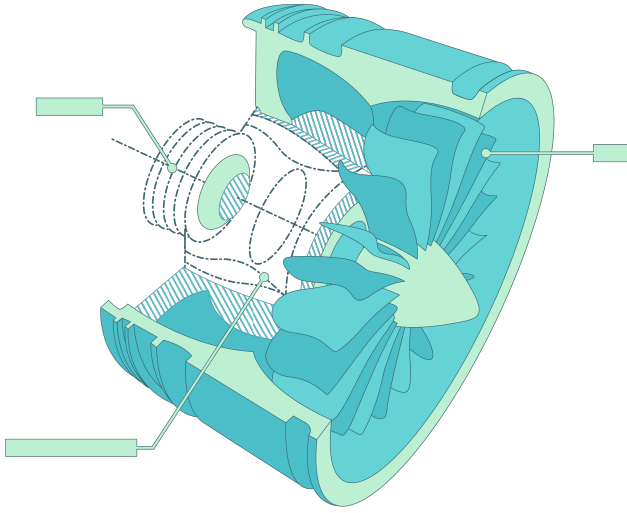
The first challenge stems from differences between the model input parameters and

the actual flown flight procedures. Operational analysis demonstrated mismatches between modelled procedures and flown tracks. Variability in flown speed, altitudes, thrust settings, and atmospheric conditions introduces uncertainties that are not fully captured by current fixed-point profiles. Although deviations of up to 3 dBA were found for individual flights, their impact on annual noise metrics cannot be quantified with the available data. In addition, because such deviations can be both positive and negative, their average effect could partially cancel out over a large number of operations. Therefore, it is impossible to determine whether accounting for this source of uncertainty would improve or worsen the agreement between measured and modelled annual noise levels.

The second challenge concerns the measurement offset introduced by background noise. This effect was quantified by examining the differences between day and night noise levels. While lower nighttime background noise contributes to reduced measured SEL values, operational factors such as increased CDA usage and fleet mix differences play a substantial role. Applying background noise corrections led to modest improvements in agreement for L_{den} (≈ 0.4 dBA), but did not fully eliminate the discrepancies.

The third addressed challenge in this comparison stems from undetected flights. Particularly in low-noise regions and for newer, quieter aircraft types such as the A21N and E295, the NMTs frequently failed to measure the flyovers. On average, 58% of arrivals and 45% of departures within 10,000 ft PCA were not acoustically detected. Correcting for these missing events improved the correlation between modelled and measured levels and reduced variability, with average adjustments of +1.2 dBA for L_{night} and +0.6 dBA for L_{den} . These findings highlight the importance of explicitly accounting for detection thresholds when validating model predictions against measurements. A recommendation is to apply a dynamic threshold methodology that accounts for real-time background noise conditions, thereby allowing a measurement system to detect lower-level noise events.

In summary, the validation of annual average noise metrics requires careful treatment of operational variability, background noise effects, and undetected flights. While Doc 29 provides reliable predictions at the system level, measurement-based validation must address biases inherent to acoustic monitoring in uncontrolled environments. The remaining discrepancies may also be partly related to limitations in the modelling approach, such as the use of NPD relations, which are known to become less accurate at larger slant distances where measurements are sparse. Future work should focus on refining the operational model input with real flight data and improving the detection of low-level noise events. Such efforts will strengthen confidence in aircraft noise modelling and support more effective policy development for communities around major airports.



4

THRUST ESTIMATION FOR NOISE MODELLING

In chapter 3, the general model assumptions and operational inputs through procedures is discussed. The results highlight the effect of the current assumed thrust estimation methods on noise model results, showing big uncertainties. Before individual model predictions can be compared to measurements, accurate input to the model is thus necessary. This chapter describes a novel thrust estimation method for reliable model input assessment. For this, the engine's rotational speed, $N1$, is used. $N1$ can be obtained acoustically (section 4.2) or through flight data. To find the thrust input, the $N1$ needs to be converted. Section 4.3 investigates three methods for calculating aircraft thrust from $N1$ and their impacts on noise predictions are assessed in section 4.4. Finally, in section 4.5 a new reliable method is found for obtaining aircraft thrust to be used in noise modelling.

Parts of this chapter have been published in the CEAS Aeronautical Journal (section 4.2) [68] and the Journal of Transportation Research Part D: Transport and Environment [66].

4.1. INTRODUCTION

Aircraft noise significantly affects the health and sleep of communities near airports [69, 70], making noise reduction a key priority for the aviation industry. Mitigation strategies include quieter aircraft designs and optimized flight paths, often guided by Noise Abatement Procedures (NAP). These procedures rely on empirical noise models such as Doc 29 [19], which use Noise-Power-Distance (NPD) tables to estimate noise exposure based on engine thrust and aircraft distance. Standardized departure procedures, documented in the Aircraft Noise and Performance (ANP) database [22], divide flight profiles into three segments: initial take-off, cut-back, and climb-out. While useful, these generalised procedures fail to capture the variability of actual operations. Sensitivity analyses [11] highlight the strong influence of thrust assumptions on predicted noise, emphasizing the need for accurate thrust estimation.

Recent studies leverage open-source ADS-B (Automatic Dependant Surveillance Broadcasted) data from the OpenSky network [45]. For example, Pretto et al. [71] improved take-off weight estimation and generated synthetic ANP profiles, while Pretto et al. [58] demonstrated enhanced low-altitude noise predictions. Other approaches combine the ADS-B data with engine and performance models [72], or integrate Eurocontrol's BADA framework to estimate weight and thrust dynamically [73, 74], reducing discrepancies between predictions and measurements.

Alternative methods estimate thrust directly from acoustic data. Fan tones, linked to the N1 spool rotational speed, provide characteristic signatures that can be analysed [75, 76] or modelled using machine learning [10]. The sonAIR model [50, 77] already incorporates N1 as input, but best-practice models require accurate conversion from N1 to thrust. Similarly, onboard systems such as the Aircraft Condition Monitoring System (ACMS) record N1% and fuel flow, but not thrust directly, again needing conversion.

In Doc 29, thrust is expressed as corrected net thrust F_n/δ [lbf], where δ is pressure ratio of the ambient-to-sea-level. By contrast, flight data typically provide N1%, generalized with a temperature correction factor θ_T [20]. The relationship between N1, thrust, altitude, speed and temperature is complex [8] and documented in proprietary engine performance manuals [78], which limits accessibility.

This chapter investigates estimating aircraft thrust from the engine's rotational speed (N1%) and its impact on noise modelling for departure operations. The goal is to assess the uncertainties inherent in thrust estimation and the validation of these estimates. Firstly, the method to estimate N1% from acoustic measurements is validated with ACMS data in section 4.2. After, three different methods are assessed to convert N1% to net corrected thrust. The first method is the current best-practice approach, utilizing the ANP database. The second method uses data from the ACMS, which relates the N1% parameter to the fuel flow in order to estimate thrust. The third method is a simulation-based approach using the Gas Turbine Simulation Program (GSP) [79]. These three methods are evaluated by comparing their thrust predictions to those derived from an airline's aircraft performance software. The remaining sections of this chapter are organized as follows. A detailed explanation of each method is provided in section 4.3. This research is performed on multiple engine and aircraft types to demonstrate how these factors influence the discrepancies between the methods. The resulting thrust estimations and subsequent noise predictions exhibit significant deviations, as discussed in section 4.4.

In section 4.5, a new method is proposed, combining elements of the ANP and GSP approaches to create a more effective and user-friendly model for thrust estimation, eliminating method's one (ANP based) limitation to a few aircraft types only. Finally, in section 4.6, the advantages and disadvantages of each method are discussed. Although the validation of thrust input is an underdeveloped aspect of noise modelling, it is an essential step towards accurate aircraft noise predictions. This chapter proposes a novel thrust estimation and validation method, aiming at addressing this gap and hence enhancing aircraft noise predictions.

4.2. N1 ESTIMATION FROM ACOUSTIC MEASUREMENTS

Aircraft noise is a combination of airframe and engine noise. Airframe noise is typically broadband noise, while engine noise includes both broadband and tonal components [49]. The fan of the engine produces a tonal sound at the blade passing frequency (BPF) and its harmonics. The BPF is a function of the fan's rotational speed and the number of fan blades. The fan is connected to the low-pressure compressor, powered by the low-pressure turbine, or the N1 spool. The rotational speed of the engine is often expressed as a percentage ($N1\%$) of the maximum rotational speed ($N1_{max}$). The $N1\%$ parameter is widely used by engine manufacturers and pilots to determine the engine delivered thrust [75]. The relation between $N1\%$ and the BPF is given by:

$$N1\% = \frac{60 \text{ BPF}}{n_{blades} N1_{max}} \quad (4.1)$$

where n_{blades} is the number of blades, and BPF is expressed in Hz.

To determine the BPF, flyover audio recordings in the form of down-sampled (8000 Hz) mp3 files are gathered from the NOMOS system. To avoid aliasing, a low-pass filter is applied to the original signal, eliminating all frequency content above 4000 Hz. Afterwards, the signal is segmented into one-second intervals and Fourier transformed. It is noted that the measurements contain ambient background noise. For the data considered in this chapter, the background noise is considerably lower than the sound levels of the BPF tones. The BPF is estimated from the tones in the resulting spectrogram. Typically, both the fundamental BPF and its higher harmonics are visible in the spectrogram. For departing aircraft, which operate at high thrust settings, the range of 70%-100% of maximum rotational speed $N1_{max}$ is used to determine the BPF tones. Based on gathered flight data, this range has been shown to be appropriate for most aircraft during departure. An example spectrogram of a departure event is given in Figure 4.1a.

Due to the Doppler effect induced by the relative motion of the aircraft, the frequencies of the received signals are shifted from those actually emitted. To eliminate these shifts, the spectrograms are de-Dopplerised using the aircraft positional information. In Figure 4.1b, the detected BPFs are shown in blue for 1-second intervals, and the corresponding de-Dopplerised frequencies are shown in green. This method is described in detail by Merino-Martinez et. al.[75], and is based on the following relationship between the emitted frequency f and the Doppler-shifted frequency f' :

$$\frac{f}{f'} = 1 + \frac{dr/dt}{c} \quad (4.2)$$

where dr/dt is derived from the relative change of radial distance r between the NMT and the aircraft as obtained from the radar data, and c is the sound speed in air. To obtain a smooth temporal profile of the estimated BPF , a moving median filter is applied. This results in estimates for $N1\%$ as a function of time as seen in Figure 4.1c.

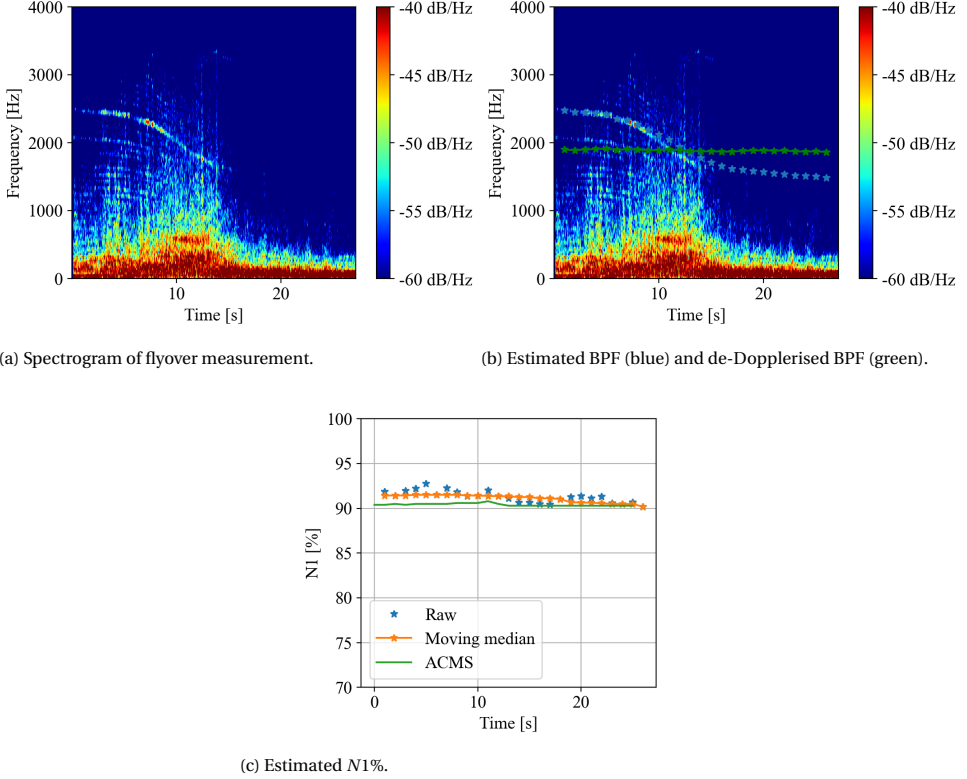


Figure 4.1: Results for $N1\%$ estimation and validation of a B737-800 departure flyover measurement.

As a validation step, the filtered $N1\%$ estimates are compared to those obtained from the ACMS data. The ACMS logs all important aircraft parameters, and is considered the golden standard for validation purposes [80]. A total of 37 departure measurements with corresponding ACMS data were available for the B737-800. The root-mean-square difference between the ACMS and spectrogram-derived $N1\%$, averaged over all 37 measurements, was found to be less than 4%. The distribution of this error over all flights is illustrated in Figure 4.2.

For arriving aircraft, flight data in idle descent indicated a rotational speed of roughly 30% of $N1_{max}$. This results in a fan tone that is intertwined with the low-frequency background ambient and airframe noise, making the extraction of the BPF less reliable. Therefore, for arrivals, the tone corresponding to the first and second harmonics is used to determine the original BPF. Since arrival operations and flight paths are more stable and consistent than departure operations, the variation in $N1\%$ among arrival events is

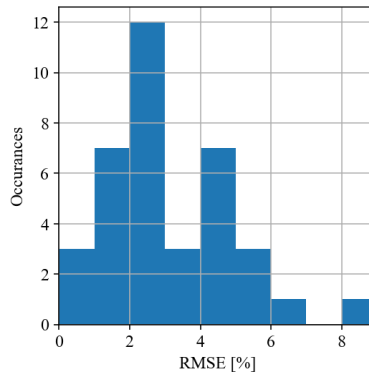


Figure 4.2: Distribution of the root-mean-square error between the N1 estimation and the ACMS.

limited. From available arrival ACMS data, the B737-800 aircraft in the descent phase of the arrival operation flew a steady 29-33 $N1\%$, matching well with the values derived from the audio recordings. Arrival thrust is not further estimated in this chapter.

4.3. METHODOLOGY FOR CONVERSION OF N1 TO THRUST

To find the thrust input for accurate aircraft noise modelling with $N1$ known, an accurate conversion between $N1$ and thrust is required. Although during the design and production of engines, every engine manufacturer creates engine-specific performance manuals, they are typically only openly available for outdated engines. Nevertheless, these performance manuals offer valuable insights into engine performance characteristics. One of the key performance characteristics documented in these manuals is the design net thrust versus generalized $N1\%$, where, for example, every 0.05 Mach increment, a different curve is given. Examples of such curves for a CF6-80C2 engine are shown in Figure 4.3, where $F_n/\delta[\%]$ is the percentage of thrust compared to the maximum flat rated thrust [78]. It is visible that next to $N1\%$, the Mach number can also significantly influence the thrust produced.

In the remainder of this section, three conversion methods are described. These methods are tested against airline-provided aircraft performance calculations as described in section 4.3.1. Afterwards, the Doc 29 model is used to evaluate the effect of different conversion methods on the noise predictions. This is accomplished by modelling the noise contours around Schiphol airport using the $N1\%$ data and flight paths derived from the airline-provided aircraft performance calculations. Each flight is modelled using the described methods, and the resulting differences in noise levels are categorised in different flight phases and distances from the aircraft to the ground. This categorisation allows for a detailed evaluation of the accuracy of the three thrust conversion methods.

4.3.1. DATA

The different $N1$ -to-Thrust conversion methods will be validated by comparing their predictions with airline-provided aircraft performance calculations. The airline model

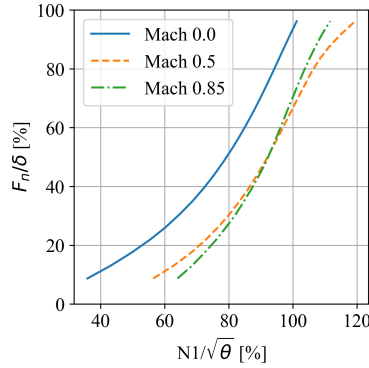


Figure 4.3: Relation between generalised $N1\%$ and thrust based on performance manual.

is, among others, used by pilots to calculate the amount of (derated) take-off thrust required for specific weather and runway conditions. The results of the model are a direct input into the Flight Management System (FMS) and thus depict the actual flown thrust profiles. In addition to local conditions, take-off weight and the degree of thrust derating are crucial inputs for this model.

For this research, airline model simulations were conducted for departure operations for the B737-800 and the B777-200 across a range of take-off weights. The data provided by these models contains, but is not limited to, positional parameters, airspeed, atmospheric conditions, engine parameters (such as $N1$ and fuel flow) and net corrected thrust per engine. Although this is simulated data, it is of the highest accuracy and quality as it is produced by aircraft manufacturers using advanced performance algorithms. Each simulated flight covers the trajectory from the end of the take-off roll up to an altitude of 3000 m (≈ 9150 ft). The take-off roll is defined from the break release point (BRP) to 35 ft altitude. An example of such a flight is shown in Figure 4.4 where the consecutive steps of acceleration and climb are visible.

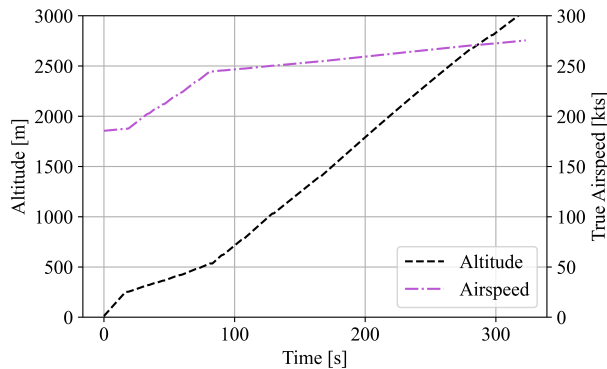


Figure 4.4: Altitude and airspeed profile of an B777-200 departure flight from the airline model.

4.3.2. METHOD 1: AIRCRAFT NOISE AND PERFORMANCE DATABASE

The first method to calculate thrust for noise modelling utilizes the best-practice method provided by Doc 29 [20]. It is based on engine-specific constants and procedural steps as shown in Table 4.1. It often assumes specific engine settings for each sequential phase of acceleration and/or climb in a standard procedure in combination with a set of derated thrust levels. Using these inputs, the net thrust is then calculated as

$$\frac{F_n}{\delta} = E_0 + F_0 V_C + G_A h + G_B h^2 + HT, \quad (4.3)$$

where E_0 , F_0 , G_A , G_B and H are engine thrust constants chosen per procedural step in units lb , $lb \times s/ft$, lb/ft , lb/ft^2 and $lb/^\circ C$, respectively. These engine thrust constants are calculated by the aircraft manufacturer and verified by EASA during implementation into the ANP database [22]. Further, δ is the pressure coefficient, V_C is the calibrated airspeed in knots, T is the ambient air temperature in Celsius and h is the altitude in feet. This equation accounts for the variations in temperature and pressure between the actual and standard atmospheres, and their impact on the engine efficiency.

Table 4.1: ANP coefficients for calculating thrust using standard procedural steps for the B777-200 [22].

Procedure	E_0	F_0	G_A	G_B	H
MaxClimb	67093.7	-85.75534	1.8498	-7.60E-05	0
MaxClimbHiTemp	82096.7	-72.2859	-0.32818	-1.79E-05	-637
MaxTakeoff	93672.6	-122.25116	1.1818	-8.06E-05	0
MaxTkoffHiTemp	114758.6	-125.38	-0.159002	-2.61E-05	-702.4

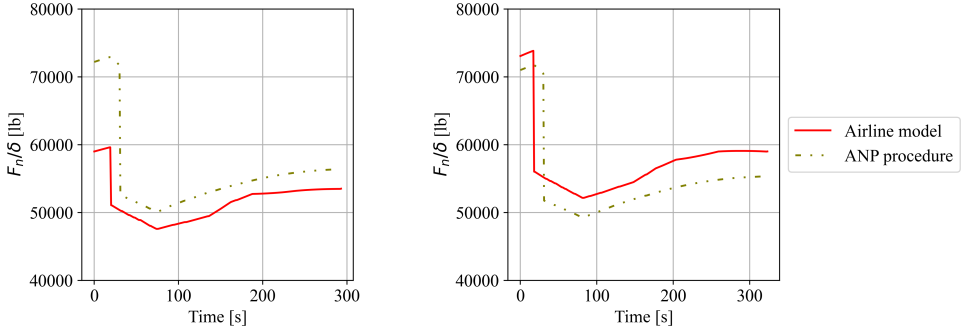
This method is fast and easy to comprehend but the procedures are often based on assumptions, for example, on the amount and timing of the thrust cutback during departure, or estimates of the aircraft's weight, which affects the required thrust for take-off. The aircraft's TOW is conventionally estimated by the distance to its destination in sets of stage lengths [20], although recent studies include more accurate weight estimations based on flight tracks and performance calculations [7, 58, 73].

By analysing actual flight tracks, such as those provided by radar data, it is possible to select the most suitable procedures. In Figure 4.5, two examples of such cases are shown. In this case, the procedures are matched with flights from the airline model for complementary TOW. It is evident that for a low gross weight, as seen in Figure 4.5a, the thrust is overestimated, while for a high gross TOW, close to the maximum, the thrust is underestimated. For both procedures, the timing of the cutback is offset and the climb thrust patterns differ.

To avoid part of the above-mentioned assumptions, Equation 4.3 can be expanded with the rotational speed $N1\%$ to account for actual flight conditions, as suggested by Doc 29 [20]

$$\frac{F_n}{\delta} = E'_0 + F'_0 V_C + G'_A h + G'_B h^2 + H' T + K_3 \left(\frac{N1\%}{\sqrt{\theta_T}} \right) + K_4 \left(\frac{N1\%}{\sqrt{\theta_T}} \right)^2, \quad (4.4)$$

where the constants K_3 and K_4 are derived from installed engine data. In this equation, the other engine constants (E'_0 , F'_0 , G'_A , G'_B and H') are set to their general values, not



(a) Standard departure procedure of stage length 5 (≈ 3200 nautical miles). (b) Standard departure procedure of stage length 8 (≈ 6200 nautical miles).

Figure 4.5: Airline modelled departure procedures compared with their respective standard ANP procedure for the B777-200.

connected to a specific procedural step, given in the ANP database which differs from the counterparts in Equation 4.3, indicated by the primes and depicted in Table 4.2.

Table 4.2: ANP coefficients for calculating thrust [22].

Type	E'_0	F'_0	G'_A	G'_B	H'	K_3	K_4
B777-200	32710	0	0	0	0	-1258	16.16
A330-300	36339.3	-31.32	-0.1297	0	0	484.645	4.0056

The use of Equation 4.4 is straightforward. From the ACMS data or the airline model data, the operational parameters V_C , h and $N1$ can be extracted, along with the atmospheric conditions at the aircraft position. These parameters are required to calculate θ_T and δ . The remaining engine constants can be found in the ANP database. The constant terms K_3 and K_4 are not available for most common aircraft types. Currently, these parameters are only available for the A330-300 and the B777-200. For this reason, these aircraft have been chosen in this research, which excludes most of the commercial aircraft departing and arriving at Schiphol. The parameters are given in Table 4.2.

An example of the use of this equation in comparison with the airline model can be seen in Figure 4.6. Although this method approximates the simulated thrust well, it still overlooks certain effects. For the B777-200, the speed and height parameters F'_0 and G' are set to 0. As both airspeed and altitude negatively correlate with thrust, the engine thrust during the acceleration phase decreases [8]. This effect is observed between 20-80 seconds. The ANP predictions remain constant during this phase, caused by the zero-values of F'_0 and G' which results in an overestimation of thrust. After 80 seconds, when a stable speed is reached and the aircraft climbs further to 3000 m, the overestimation grows due to decreasing atmospheric pressure and temperature, factors that the ANP does not account for.

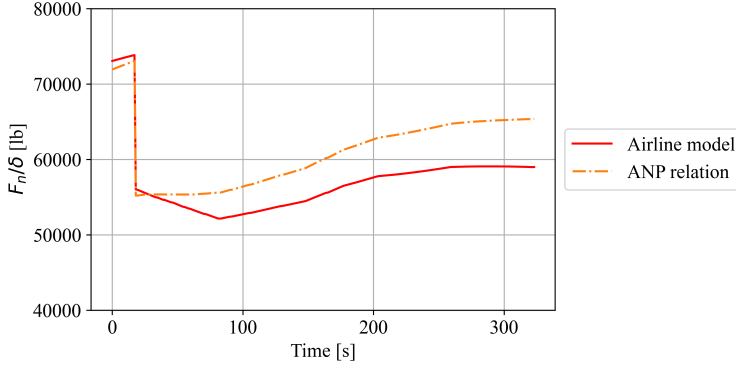


Figure 4.6: Airline simulated flight of B777-200 modelled with ANP relation.

4.3.3. METHOD 2: FUEL FLOW RELATION

The previously described method is based on models developed for engine performance. In this chapter, a new empirical method is proposed, which uses fuel flow to the engines, $\dot{m}_{ff}$, as gathered from ACMS data and couple this to used N1. Fuel consumption of aircraft engines is directly linked to the requested delivered power [81]. This relationship between $\dot{m}_{ff}$ and thrust F_n forms the basis of the proposed method. In contrast to the other methods, this new method is fully based on empirical data obtained by real flight data.

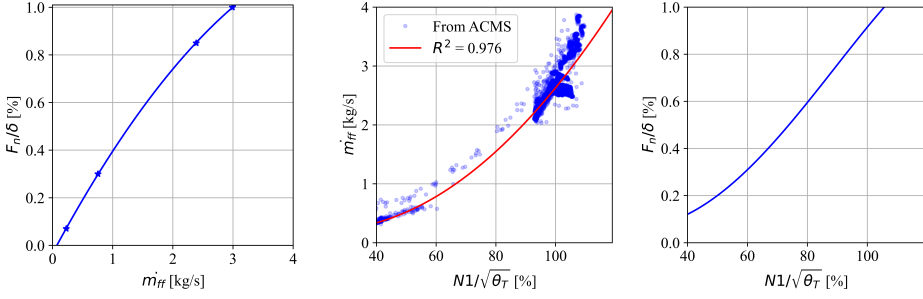
In the ICAO engines emission database, all certified engine types are documented along with their emission characteristics and fuel burn for different stages [82]. These values are documented and tested during the certification of the engines. The tests are static thrust tests on an uninstalled engine in which values such as the fuel flow per Landing and Take-Off (LTO) cycle or the maximum rated thrust are determined. An example of a result is given in Figure 4.7a. It is important to note the distinction between different types of thrust ratings: maximum flat-rated thrust, maximum continuous thrust, and maximum certified thrust. Although the first is often reported, maximum flat-rated thrust is not often used in operation, only in emergencies as it severely decreases engine life.

The second step in this method is to find a relation between the recorded fuel flow and N1. This is performed by filtering the data of the ACMS for take-off up to 5000 ft and taking all N1% and recorded fuel flow values for each aircraft type. For the A330-300, a least-squares fit is found to be

$$\dot{m}_{ff} [kg/s] = 4.497 \times 10^{-4} \left(\frac{N1\%}{\sqrt{\theta_T}} \right)^2 - 2.59 \times 10^{-2} \left(\frac{N1\%}{\sqrt{\theta_T}} \right) + 0.7175 \quad (4.5)$$

and is visualised as the red fit in Figure 4.7b.

To then couple the ACMS fuel flow to thrust levels, the ACMS reported fuel flow rates at altitude need to be converted to static sea level conditions, as reported in the ICAO



(a) Relation between % of maximum thrust and fuel use from ICAO database. (b) Fit from ACMS data between fuel-flow and N1%. (c) Found relation between N1% and % of maximum thrust.

Figure 4.7: Relations used for determining the N1% to thrust conversion for departures of the A330-300.

database. This is done using Equation 4.6 and the Boeing Fuel Flow Method 2 [83].

$$W_{ff} = \frac{\dot{m}_{ff}}{\delta} \left(\theta_T^{3.8} e^{0.2M^2} \right), \quad (4.6)$$

where M is the mach number and W_{ff} is the corrected fuel flow.

After conversion to ISA sea level conditions, a correction r is applied to account for any installation effects [83]. Combining these fuel flow values and the fits indicated in Figures 4.7a and 4.7b, results in a relation between N1 and thrust as illustrated in Figure 4.7c. This final relation between N1 and thrust is specific to this engine type is fully derived from empirical data. For all engine types in this chapter, this direct relation between N1 and thrust is found and then used for the performance analysis.

During the analysis, two observations were made. Notably, the ACMS data showed unusually high N1 values, which can likely be attributed to the season in which the data was collected, since the A330-300 dataset is from hot summer days on which the aircraft were likely fully loaded. Furthermore, in all analysed aircraft types, a higher fuel flow was recorded in the ACMS than the maximum of the ICAO database. The values reported in that database are for average emission in the Landing and Take-Off (LTO) cycle, which is only valid below 915 m (3000 ft) [82]. This brings the question of the validity of this engine emission databank for this purpose. In Chati and Balakrishnan [84], this underestimation of fuel flow in the take-off and climb-out phases was also found and Patterson et al. [85] found fuel flow rates exceeding the ICAO certifications.

In Figure 4.8 the fuel flow method is applied to an airline simulated flight. Due to the higher recorded fuel flows in the ACMS data than described in the ICAO database, this results in an overestimation of thrust. Further, it is visible that the effect of airspeed is not taken into account in this method, similar to what is observed in section 4.3.2.

4.3.4. METHOD 3: GAS TURBINE SIMULATION PROGRAM (GSP)

A simulation-based approach to estimate aircraft thrust involves the Gas Turbine Simulation Program (GSP) [79], which is a software tool designed to calculate gas turbine performance. The GSP tool is used for high-end engine simulations to perform design

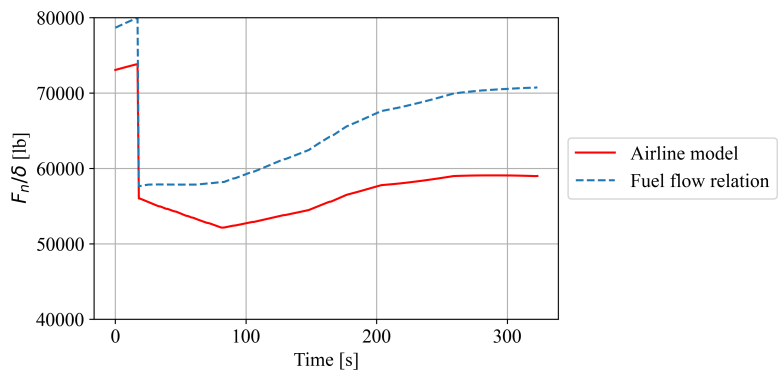


Figure 4.8: Airline simulated flight of B777-200 modelled with the derived fuel flow relation.

studies of engine efficiency and emissions. A recent use of this GSP model is to analyse the effect of different design parameters on the climate impact of aircraft [86]. The GSP can also be used to calculate all parameters needed for engine noise calculations for more advanced aircraft noise models such as ANOPP [87, 5], which can consequently be applied in noise studies to estimate the effect of changing engine parameters [49].

For the engines of each aircraft studied in this research, GSP is used to simulate thrust for different altitudes, Mach numbers and N1 settings, as shown in Table 4.3. This method generated a total of 14274 simulations for the B777-200. The simulations were performed under the international standard atmosphere (ISA) conditions at sea level, with pressure and temperature varying according to altitude in the model. The outputs of this simulation are but are not limited to, net corrected thrust, fuel flow and pressure and temperature ratios at different stages of combustion within the engine.

Table 4.3: Simulation range of GSP for different engine types.

	Altitude [m]	Mach [-]	N1%
	0 - 3000	0 - 0.6	20 - 104
Δ	50	0.05	5

From this large dataset, a multi-variable linear interpolation method is used to determine the thrust level for specific flight conditions. While the GSP is modelled for ISA temperatures (15 degrees), the airline model simulations are for ISA-10 (5 degrees). Lower temperatures yield higher thrust under similar engine settings. This introduces an offset between the airline model and the GSP simulation. To correct for this discrepancy, a temperature correction is applied, based on the engine jet coefficients from the ANP database. The resulting temperature-corrected GSP thrust profile, shown in Figure 4.9, closely matches the airline model with only minor deviations.

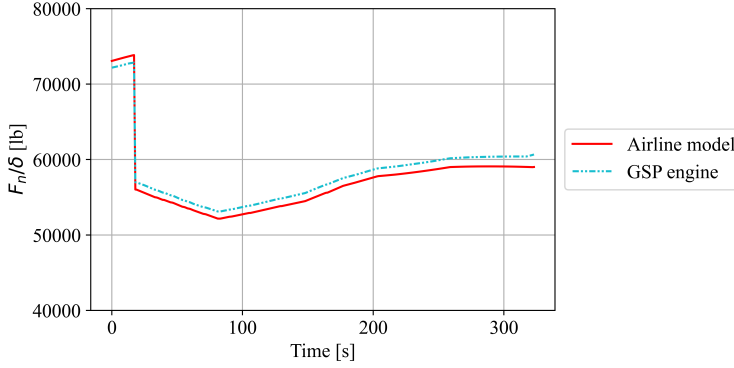


Figure 4.9: Airline simulated flight of B777-200 modelled with GSP data.

4.4. RESULTS

4.4.1. DIFFERENCES IN THRUST ESTIMATIONS USING CONVERSION METHODS

In this section, the above-described methods are compared to each other using two data sets. First, they are applied to the airline models' tracks to analyse the differences in N1-to-thrust conversion across the methods. The methods are then applied to actual flight data from the ACMS to assess their performance using more realistic input data. This two-step approach highlights the strengths and limitations of each method in different contexts.

AIRLINE-PROVIDED AIRCRAFT PERFORMANCE CALCULATIONS

The thrust is modelled using the three methods for seven different take-off weights. A typical example of the results for a flight with maximum take-off weight is presented in Figure 4.10. Considering the airline model as a reference, Figure 4.11 illustrates the average deviations and the corresponding standard deviations (calculated across the seven take-off weights) as a function of altitude. The right axis depicts the deviation as a percentage of the maximum flat rated thrust at mean sea level. A few observations are highlighted.

The first method, the ANP relation, gives stable results when looking at the different departures, indicated by a very small standard deviation. Furthermore, it is visible that the discrepancies in thrust relative to the airline model grow over altitude. This is likely because, for this aircraft, the coefficients F_0 , G_A and G_B are set to 0. As a result, the effects of speed and altitude on thrust are not accounted for in the calculations.

The second method, which uses the fuel flow, exhibits a similar trend of increasing thrust over time as observed with the ANP relation. However, during the development of this method, the effect of speed is not considered in the relation. This method has a large, although constant, standard deviation when comparing different take-off weight departures.

Finally, the third method, using the GSP database, gives the best result with only a small, but constant, offset. It shows a good approximation of the climb phase and thus

altitude, speed and temperature have been compensated for in the modelling.

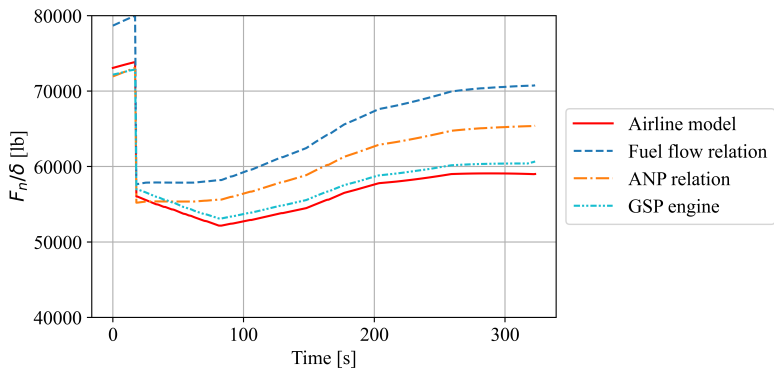


Figure 4.10: Example of the airline model flight thrust profile of the B777-200 derived from N1% using three conversion methods.

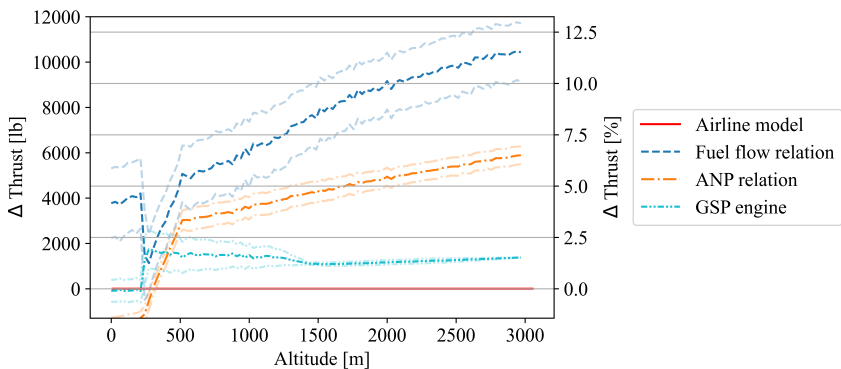


Figure 4.11: Average deviation and standard deviation of thrust compared to the airline model of 7 different take-off weights of the B777-200.

AIRCRAFT CONDITION AND MONITORING SYSTEM

The above-described methods are also applied to real flight data from the ACMS. This analysis aims to evaluate how the methods perform under different scenarios than a consistent ISA standard departure. Using the ACMS, parameters such as position, speed and N1% are taken and thrust is calculated using the same methods described earlier. The results are presented in Figure 4.12. In this figure, the thrust estimations from the three methods are presented, each based on the same input information (height, speed and N1%). As can be observed, the actually followed thrust pattern shows more rapid fluctuations. This time, there is no golden truth to compare these methods with.

The sharp peaks in the figure are caused by an inconsistent N1%, switching between for example 88% and 89%. Apart from these variations, a similar pattern is visible in this

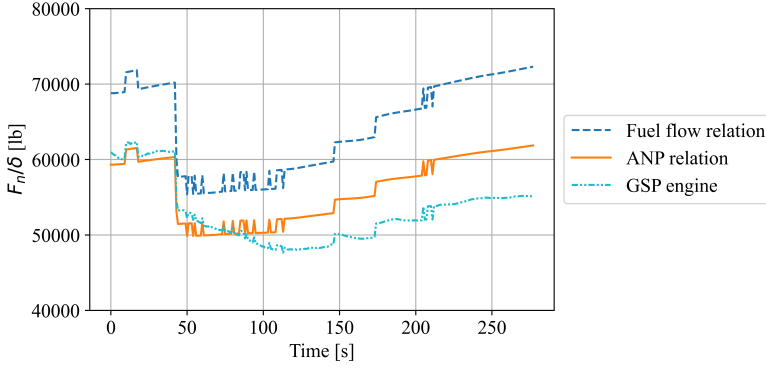


Figure 4.12: ACMS flight data of the B777-200 converted into thrust using three conversion methods.

procedure as to the airline model, where the first 50 seconds correspond to a take-off, followed by a cut-back and a climb-out phase. Both the ANP and fuel flow methods show a flatter curve during the acceleration phase (60-120 seconds) and a strong growing thrust during the climb phase. These methods however do not fully account for atmospheric effects or changing speed. In contrast, the GSP method shows a decrease in thrust during acceleration and a more nuanced curve with growing altitude. Again, the fuel flow method produces the highest thrust estimates, while the GSP shows the lowest estimates.

For a different aircraft type, the A330-300, the three methods exhibit similar behaviour, presented in Figure 4.13. Contrary to the B777-200, the ANP relation for this aircraft includes non-zero coefficients for F_0 and G_A , which results in a thrust estimation that includes speed and altitude. The GSP thrust estimation is again lower than the ANP but follows a comparable pattern. The fuel flow method, depicted in dark blue, produces a higher thrust estimation than the ANP, although with a significantly smaller absolute offset than for the B777-200.

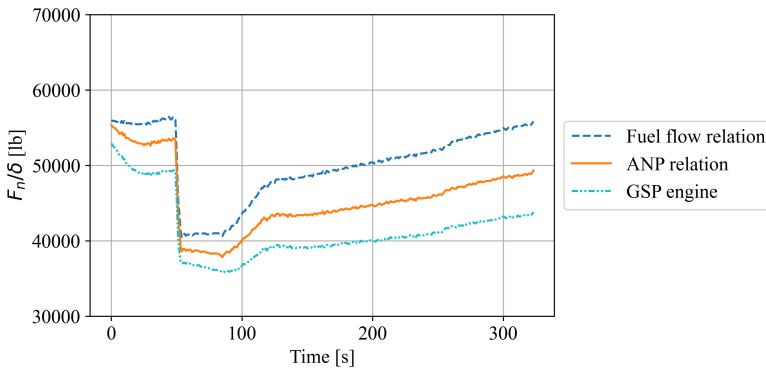


Figure 4.13: ACMS flight data of the A330-300 converted into thrust using three conversion methods.

4.4.2. EFFECT OF THRUST MODELS ON NOISE CONTOURS

The calculated thrust is now used for noise modelling. The most common output of noise models is a contour of expected noise levels in dBA. For this research, Sound Exposure Levels (SEL) are modelled for a grid size of about 25 by 30 km for a single departing flight. As mentioned in section 4.3.1, the airline model is considered the most reliable and is therefore used as a baseline for comparing the different noise contours. Figure 4.14 illustrates the expected noise levels for a B777-200 departure. The departure runway 24/06 is highlighted in green and the orange triangle indicates the location of the air traffic control tower (0,0).

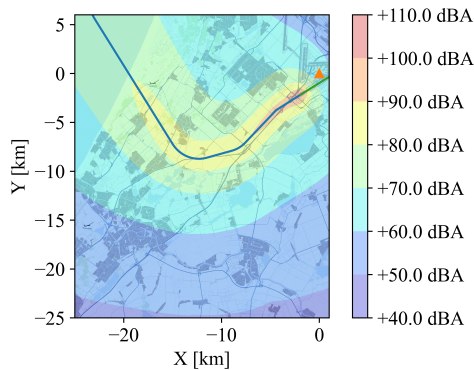


Figure 4.14: SEL contour of a single departure operation of the B777-200 using the airline modelled thrust data. The background shows a schematic representation of the surrounding area, including buildings and vegetation.

Noise contours for the three methods were generated, and their differences with the baseline are presented in Figure 4.15. Negative values (blue colour) in these figures indicate that the predicted noise levels are lower than the baseline level. The noise contours resulting from using the ANP relation, visible in Figure 4.15d, reveals a slight underestimation of the noise over the start area up to 0.5 dBA difference. This is expected as the thrust estimated during the initial take-off is lower than that predicted by the airline model. This increases to a maximum of 1.8 dBA overestimation in later flight phases. Figure 4.15e shows the differences between the baseline and fuel flow method. These differences are much larger, about 3 dBA maximum, mostly in the later flight phases. This highlights the effect of the overestimated thrust in the fuel flow model. Finally, Figure 4.15f illustrates the differences in noise contour between the baseline and the GSP-modelled thrust. This method shows a slight underestimation of 0.4 dBA in high-noise areas and an overestimation of 0.3 dBA in low-noise areas (beyond a 10 km slant range).

4.5. ESTIMATION OF NEW ANP PARAMETERS

The previous sections highlight that the ANP relation is a promising and straightforward method for N1-to-thrust conversion, as it captures the main influencing parameters affecting this conversion. However, the necessary engine parameters (E_0 to K_4) are not available for most aircraft. From section 4.4.2, it is evident that the GSP also takes all in-

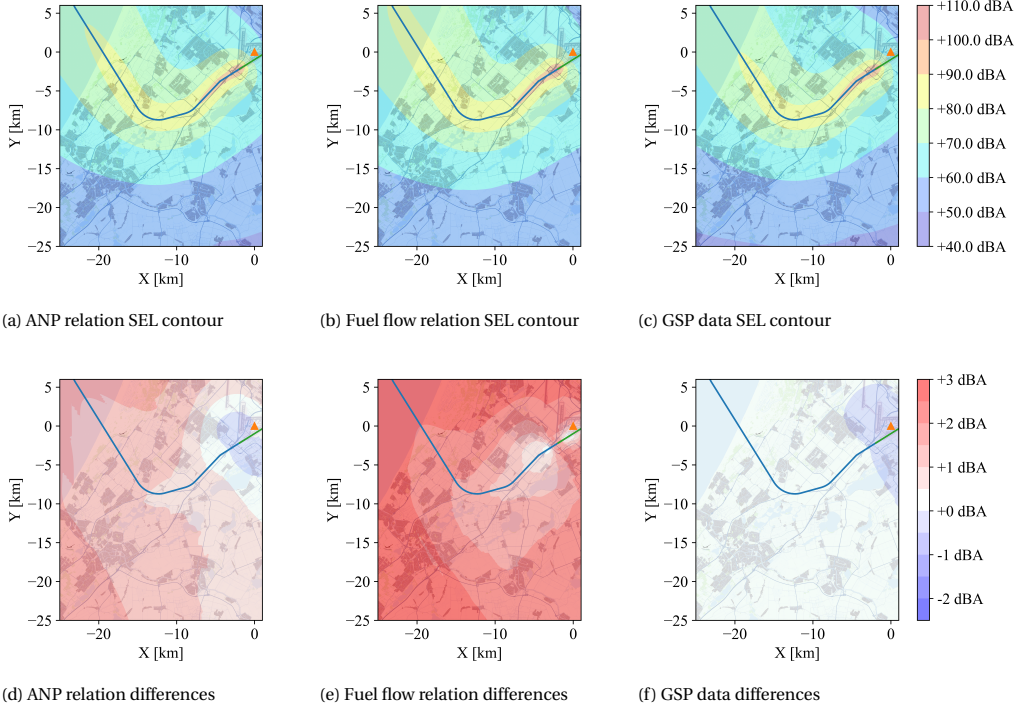


Figure 4.15: Noise contours of the differences between three calculation methods with the airline model for B777-200.

fluencing parameters into account and provides thrust estimates that are in good agreement with those of the airline model, although with a higher computational burden. In this section, new ANP coefficients are estimated from the large GSP dataset using the least squares methods. This is useful to expand the current ANP database with new or updated aircraft types.

4.5.1. TWO LEAST-SQUARES-BASED METHODS

When looking at the existing coefficients in the ANP database for different aircraft types, a few observations can be made. For example, the speed coefficient F_0 is always negative, as is the temperature coefficient H . This aligns with physical principles as, for example, thrust decreases with increasing temperature [8]. To estimate the seven engine parameters (as provided in the ANP database) from the GSP data, two least-squares-based methods, namely (unbounded) least squares (LS) and bounded least squares (BLS) are used. A BLS approach is chosen to incorporate prior information by setting lower and upper bounds on certain parameters, ensuring they remain within their expected ranges. The BLS method used in this chapter utilizes a generalized optimization algorithm based on a non-negative least squares (NNLS) problem used in Amiri-Simkooei [88].

Table 4.4 shows the original ANP coefficients, together with the coefficients estimated from GSP data. These coefficients are estimated from the GSP dataset prior to the

temperature correction. The second row shows the results of the LS method. Contrary to what is expected, H is a large positive number, while E_0 is fairly small. When approximating a model with least-squares, the model residuals $\hat{e}$ are minimized. However, prior information about physical principles shows that there is a negative correlation between temperature and thrust, thus the smallest $\hat{e}$ does not necessarily provide realistic results. If H is bound to be negative, the results change to the coefficients provided in the third row using the BLS method. Not only do the values for H and E_0 change but the coefficient G_A also changes. This is because temperature decreases with altitude and these parameters are thus not fully independent variables. The estimated correlation coefficient ρ between the two parameters H and G_A is close to one for this dataset ($\rho = 0.999$). This indicates that these two LS estimates can interchangeably be affected by each other while resulting in the same LS fit (very similar $\hat{e}$). This is, however, only the case for modelling within the range of the GSP dataset.

Table 4.4: Old and new ANP coefficients of the B777-200.

Method	E_0	F_0	G_A	G_B	H	K_3	K_4
ANP	32710	0	0	0	0	-1258	16.16
LS	7825	-69.51	1.608	1.46e-06	921.6	-654.2	12.49
Bounded LS	22124	-69.51	-0.2805	1.46e-06	-31.67	-654.2	12.49

Applying all above-estimated coefficients to an airline-modelled flight yields the results shown in Figure 4.16. Although the differences in $\hat{e}$ between the LS- and BLS-estimated coefficients are small, they give rise to significantly different results for the estimated parameters. The LS-based relation exhibits a large negative offset compared to the GSP results, whereas the BLS estimation shows only a small offset. This highlights the improved alignment of the BLS coefficients with the modelled thrust profiles. To fur-

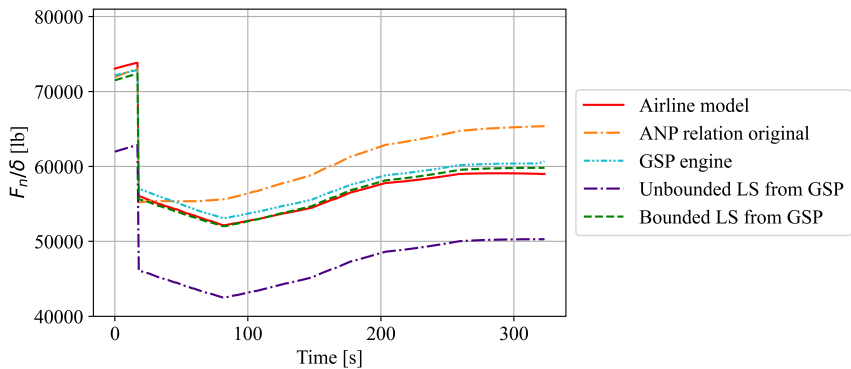


Figure 4.16: Airline simulated flight modelled with different ANP coefficients for B777-200.

ther explain the differences observed between the two least-squares methods and the GSP results, a detailed analysis was conducted. From the analysis, it became clear that the discrepancies can be attributed to the atmospheric simulation ranges. As noted in

section 4.3.4, there is a 10-degree temperature difference between the GSP dataset and the airline model. As there is no independent temperature variable in the GSP dataset, the interrelated impact of the height G_a and temperature H variables on the thrust is estimated simultaneously during the LS. This interrelation can have a significant impact on the estimated parameters, and in fact, the primary reason for the differences between LS and BLS as illustrated in Figure 4.16. When the LS and BLS methods were applied to a flight under ISA conditions, the results showed no significant discrepancies between the two methods, with only limited deviation (<300 lb) from the GSP method.

To adopt a more conservative approach and mitigate the impact of the high correlation between G_a and H on the parameter estimation, BLS is preferable over the LS method. By incorporating physical principles, BLS can better account for the interdependent variations of these highly correlated variables. Conversely, by expanding the dataset to include a broader range for both temperatures and altitudes, this linear dependency (correlation) can be reduced. This reduction in correlation would consequently result in more accurate and realistic estimates of the two parameters when using the LS method.

To validate the BLS estimated temperature coefficient H , the GSP dataset is expanded with an additional flight example from the airline model (GSP+). Since the dataset now includes data from two different atmospheric conditions, the LS method is expected to provide a better estimate of the temperature effect on the thrust. The new ANP coefficients were subsequently estimated through the unbounded LS method (Table 4.5). Although the resulting values are slightly different from the BLS results, the thrust estimation, depicted in Figure 4.17, is quite similar. This indicates that while the GSP dataset can provide useful insights into thrust relations, it is important to validate the results with either physical principles or additional data that extend beyond the limited range of conditions present in the original dataset. Nevertheless, the results obtained using BLS provide promising initial outcomes and will serve as a foundation for further research in this study. In conclusion, these findings demonstrate that BLS can accurately estimate the temperature effect on thrust, aligning closely with the temperature correction applied to the GSP dataset.

Table 4.5: New ANP coefficients of the B777-200 obtained from GSP and airline data and the relative change with respect to the BLS.

Method	E_0	F_0	G_A	G_B	H	K_3	K_4
LS from GSP+	22041	-69.53	-0.272	1.55e-06	-25.34	-654.0	12.49
Change from BLS	-83	-0.02	0.0085	-1.4e-05	6.33	0.2	0

In Figure 4.18, the differences in thrust estimation using the new method compared to the airline model are visualized across all seven take-off weights. The results indicate that not only is the difference between thrust estimation minimal, but it is also consistent over all flights. The impact of these differences on the noise contour is illustrated in Figure 4.19, resulting in a maximum deviation of less than 0.6 dBA. Given that such a deviation is practically negligible, the proposed method is considered reliable and suitable for this application.

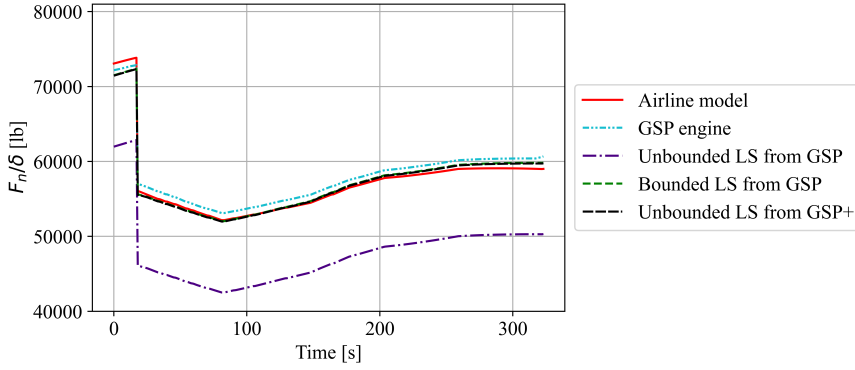


Figure 4.17: B777-200 simulated flight modelled with ANP for different LS methods.

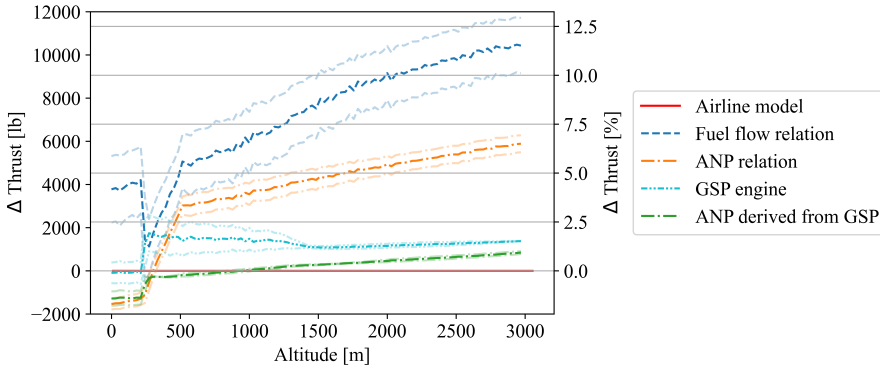


Figure 4.18: Average deviation and standard deviation of thrust estimations compared to the airline model of 7 different take-off weights of the B777-200.

4.5.2. CHECKING VALIDITY OF THE METHOD FOR THE B737-800

The benefit of the proposed method is that it enables the estimation of the ANP coefficients for all aircraft. This gives the opportunity to expand the current ANP database with newer aircraft types or with aircraft that are currently missing from the database. For example, one of the most common aircraft at Schiphol Airport, the B737-800, is used here for testing, as both the airline model and GSP data are available for this aircraft. It is important to note that B737-800 is an older model, and the resulting airline-provided aircraft performance calculations are also based on an older version. This might introduce slight discrepancies in the results. The estimated LS and BLS coefficients are presented in Table 4.6, and an example flight is visualized in Figure 4.20.

For the B737-800, similar results are found as for the B777-200. The GSP method slightly overestimates the thrust compared to the airline model. The LS approximation gives a high value for H and hence underestimates the thrust. When H is constrained to be negative, the new BLS produces a more accurate thrust estimate, closely following the airline model. This outcome was further validated by expanding the GSP dataset

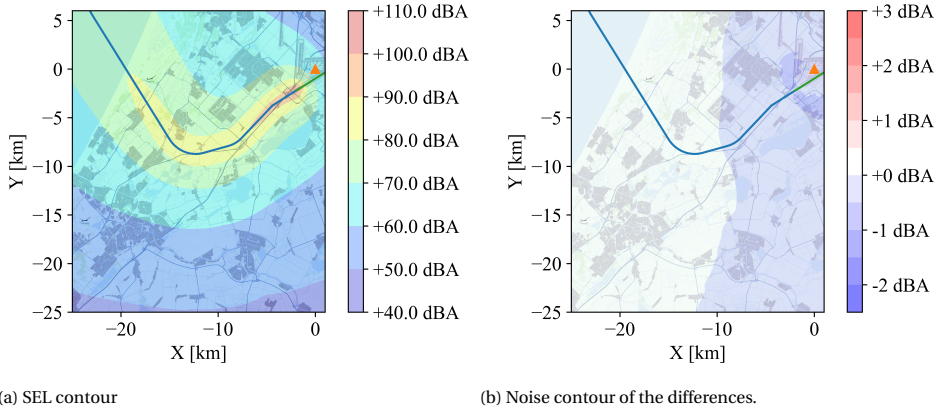


Figure 4.19: Noise contour of the new BLS-derived ANP method and the differences with the airline model for the B777-200.

with an airline-modelled flight. Applying the LS or BLS method to this expanded data gave (again) similar results to the BLS values presented in Table 4.6.

While this method has been validated using the B737-800, further validation would benefit the inclusion of a broader range of aircraft types. Additionally, a notable limitation of this study is the limited number of flights within the dataset. This constraint could be addressed by extending the research to include a variety of take-off procedures and diverse weather conditions.

Table 4.6: New ANP coefficients of the B737-800 derived from GSP data.

Method	E_0	F_0	G_A	G_B	H	K_3	K_4
Least-squares	1919	-15.77	0.376	3.68e-07	216.8	-172.5	3.661
Bounded LS	5260	-15.77	-0.0653	3.68e-07	-5.934	-172.5	3.661

The resulting noise contours for the two methods are presented in Figure 4.22, providing quite similar results with the airline model. The GSP-based contour exhibits differences ranging from 0 to 1.2 dBA, mainly due to the higher estimated thrust after acceleration. The BLS-derived noise contour, shown on the right, also closely matches the airline model, though with minor deviations: a slight underestimation during take-off (-0.3 dBA), and an overestimation of up to 1.3 dBA in later flight phases.

4.6. CONCLUSIONS

This chapter assesses different methods of estimating the thrust of departing aircraft and their effect on noise modelling. For the methods investigated, the approach is to calculate aircraft thrust from the engine's rotational speed N1. This N1 can be found acoustically and is validated using flight data from the Aircraft Condition and Monitoring System (ACMS). The conversion from N1 to net corrected thrust is investigated using three different methods. The estimates are validated with airline-provided aircraft per-

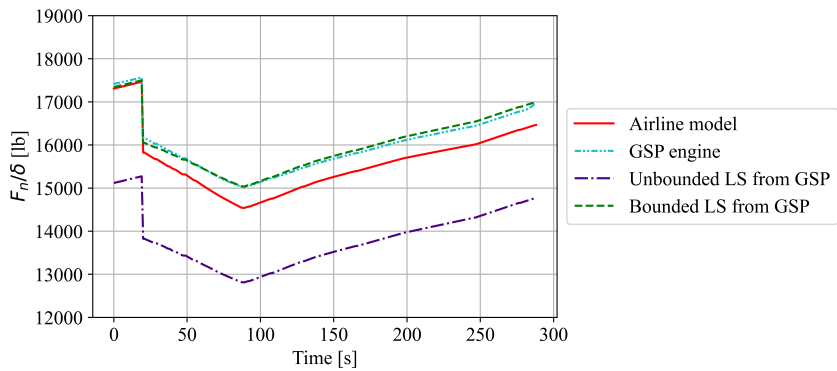


Figure 4.20: Example flight of the B737-800 with GSP and GSP derived thrust estimation compared to the airline model.

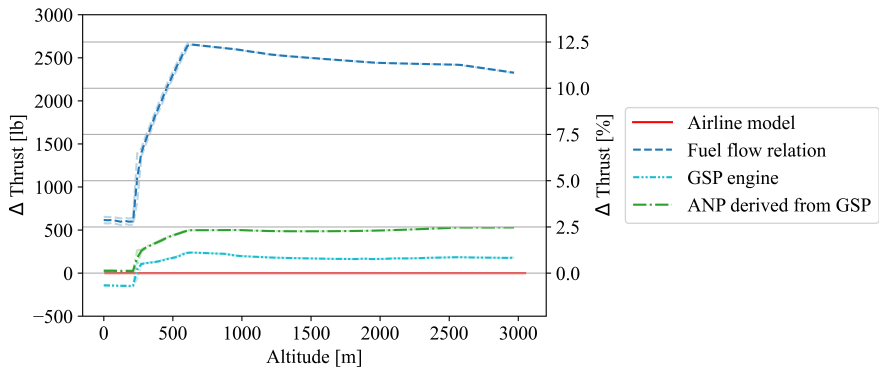
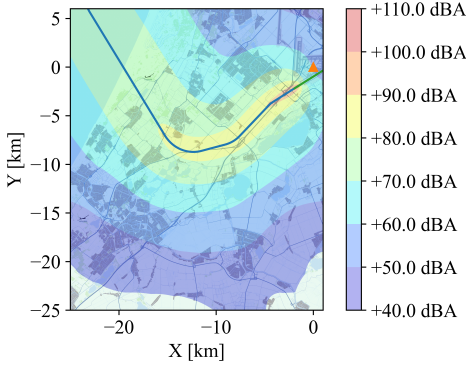


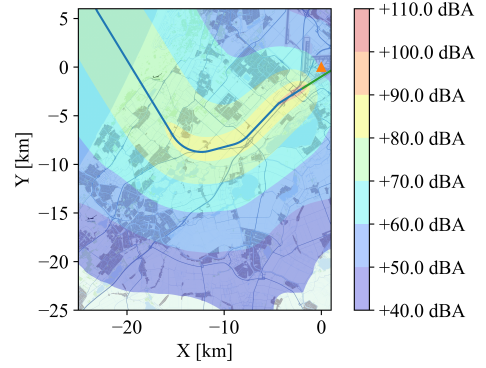
Figure 4.21: Average deviation and standard deviation of thrust compared to airline model of 3 different take-off weights of the B737-800.

formance calculations. The first method is the best-practice method from the Aircraft Noise and Performance (ANP) database. For a second method, a relation was established between thrust and the fuel flow to the engines gathered from ACMS data. This method is fully empirical and thus significantly different from the previous methods. The final method is based on the Gas Turbine Simulation Program (GSP). The three methods were then used to find thrust input to the Doc 29 noise model to compare their thrust profiles and corresponding noise footprint.

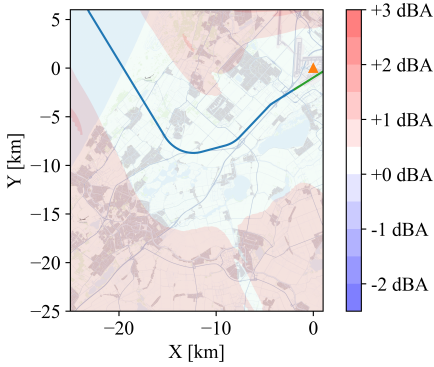
The current best-practice method approximates the thrust well but currently has a limited range of aircraft types for which it can be applied. The fuel flow method gives good insight into actual flight data and the important parameters for thrust estimation but shows large deviations from the airline model. The GSP method is found to provide a good approximation of the thrust. The effect of these different methods on the noise predictions was up to 3 dBA in departures. To improve the performance of the current best practice methods, the advantages of the above methods were combined. New engine



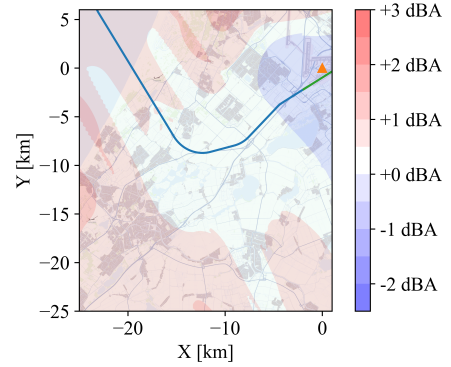
(a) SEL contour when using the GSP.



(b) SEL contour when using the new LS-derived ANP method.



(c) Differences in calculated noise contour when using the GSP.



(d) Differences in calculated noise contour when using the new LS-derived ANP method.

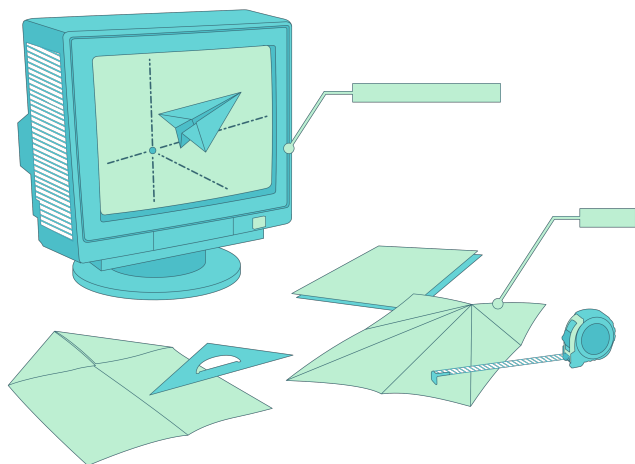
Figure 4.22: Noise contours of the differences between multiple calculation methods with the airline model for the B737-800.

coefficients were estimated from the GSP database with bounded least-squares and implemented into the ANP method. Although the updated results still showed differences with the GSP method, it is more accurate than current best-practice models.

In conclusion, this chapter gives insight into the advantages and disadvantages of the different thrust estimation methods and their effect on aircraft noise estimations. A very important result is that methodologies such as GSP can be used to derive coefficients for determining thrust, accounting for the N1, fully in line with those currently used in the ANP database. Despite the computational requirements, this approach is cheap compared to real engine tests. In addition, it can account for new engine types and for the full range of engine types currently used by expanding the current ANP database. However, the limitation of available validation data for public use remains a challenge.

Following this new method is a step towards better aircraft noise modelling, for which the accuracy of the thrust input is crucial. By improving the representation of actual

aircraft operating conditions, the proposed method facilitates a closer correspondence between modelled and measured noise levels, thereby supporting more reliable model validation and noise impact assessments.



5

CALIBRATION OF NOISE-POWER-DISTANCE VALUES

With accurate model input established in chapter 4, this chapter focusses on evaluating the Noise-Power-Distance (NPD) tables employed in the European Doc 29 noise model. The measurement data set used in this research is described in section 5.2. Even with accurate input parameters, in section 5.3 discrepancies are observed between modelled and measured noise levels, which can be attributed to the inaccuracies in the NPD tables. To further investigate this, empirical thrust-noise relations are derived from the measurements in section 5.4. These derived relations are found to differ from those in the original NPD tables. The empirical thrust-noise relations are used to calibrate the model in section 5.5, for which the agreement between the modelled and measured mean noise levels improves. The standard deviation of the differences gets reduced by 25% for departure operations. This finding is subsequently confirmed using independent measurements around Oslo Airport Gardermoen. Beyond improving current best-practice noise modelling, the methodology presented in this research offers insight into the development and validation of NPD tables.

This chapter has been published in the CEAS Aeronautical Journal [68] and parts have been published in the conference proceedings and presented at the 30th AIAA/CEAS Aeroacoustics Conference Rome 2024 [89].

5.1. INTRODUCTION

The aviation industry is continuously growing, potentially resulting in increased noise exposure for communities surrounding airports. To investigate the effects of aircraft noise on these communities, predictive models have been established to calculate noise levels on the ground. These noise models are commonly used to regulate the number of operations or to create new flight routes to limit noise at specific times and locations. The models used for these applications are mainly (semi-)empirical models, i.e. based on measured data, with limited computational times, which is essential given the high volume of aircraft operations.

In Europe, a harmonised approach for noise modelling was deemed important. As such, the European Civil Aviation Conference (ECAC) developed the Doc 29 series of reports [19, 20, 21]. They present the methods for calculating aircraft noise following the current best-practice standards. This modelling framework, originally introduced in the 1970s, has been periodically updated throughout the years to take newer aircraft models and new modelling insights into account. Similar to other best-practice noise models, such as the Aviation Environmental Design Tool (AEDT) [15] and the Dutch Noise Model (NRM) [16], Doc 29 makes use of Noise-Power-Distance (NPD) tables, which provide noise level data as a function of power (thrust delivered by engines) and the distance between the aircraft and the receiver. NPD tables provide multiple noise metrics for both approach and departure operations. This research focuses on two key noise metrics commonly used for noise contour calculations: $L_{A,max}$, the maximum A-weighted overall sound pressure level, and Sound Exposure Level (SEL) [19]. Both metrics are calculated per event, where SEL is used to calculate time-averaged levels such as L_{den} . The noise levels in the NPD tables are empirically determined through acoustic measurements and are standardised to the standard atmosphere and a reference speed of 160 kts, as specified in AIR-1845 [13]. These measurements are of a limited set of distances and operational conditions and subsequently extrapolated to obtain entries for the full NPD table. Other models used for noise regulation, including the Swiss sonAIR model [6] and the German Anleitung zur Berechnung von Lärmschutzbereichen (AzB) [90], do not rely on NPD tables. Instead, they utilise more detailed spectral data and directivity patterns. The sonAIR model is further analysed in chapter 7.

Studies related to the validation of models, such as Doc 29, have consistently reported differences between measurements and model predictions. Although the Doc 29 model is more often used for long time scales, such as yearly L_{den} calculations, validation studies for these metrics are limited. Reported discrepancies in L_{den} are on the order of at least 1 dBA when compared with measurements [60, 59]. Official documentation, AIR-1845, indicates a typical prediction accuracy of 1-2 dBA for locations directly beneath the flight path [13]. More commonly, however, the model is validated at the single-event level, where deviations can become larger [91, 92, 80, 93]. Hogenhuis and Heblj [92] stated that such discrepancies may arise from uncertainties in the input parameters (thrust and weight) or from the current weather correction methods. To improve the model input, multiple methods have been proposed to retrieve thrust and weight from historical tracks, as an alternative to standard procedures [73, 11]. However, even with accurate thrust input, differences between predicted and measured noise levels will remain [75].

Rhodes and Ollerhead [80] argue that the differences are caused by the unavailability of NPD tables for certain aircraft types. Other studies have similarly identified such gaps in NPD tables as a possible source of error in noise modelling [94, 95]. To mitigate the contribution of this possible source of error, calibration of NPD tables has been proposed. For example, Sari et al. [96] used year-round long term noise measurements and L_{den} predictions to calibrate Doc 29. Trow and Allmark [97] presented a calibration method using single-event differences between model predictions and measurements. The aircraft thrust and position were modelled using procedural thrust profiles. The average difference from multiple flights was used to adjust the corresponding value in the NPD table. These corrections were then interpolated or extrapolated across the entire table. The disadvantage of this approach is that it is strongly affected by outliers. Although differences remained, the calibrated model was more accurate than the original model, and it altered the noise contour shapes [97].

The research objective of this chapter aligns with the research described above, aiming to improve aircraft noise modelling by evaluating the Doc 29 input parameters and improving NPD tables using acoustic measurements. The main contributions of this chapter are twofold. First, instead of estimating thrust from flight profiles, this study derives thrust directly from acoustic measurements, supported by actual flight data. Second, instead of adjusting the entries of the NPD table for each distance and thrust setting combination, the noise measurements are used to identify a relationship between thrust and noise level. These relations are then used to systematically update the NPD tables. The impact of this calibration method is investigated using noise measurements around Amsterdam Airport Schiphol (AMS) and Oslo Airport Gardermoen. Validation is accomplished using flight data from the Aircraft Condition and Monitoring System (ACMS). The updated NPD tables are used to improve noise modelling by reducing the mean prediction error and the standard deviation of the differences by 25%.

5.2. DATA AND METHODOLOGY

In this research, measurements are used to validate and improve the Doc 29 model. For a fair comparison between the model results and measurements, accurate model input is necessary. To better understand the functioning and limitations of the Doc 29 model, an in-depth analysis of its input parameters is performed. Further, when comparing model results with measurements around Schiphol and Gardermoen airports, the characteristics and uncertainties of the microphone systems need to be accounted for. This section addresses these subjects in detail.

5.2.1. SCHIPHOL NOMOS MEASUREMENTS

The Noise Monitoring System (NOMOS) encircling Schiphol Airport, described in section 1.3, is used for this research. For a select number of NMTs, the noise metrics $L_{A,max}$ and SEL are used in the analysis to update the entries in the NPD table. The NMTs also provide down-sampled (8000 Hz) mp3 files for the N1 estimation as described in chapter 4.

Most NMTs operate with a fixed 60 dBA threshold for $L_{A,max}$, registering noise events that exceed this limit. To minimise the impact of background noise, only measurements

with $L_{A,max} > 70$ dBA are used for updating the NPD table. Furthermore, measurements with aircraft elevation angles $\beta > 60^\circ$, relative to the NMT, are selected to reduce lateral attenuation and microphone uncertainties, aligning with ISO 20906 standards [30]. Additionally, only recordings taken under weather conditions compliant with ISO 20906, i.e. no precipitation and wind speed < 10 m/s, are considered in the analysis.

The measurement conditions explained above resulted in a dataset summarised in Table 5.1. The data cover all valid measurements from 2021 and 2022. This study focused specifically on the B737-800, the most common aircraft type flying at Schiphol. Other aircraft types, such as the A330-300 and the B777-300, were also analysed but are not discussed in detail in this chapter.

Table 5.1: Number of considered measurements of the B737-800 per NOMOS NMT.

NMT	1	10	12	14	21	30	34	40	41
departures	-	1121	39	57	25	204	581	1725	114
arrivals	1023	82	-	1314	24	-	-	-	-

5

5.2.2. OSLO MEASUREMENTS

To validate the findings around Schiphol, measurements are taken around Oslo airport, Gardermoen. Gardermoen Airport is equipped with 11 fixed NMTs, including two terminals at the end of the runways (NMT 4 and 5) and nine in departure and/or arrival corridors. The area around Oslo is much less populated in comparison to Amsterdam. This results in lower background noise levels, down to 35 dBA for some NMTs. This makes most NMTs suitable for research purposes. The locations of these NMTs are illustrated in Figure 5.1, with respect to the local control tower.

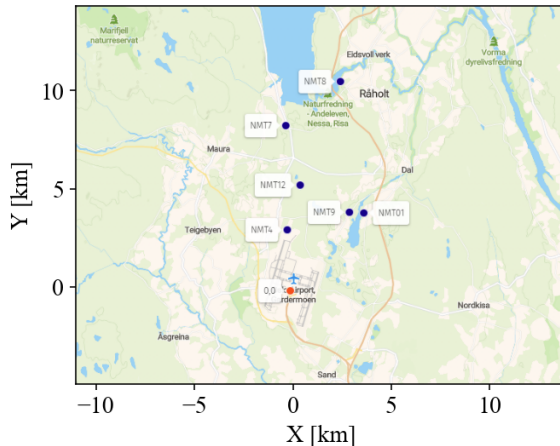


Figure 5.1: Locations of the NMTs around Gardermoen airport.

The system used around Oslo has similar functionality and output to the NOMOS

system. Due to the low background noise levels in this area, lower measured noise levels will remain reliable and a minimum threshold of $L_{A,max} = 60$ dBA is taken. For consistency, similar requirements on operational conditions as those used for the NOMOS measurements are adopted here. An additional requirement is that the ground should be free of snow, as its cover significantly attenuates the measured sound. These criteria gave a set of measurements per NMT over the selected days in 2023, as presented in Table 5.2. This dataset is more limited than the one available for Schiphol. In particular, the arrival measurements are gathered from a single NMT, which can introduce bias.

Table 5.2: Number of considered measurements per Oslo NMT.

NMT	1	4	7	8	9	12
departures	9	2	47	28	5	45
arrivals	-	-	-	93	-	-

5.2.3. DOC 29 MODEL

This research utilises the data and Doc 29 methodology as described in chapter 2. The thrust estimation is based on the methodology of N1 estimation from NOMOS audio recordings as described in chapter 4.

As the primary focus of this research are the NPD tables, it is important to note the assumptions within. Firstly, NPD tables are for general aircraft types. For example, the B737-700 and B737-800 make use of the same NPD table. The aircraft substitution correction is a single offset in dBA applied uniformly to all NPD values, depending on whether the operation is departure or approach. Over the years, the introduction of newer and more efficient engines has led to changes in these correction factors. It should be noted that the levels in the NPD are for total aircraft noise, i.e., resulting from both engine and airframe noise, where the latter can be dominant during arrival [98].

Further, the NPD tables are given for a set of standard conditions (right underneath the flightpath, ISA atmospheric conditions, etc.). For operations deviating from these standard conditions, additional correction factors are applied. These correction factors can significantly influence the calculated noise level. In this study, the correction factors used in Doc 29 are assumed to be accurate.

5.3. MODEL DATA COMPARISON USING STANDARD NPD TABLES

5.3.1. BASELINE DATA SET USING N1%

The baseline data set used in this research consists of roughly 3800 B737-800 departures from Schiphol Airport in 2021 and 2400 arrivals in 2022. These operations fall within the requirements stated in section 5.2. As previously mentioned, the NOMOS provides measurements of both $L_{A,max}$ and SEL, and hence model results will be compared against these parameters. For simplicity, only $L_{A,max}$ will be presented in the plots. Figure 5.2a shows the NOMOS measured $L_{A,max}$ levels for departure operations, plotted against the acoustically estimated N1% and the distance between the aircraft and NMT at the time of the measured $L_{A,max}$. As expected, a clear inverse relation is observed between mea-

sured sound level and distance. A clear correlation between measured levels and engine setting is not immediately visible for the departure measurements. For arrivals, depicted in Figure 5.2c, some influence of $N1\%$ on noise level is observed, though it remains difficult to see in the figures. The verification data set from Oslo airport is presented in Figures 5.2b (departures) and 5.2d (arrivals). Similar patterns are visible as those observed in the Schiphol data set.

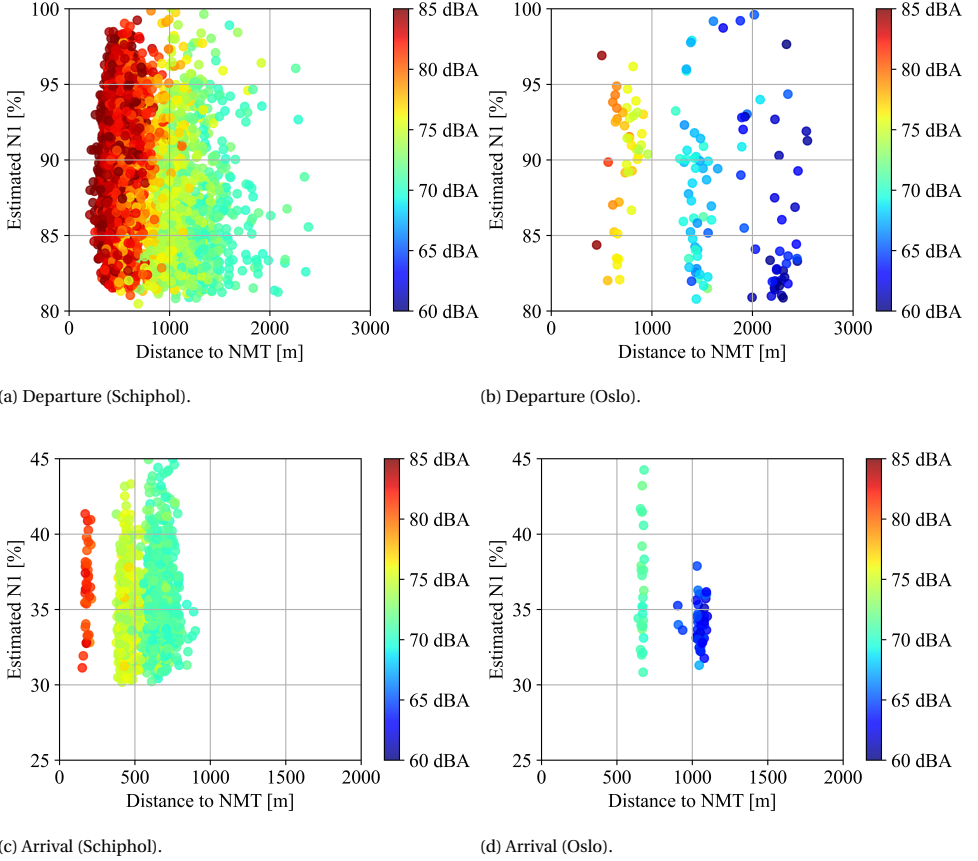


Figure 5.2: Sound level of measurements ($L_{A,max}$) for B737-800 as a function of distance and $N1\%$ for the baseline (Schiphol) and verification (Oslo) dataset.

5.3.2. DIFFERENCE IN SOUND LEVEL BETWEEN MODEL AND MEASUREMENT

Figure 5.3 illustrates the measured $L_{A,max}$ against that predicted by the Doc 29 model (with original NPD tables). The difference between the model and measured results is given by

$$\Delta L = L_{model} - L_{measured} \quad (5.1)$$

where a negative ΔL indicates an underestimation of the levels by the model. The agreement between model predictions and measurements is summarised in Table 5.3, where

μ (indicating a bias) is the average difference between the model result and its corresponding measured values for all data events, and σ is the standard deviation of ΔL (indicating the precision). For both departure and arrival operations at Amsterdam Airport Schiphol, the model underestimates the noise levels. The measured noise levels at Oslo airport in the verification data are lower, which is likely due to lower background noise levels at those measurement locations, which in turn results in smaller underestimations. This holds true both for $L_{A,max}$ and SEL values.

Table 5.3: Mean and standard deviation of the model results minus their corresponding measured values (mean and std. dev. of ΔL).

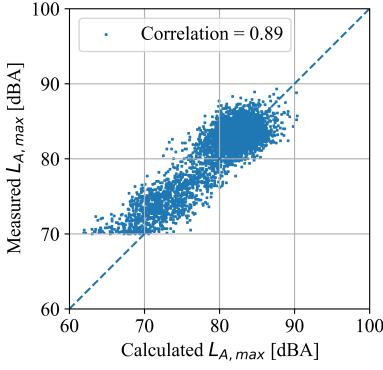
Airport	Operation	$L_{A,max}$ [dBA]		SEL [dBA]	
		μ	σ	μ	σ
Schiphol	Departure	-0.9	2.3	-0.9	1.8
	Arrival	-2.8	1.6	-1.3	1.4
Oslo	Departure	-0.5	2.5	0.0	2.1
	Arrival	-1.7	1.4	-0.7	1.4

The results indicate differences between arrival and departure operations. For arrivals, a larger offset μ is visible, while the estimated standard deviations are relatively small. In contrast, departures exhibit a smaller offset but larger standard deviation. This larger variation in departure operations is consistent with findings in the literature [99, 100].

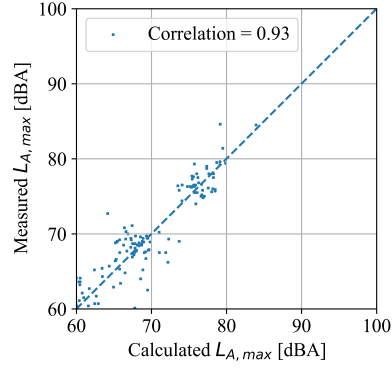
The arrival results are clustered around the NMTs, resulting in a small standard deviation. A clear spatial trend is observed: the offset appears to increase with distance from the runway. The larger the distance is (lower noise level), the larger the bias will be. The noise level is overestimated at NMT 10, while underestimated at NMTs 1 and 14. This can likely, in part, be explained by differences in approach speeds. At NMT 10, aircraft speeds are around 140 kts, compared to around 175 kts at NMT 14. The NPD tables have been calibrated for an approach speed of 160 kts, and apart from a modelled duration correction for SEL, no additional noise corrections are applied for speed differences. This duration correction is needed because SEL is an integrated metric, whereas $L_{A,max}$ is a point metric. This would also explain the differences in results between $L_{A,max}$ and SEL, as currently the $L_{A,max}$ model predictions are independent of aircraft speed. A similar finding was recently reported during a validation study with the AEDT at San Francisco Airport [53], where a 2.7 and 0.8 dBA underestimation is found for $L_{A,max}$ and SEL, respectively. Although these speed-related observations are noteworthy, they fall outside the scope of this research.

To improve modelling results, the overall offsets can be reduced by implementing a general correction factor, such as the aircraft substitution correction factor. However, such corrections do not address the variation between modelled and measured values. To increase the accuracy and reliability of the model, this variation needs to be reduced.

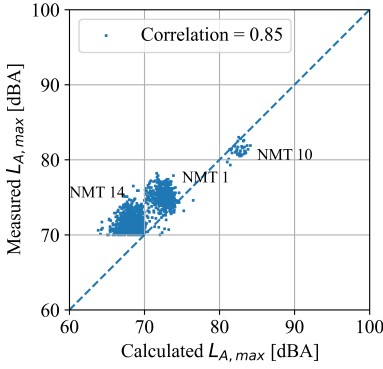
To investigate the causes of these noise level differences ΔL , a correlation analysis is performed on the two main input parameters: distance and thrust. Although the Pearson's correlation coefficient showed no significant relation between ΔL and distance, a



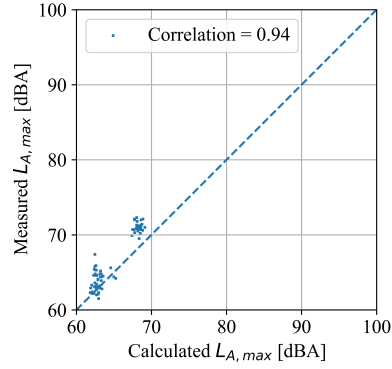
(a) Departure (Schiphol).



(b) Departure (Oslo).



(c) Arrival (Schiphol).



(d) Arrival (Oslo).

Figure 5.3: $L_{A,max}$ measurements of B737-800 with respect to Doc 29 model results (with original NPD tables), including corresponding correlation coefficient.

stronger correlation was found between the thrust and ΔL during departures. For arrivals, correlation with thrust was weaker but still present. Figure 5.4 illustrates the ΔL against the estimated thrust for both operations, where again a negative Δ indicates a model underestimation. The p-value for both results is smaller than 10^{-10} , indicating their statistical significance. These findings motivated a deeper investigation into the relationship between thrust and measured noise levels.

5.4. NPD TABLE DEVELOPMENT

In this section, the relation between the measured noise levels ($L_{A,max}$ and SEL) and the aircraft thrust is derived and compared with the current relation in the NPD table. The measured levels are back-propagated to the source by correcting for propagation effects. This is achieved by inverting the Doc 29 correction factors applied in the model, accounting for actual geometry and meteorological conditions during measurements.

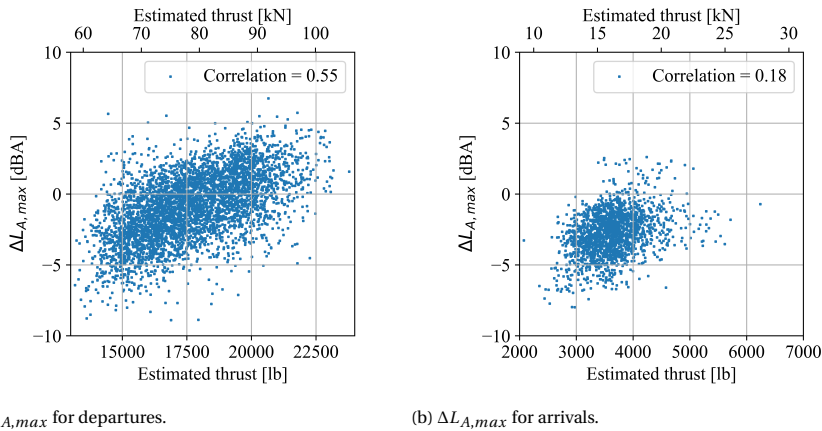


Figure 5.4: The differences between model results and NOMOS measurements versus the estimated thrust (including corresponding correlation coefficient).

For $L_{A,max}$ measurements, these corrections are rather straightforward. The applied engine-frame model, ground impedance, engine installation and lateral attenuation corrections are inversely applied to the measurements. For the SEL measurements, however, this procedure is more complex. Unlike $L_{A,max}$, SEL represents the integrated energy over multiple flight segments, each with distinct distances, thrust settings, speed and other correction factors. Since NOMOS provides only a single SEL value per event, the individual segment contributions to the total SEL are not directly available. In this study, an approximation is made: it is assumed that the correction factors for the measured segments are the same as those for the modelled segments, apart from a constant offset equal to the difference between the total measured and total modelled SEL. This approximation is then used to correct the measured SEL values. A sensitivity analysis (not shown here) conducted on a set of predicted and measured SEL values indicates that the uncertainty introduced by this approximation is limited to ± 0.3 dBA.

To correct the measurements for atmospheric effects, it is necessary to account for variations in weather conditions and measurement distances. These effects are frequency dependent. For the conversion of the measured values to those that would have been taken under standard atmospheric conditions, the frequency spectrum of the emitted sound needs to be accounted for. Using the frequency spectrum of the acoustic measurement, along with the corresponding meteorological data, the expected attenuation rates can be calculated. However, since NOMOS mp3 files are sampled with a sampling rate of 8000 Hz, the spectral information above 4000 Hz is not available. Therefore, the spectral information (also known as spectral classes) of the aircraft from the ANP database is used as a substitute. This use of spectral classes has been validated by van der Grift et al.[101].

After applying all corrections and propagating the measurements to a reference distance of 1000 ft (305 m), the corrected noise levels are obtained at the reference distance. The relation between these levels and thrust is then made. This relation is illustrated in Figure 5.5 for both departure and arrival measurements, and for both $L_{A,max}$ and SEL.

In general, the values derived from the NOMOS measurements and those documented in the NPD tables match within a couple of dBs. Previous studies indicate that the variation due to weather effects, next to atmospheric attenuation effects, can account for about 2 dB [102, 103], which partly explains the observed spread in the measurements. The other observation is that during departure operations, the measured noise level appears to depend less on the estimated thrust than originally assumed in the NPD tables. Assuming a measurement error (i.e. standard deviation σ_e) of 5 dBA, the 95% confidence interval for the slope of the fitted relation in Figure 5.5b is $(3.9 \pm 1.2)10^{-4}$ dBA/lb. This dependence is thus statistically significant, which is also confirmed by the estimated correlation coefficient of 0.30 and a p -value of 10^{-27}). Figure 5.5a and Figure 5.5b also show the thrust-noise level combinations based on thrust values obtained directly from the ACMS data, which further confirm the observed dependence. The slope estimated from the NOMOS data is approximately three times smaller than that of the NPD tables.

For the arrivals, the thrust-noise relation derived from the NOMOS data has a better alignment with the NPD table. Although thrust is generally assumed to be non-dominant during arrival, the NOMOS measurements show that the thrust setting is not insignificant and hence influences the measured noise levels. This is consistent with the findings of other studies on arrival measurements [40]. It is important to note that the thrust ranges differ significantly between the two operations: approximately 4000 lb for arrivals and 18,000 lb for departures.

To investigate whether the observed dependence in the departure measurements is consistent with other aircraft types, the analysis is repeated for the A330-300 and the B777-300ER, as seen in Figure 5.6. Consistent with previous findings, the slope of the measured thrust-noise relation is smaller than that of the NPD data for both aircraft, although differences are visible between these two aircraft.

These insights are used to work towards modified NPD tables. Instead of calibrating the NPD values directly from measurements, the noise-thrust relations such as those depicted in Figure 5.5 are used to create completely new NPD tables. Each NPD table lists noise levels at ten reference distances in the range of 200 to 25000 ft. For each distance, a thrust-to-noise level relationship is established using polynomial fitting. An example of such a fit at 1000 ft is illustrated in Figure 5.5. The order of the polynomial is determined by validating the reduced chi-squared χ^2_v statistic as a function of this polynomial order. Across all distances in this data set, the linear fit consistently provided the best results, which aligns with the current NPD assumptions that sound level increases linearly with thrust. This process results in ten linear fits, for which the noise levels at five thrust settings are extracted. This method leads to a new NPD table fully based on measurements and independent of existing NPD values. For the departure data set, it reveals a weaker dependence of noise on thrust compared to the original NPD table. Conversely, the arrival data set shows trends similar to the ones from the ANP database. There seems to be an even slightly stronger thrust-noise relationship.

A possible explanation for the above described differences lies in the origin of the NPD tables themselves. Tables like that for the B737-800 were created during the first introduction of the aircraft with the engine technology available at that time. Over the last 20-30 years, newer and hence quieter engines have been developed. A general correction factor, known as EASA aircraft substitution, is often applied to take this effect into

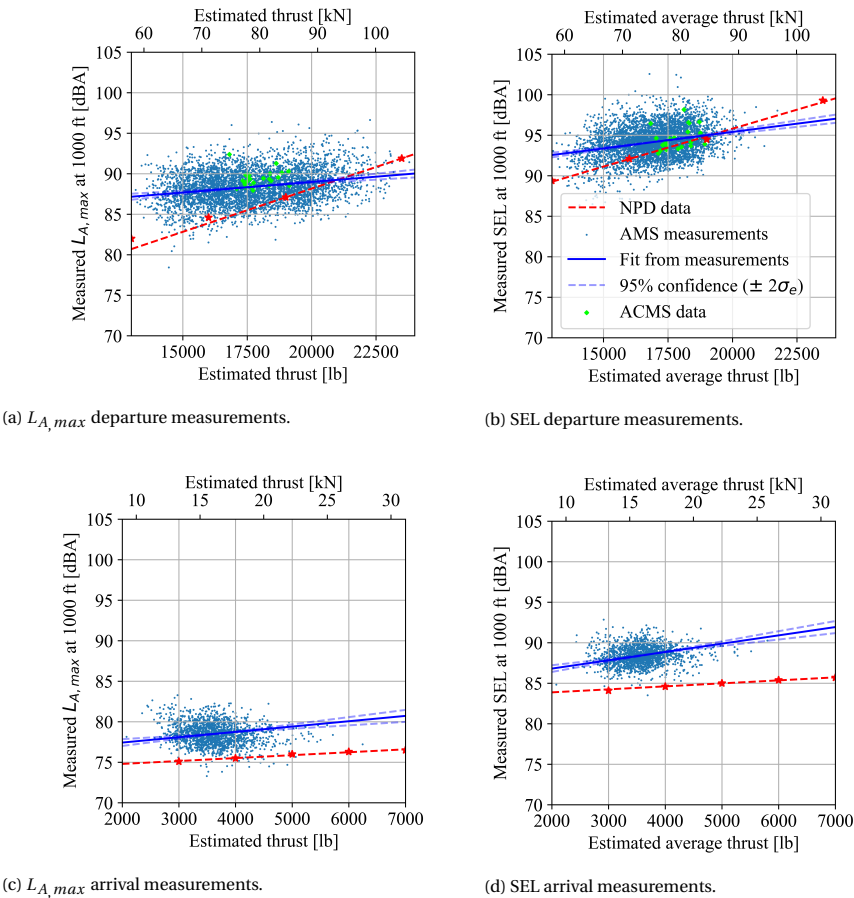


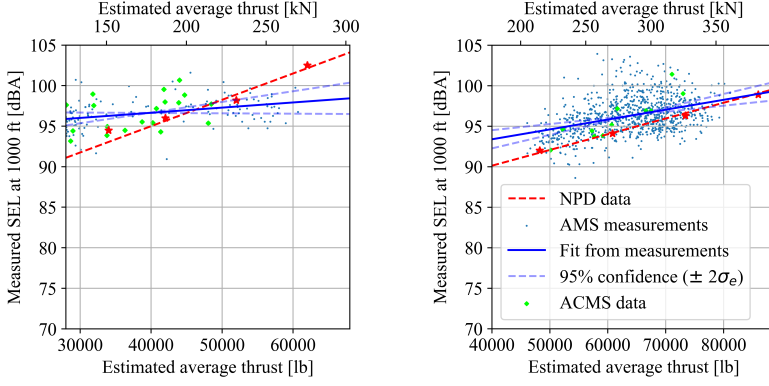
Figure 5.5: Measurements of B737-800 standardised to a reference distance of 1000 ft. The graphs' legend is visible in the top right figure.

account. This substitution correction factor tends to be small for arrival operations (typically around -0.1 to -0.2 dBA), but larger and more variable for departure operations, ranging from -3 to +0.5 dBA, depending on the specific engine type. This correction factor, however, is a single dBA value and does not capture changes in the thrust-noise relation due to newer engine technology. This can likely explain the large discrepancies observed between the modelled and measured noise-level changes with thrust during the departure operations.

5.5. APPLICATION OF NEW NPD TABLES

5.5.1. EFFECT ON SINGLE EVENT MEASUREMENTS

To analyse the effect of using the new NPD table in Doc 29, the available data is split into a calibration and verification data set. The calibration data is used to establish the noise-



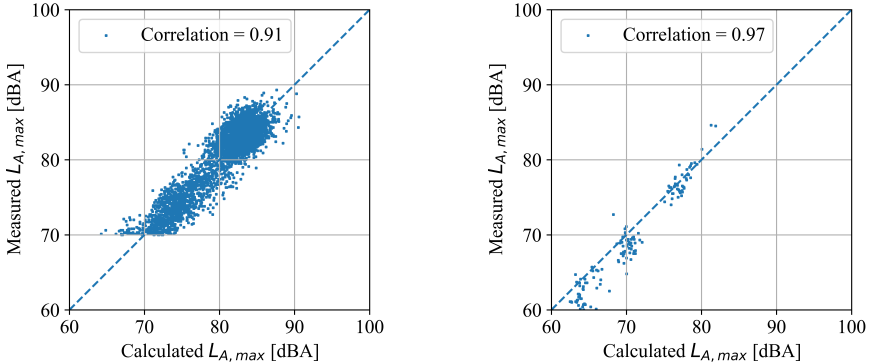
(a) SEL departure: A330-300.

(b) SEL departure: B777-300ER.

Figure 5.6: SEL measurements of the A330 and B777 standardised to a reference distance of 1000 ft.

5

thrust relations, and the verification data is subsequently used to validate the results. The data gathered around Schiphol airport is used for calibration, while the independent Gardermoen data is used for validation. The results are illustrated in Figures 5.7a and 5.7b for the departures, and in Figures 5.8a and 5.8b for the arrivals. The mean μ and standard deviations σ of the new results are given in Table 5.4.


 (a) $L_{A,max}$ Schiphol calibration data set.

 (b) $L_{A,max}$ Gardermoen validation data set.

 Figure 5.7: $L_{A,max}$ model results versus measurements of departure operations using new NPD tables (including the corresponding correlation coefficients).

We start with the calibration data set, where the results differ noticeably between departure and arrival operations. For the departure operations, the new method removes the small offset μ , but at the same time, the standard deviation decreased by 20%-30%. This effect is also reflected in the correlation coefficient between model output and measurements, which increases for the departures. This indicates the accuracy improvement of the model results. In contrast, the arrival data set shows different behaviour. While the

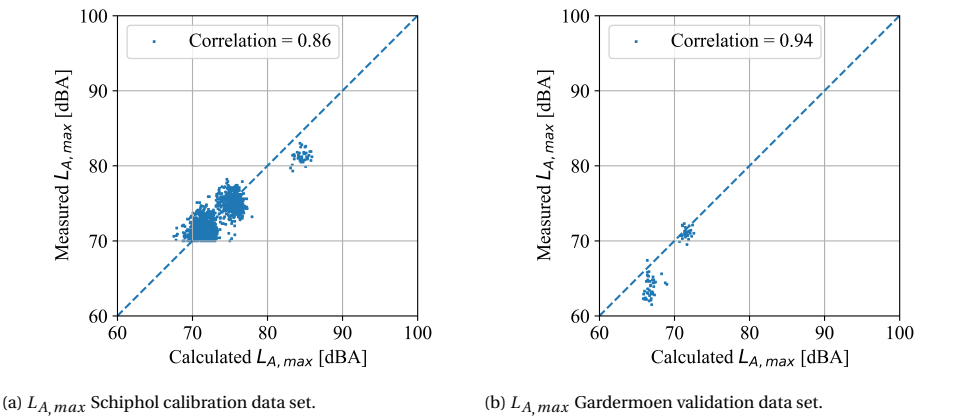


Figure 5.8: $L_{A,max}$ model results versus measurements of arrival operations using new NPD tables (including the corresponding correlation coefficients).

Table 5.4: Results of ΔL for the model using standard and new NPD values.

Operation	NPD	Data set	$L_{A,max}$ [dBA]		SEL [dBA]	
			μ	σ	μ	σ
Departure	Standard NPD	AMS - Calibration	-0.9	2.3	-0.9	1.8
		Oslo - Validation	-0.5	2.5	0.0	2.1
	New NPD	AMS - Calibration	0.0	1.8	0.1	1.4
		Oslo - Validation	1.3	1.6	0.4	1.5
Arrival	Standard NPD	AMS - Calibration	-2.8	1.6	-1.3	1.4
		Oslo - Validation	-1.7	1.4	-0.7	1.4
	New NPD	AMS - Calibration	0.3	1.4	0.4	1.6
		Oslo - Validation	2.0	1.6	1.6	1.3

new NPD successfully removed the offset μ , it has minimal impact on σ . For arrivals, the new NPDs prove less effective at reducing the variation compared to their performance with the departure data set.

The validation data reveals a slightly different pattern. For both departure and arrival data sets, the offset μ of ΔL of the validation data is smaller than in the calibration data set when using standard NPD. However, the reduction in standard deviation at departures is as large as 30-35% when using the new NPD. This validates the model enhancement during the calibration. Arrivals present a contrasting outcome in the validation phase. The new NPD tables produce a large overshoot in the model predictions, and the previously low standard deviation even increases slightly. For the arrival operation, the new NPD tables therefore do not provide an improvement. A possible explanation is that NPD tables do not capture the variations in airframe noise at different operational phases, such as deployment of landing gear and high-lift devices. Further research is recommended on how to incorporate these components into best-practice noise models.

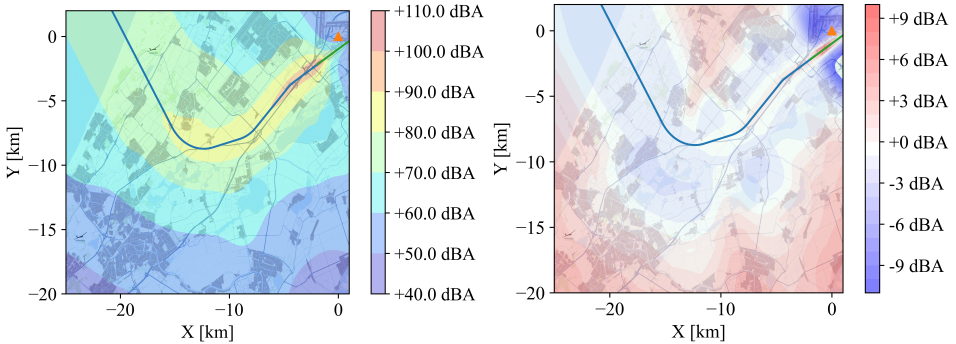
In addition, the largest discrepancies between model predictions and measurements at Oslo occur at the lowest noise levels (< 70 dBA $L_{A,max}$), which were discarded from the Schiphol dataset during the creation of the new NPD tables.

Despite this mixed performance across operation types, the method presented in this study produces more accurate model outcomes. When comparing the modelling methods, the new NPD, based on recent measurements instead of standard values, is a more dynamic approach to noise modelling.

5.5.2. EFFECT ON SEL CONTOUR

Doc 29 is primarily used to calculate the aircraft noise impact on areas surrounding airports. This is done through calculations over a grid for numerous flights, creating, for example, L_{den} contours. In this contribution, focus is on the SEL contour for a single flight, using the flight path and $N1\%$ setting from ACMS data. As expected, applying the new NPD tables affects the resulting contour. Figure 5.9a shows the modelled SEL contour for a departure flight, while Figure 5.9b illustrates the differences between the baseline model (using original NPD tables) and the updated model. Here, a negative ΔL (blue) indicates that the new model predicts a lower SEL value than the baseline model, while a positive ΔL (red) indicates a higher SEL value. The new NPD table results in lower predicted noise levels during the initial phase of the departure when high thrust levels are used. In contrast, higher predicted noise levels are observed at later stages in flight and at greater distances between the aircraft and the observer.

The arrival contour, not shown here, exhibits an overall increase in modelled noise due to the large offset present in the baseline model.



(a) Modelled SEL contour using standard NPD tables.

(b) Difference in SEL contour when using calibrated NPD tables.

Figure 5.9: Difference in SEL contours between baseline and calibrated models for a departure operation.

5.6. CONCLUSIONS

This chapter presented a method to improve aircraft noise predictions by refining the input parameters and updating the Noise-Power-Distance (NPD) tables of the best-practice model Doc 29. In the first step, the uncertainty of the model input was reduced by using

the flown track and acoustically derived thrust settings.

The second step involved the evaluation of the NPD tables currently in use. These NPD values were originally derived through a limited number of measurements and are used in most best-practice methods. In this research, the NPD values were evaluated by comparing measured noise levels with model predictions that incorporate the actual thrust setting and distance, rather than relying on the default flight profiles. By minimising the errors in these input parameters, the remaining differences between model results and measurements (ΔL) can be attributed to inaccuracies in the NPD table. For the B737-800 data set, consisting of around 3800 departing and 2400 arriving flights, the offset μ was under 1 dBA for departures and 3 dBA for arrivals. The standard deviation σ of these differences was around 2 dBA and 1.5 dBA, respectively. Based on this analysis, a new NPD table was created from NOMOS measurements around Schiphol Airport.

All measurements in the data set were standardised to the reference conditions used in the NPD tables. Several key insights emerged from this analysis. For the departure flights, the relation between thrust setting and sound level was less pronounced than originally expected. Incorporating these revised thrust-noise relations to create a new NPD table resulted in a 25% reduction in the standard deviation of differences between model and measurement. This improvement was consequently validated by applying the updated NPD tables on an independent data set at Oslo Gardermoen airport. For the arrival operations, different results were observed. The new NPD removed the offset μ between the measurements and the model results but did not reduce the standard deviation σ . This implies that the estimated thrust setting to noise ratio is not directly the cause of the differences seen between measurement and modelling results. Although updating NPD tables helps reduce the offset μ , further research is required to address the variation observed in arrival aircraft noise prediction.

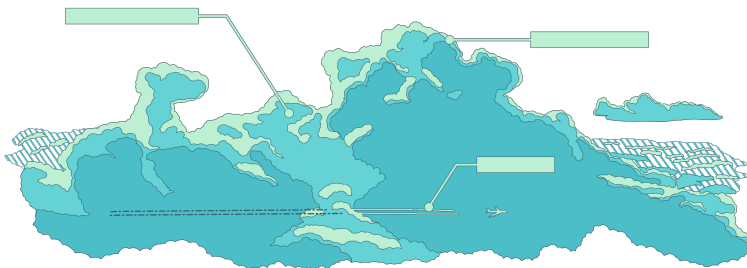
Although this research used data from Schiphol and Gardermoen Airport, the proposed methodology is applicable to any airport. While each airport has its own set of arrival and departure procedures, the NPD tables themselves are general and not airport-specific. To apply the methodology elsewhere, local thrust procedures must be validated. A limitation, however, is the need for validation data in the form of audio recordings (N1 estimations) or flight data. Once thrust is accurately determined, new NPD tables can be generated independently of the specific airport operation.

Measured thrust-noise relations, and consequently new NPD tables, can improve Doc 29 model predictions at the single-event level. Beyond improving the best-practice noise model, the methods described in this research give insight into the creation and validation of NPD values.

6

VALIDATION OF THE ANP DATABASE SOURCE SPECTRA

Next to the NPD tables investigated in chapter 5, the Aircraft Noise and Performance (ANP) database contains several standardised source spectra, known as spectral classes, which are used for correcting the NPD tables for differences in sound propagation due to changing atmospheric absorption. This chapter focuses on the agreement of these spectral classes with measurements taken around Amsterdam Schiphol Airport, and quantifies the effect of differences in these spectra for the Doc 29 weather correction. Section 6.2 describes the measurements taken by an acoustic array close to the runway and by NOMOS at long range. These measurements are propagated to the standard distance of 1000 ft, taking into account the geometrical spreading and the actual atmospheric absorption. In section 6.3, the results for two aircraft types are discussed. Differences in shape are found between the two measured spectra and the spectral class. This is partly due to the low signal-to-noise ratio for the high frequencies in the case of large distances between the aircraft and the measurement system. Section 6.4 concludes that the effect of the application of the measured spectra on the Doc 29 weather correction is smaller than 0.5 dBA for the NOMOS positions, indicating the suitability of the current ANP spectral classes for the weather correction.



A previous version of this chapter has been published in the conference proceedings and presented at the 29th AIAA/CEAS Aeroacoustics Conference, San Diego 2023 [101].

6.1. INTRODUCTION

The aviation industry is growing, and with it the noise nuisance in communities around large airports. To regulate flights and design noise abatement procedures, the expected noise inflicted on the ground is calculated using aircraft noise models. The most common noise models are empirical models such as the European Doc 29 standard [19, 20, 21] and the Dutch calculation model (NRM) [16]. These so-called best-practice models make use of empirical relations gathered in Noise-Power-Distance (NPD) tables. These tables give the A-weighted noise level for a specific power setting of the aircraft engines and a specific distance of the aircraft to the observer on the ground. The simplicity of this modelling technique allows for computing a large number of flights in a short time. The disadvantage is that a number of assumptions are made. These NPD tables are made for standard conditions, such as standardised atmospheric conditions. For situations differing from these standard atmospheric conditions, a weather correction is used. Any deviations in local weather affect the absorption of aircraft noise in the atmosphere through a change in the absorption coefficient. The absorption coefficient is frequency dependent, thus to find the contribution of this effect, an emission spectrum is needed. These spectra are typically used for a large variety of aircraft and are denoted as spectral classes. In total 18 departure and 23 approach spectral classes exist in the Aircraft Noise and Performance (ANP) database [22], of which 4 are for commercial 2-engine turbofan aircraft. This aircraft type is most common in large hub airports such as Schiphol.

The use of spectral classes is a modelling assumption as each aircraft type has its own characteristics in its emitted noise spectrum. In this research, the agreement of these spectral classes with measurements taken around Schiphol airport is investigated as well as the effect deviations have on the modelling results. The focus is on the B737NG and A330 aircraft types. The spectra are determined using close-range and long-range measurements, the set-up and processing of which are explained in section 6.2. The acquired spectra are compared to each other and the corresponding spectral class. The differences are analysed in section 6.3. The application of the measured spectra in the Doc 29 best practice noise model shows the influence of differences in the standard and measured spectra to be small, which is further discussed in section 6.4.

6.2. METHODS

In Doc 29 [20] a method to apply a weather correction is given. This weather correction is used to take the change in atmospheric absorption of sound with changing atmosphere into account. This correction factor is applied by calculating $\Delta L_A(T, p_a, h_{rel}, d_i)$ for every distance d_i in the NPD table and adding those values to the existing table. ΔL_A is the difference in absorption in actual atmosphere $L_{A,atm}$ and in the standard atmosphere $L_{A,ref}$. This factor is calculated by removing the standard atmospheric absorption $\alpha_{n,ref}$ and calculating the new α_n for every frequency band n using temperature T , atmospheric pressure p_a and relative humidity h_{rel} according to the SAE-ARP5534 method [39]. Note that $\alpha_{n,ref}$ are normalised average atmospheric attenuation rates obtained in SAE AIR-1845, and thus not directly linked to a single reference atmosphere [13]. Consequently, even for noise calculations in standard ISA conditions, an atmospheric correction factor is applied.

This is done by using the given engine spectrum from the ANP database $L_{n,ref}$, which contains the expected sound levels of 24 1/3rd octave frequency bands at 1000 ft (d_{ref}) from the aircraft as seen in Table 6.1. The centre frequencies of the 1/3rd octave bands run from 50 Hz to 10,000 Hz corresponding to band numbers 17 and 40, respectively. The weather correction factor is calculated through

$$\begin{aligned}\Delta L_A(T, p_a, h_{rel}, d_i) &= L_{A,atm}(T, p_a, h_{rel}, d_i) - L_{A,ref}(d_i) \\ &= 10 \log_{10} \sum_{n=17}^{40} 10^{(L_{n,ref} + \alpha_{n,ref} d_{ref} - \alpha_n d_i - A_n)/10} \\ &\quad - 10 \log_{10} \sum_{n=17}^{40} 10^{(L_{n,ref} + \alpha_{n,ref} d_{ref} - \alpha_{n,ref} d_i - A_n)/10}.\end{aligned}\quad (6.1)$$

The correction is thus accounting for the frequency dependence of the spectrum. As the spectral classes are given in dB and the NPD tables in dBA, the spectra are A-weighted using A_n before summation.

To investigate the validity of the spectral classes, noise events of departing and landing aircraft are measured and the resulting spectra are compared to their respective spectral class in the ANP database. For this research, two measurement set-ups, presented in section 6.2.1, are used containing close and long-range measurements. In section 6.2.2 the processing of the measurements into the required data is discussed.

Table 6.1: Spectral classes and their associated Pressure Band Levels [dB] assigned to the B737-800.

Spectral Class ID	Op Type	Center Frequency [Hz]					
		50	63	80	100	125	160
104	Departure	57.3	56.3	61.5	67.7	71.4	73.7
206	Approach	63.3	65.4	64.1	63.2	66.0	66.6
		200	250	315	400	500	630
104	Departure	67.0	72.1	73.8	74.1	71.3	70.4
206	Approach	69.6	70.1	71.5	67.1	71.0	70.4
		800	1000	1250	1600	2000	2500
104	Departure	70.9	70.0	68.2	67.3	63.4	60.9
206	Approach	71.8	70.0	69.6	66.6	62.9	62.0
		3150	4000	5000	6300	8000	10000
104	Departure	56.6	53.2	47.8	40.5	31.7	27.9
206	Approach	62.7	59.1	58.8	53.3	50.2	40.6

6.2.1. EXPERIMENTAL SET-UP

A single spectral class is given for the full departure or arrival operation. To check the validity of the spectral classes for all flight phases in the operation, measurements are performed close to the runway (i.e. during final approach and take-off) and measurements are taken at a longer range, typically 500-2000 meters (i.e. during phases such as

climb-out or glide descent).

The first set of measurements, close to the runway, is performed using an acoustic array at the north side of the Zwanenburgbaan at Schiphol Airport. The array set-up can be seen in Figure 6.1. As this research is focused on measuring spectra, the array is not used for noise source localisation. The spectra of the middle 8 microphones are averaged. The exact measurement setup and processing are explained in Vieira et al. [104, 49]. For this research, a data set consisting of 10 take-off and 10 landing measurements for the B737-800 and 10 take-off and 5 landing measurements for the A330, acquired during three different days of the measurement campaign, is used. During these measurements, the aircraft flew straight over the array at an altitude of around 100-300 meters.

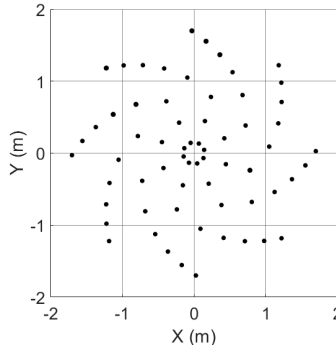


Figure 6.1: Acoustic array configuration

The second set of measurements is taken at a longer range by the continuous unmonitored noise measurement system NOMOS, which consists of 41 Noise Measurement Towers (NMTs). These NMTs are placed on 10 meter poles in the neighbourhood of Schiphol and equipped with class 1 microphones, which have an uncertainty of 0.7-0.9 dB [105]. For this research, NMTs 10, 14 and 21 are used for landing measurements (number of flights # per aircraft: $\#_{B738} = 1288$, $\#_{A330} = 245$) and NMTs 14, 30, 34, 40, and 41 for take-off measurements ($\#_{B738} = 1179$, $\#_{A330} = 241$). The data collected from these NMTs contains Pressure Band Levels (PBL) for all 24 frequency bands for each second of the recorded noise event. Additionally, audio files of each noise event are saved with a sampling frequency f_s of 8000 Hz, meaning spectral information above 4000 Hz is not available for this data set. As these NMTs are not in a controlled environment, only measurements adhering to the ISO 20906 requirements [30] are selected to provide the most accurate readings (i.e. during the measurement it is not raining, wind speed is less than 10 m/s, and the elevation angle β of the aircraft is larger than 60°). Next to noise data, operational data in the form of ADS-B and radar data is available.

6.2.2. MEASUREMENT PROCESSING

The measurements from both data sets are taken under different weather circumstances and at different distances. To be able to compare the measurements with the ANP spectral class, the measured spectra are standardised as well. For each Pressure Band Level (PBL), the level is adjusted for the difference in absorption and geometrical spreading

according to

$$PBL_{d_{ref}}[dB] = PBL_{d_m} - a_{n,ref}d_{ref} + a_nd_m + 20\log_{10}(d_m/d_{ref}). \quad (6.2)$$

The absorption rates a_n are calculated with data from a nearby weather station that gathers temperature, pressure and relative humidity for the day and time of the recorded flights [44]. The distance between the aircraft and the measurement location d_m is taken from radar and ADS-B data for the NOMOS measurements and array measurements, respectively. The reference distance d_{ref} is set to 1000 ft in accordance with the spectral class data. As all measurements are taken at an elevation angle $\beta > 60^\circ$, it is assumed that the aircraft is a point source and the emitted spectrum is omnidirectional, so any change in the spectrum over lateral or longitudinal axes is not taken into account. The spectral classes in the ANP database are "... for historical reasons, normalised to 70 dB at 1000 Hz." [20] All spectral classes are thus shifted so the PBL of the 1000 Hz band equals 70 dB. This means that the spectral classes offer only information regarding the shape of the spectrum and not the overall sound pressure level of the source. This latter information is incorporated into the NPD table. For this research, both measured levels and normalised data are shown. For each frequency band, the normalised PBLs of all measurements are averaged, and the standard deviation σ is calculated. This is done separately for arrival and departure operations for both aircraft.

Figure 6.2 shows an example of measurements taken by the NOMOS system. Figure 6.2a presents the PBLs (not normalised) as a function of time. In Figure 6.2b the measurement at the instant of maximum A-weighted sound level is shown (blue), together with the resulting normalised PBL corresponding to a 1000 ft source-receiver distance and 70 dB at 1000 Hz. The normalised PBLs become unrealistically high for the higher frequencies. This is most likely due to other contributions to the measured noise levels that are more dominant than the noise of the aircraft. For this reason, the PBLs above 5 kHz gathered from the NOMOS measurements are disregarded.

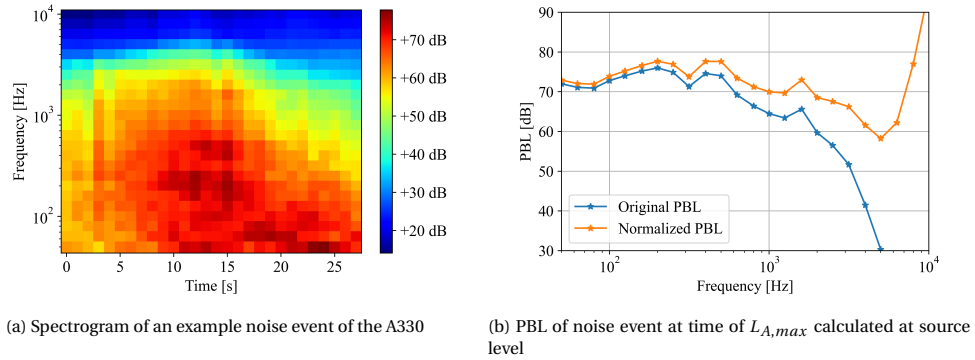


Figure 6.2: Example measured noise event of the A330 at microphone and calculated at source level.

Finally, in the aviation industry, it is standard to calculate the noise levels with A-weighting. The NPD tables given in the ANP database are also A-weighted, but the spectral class is given in dB. The A-weighting is, however, accounted for in the correction conform Equation 6.1.

6.3. RESULTS

6.3.1. MEASURED SPECTRA

The close and long-range spectral measurements are processed, and the outcomes are presented in this section. For the B737-800, the averaged measured spectra and their corresponding standard deviation are shown in Figures 6.3a and 6.3b in orange and green for the NOMOS and array measurements, respectively. In accordance with standard practice, the measurements are then normalised to be compared to their respective spectral class (Table 6.1), shown in blue (Figures 6.3c and 6.3d). For the A330, with spectral classes 102 and 202 for departure and arrival, respectively, the average measurements and their standard deviation per PBL are shown in Figure 6.4.

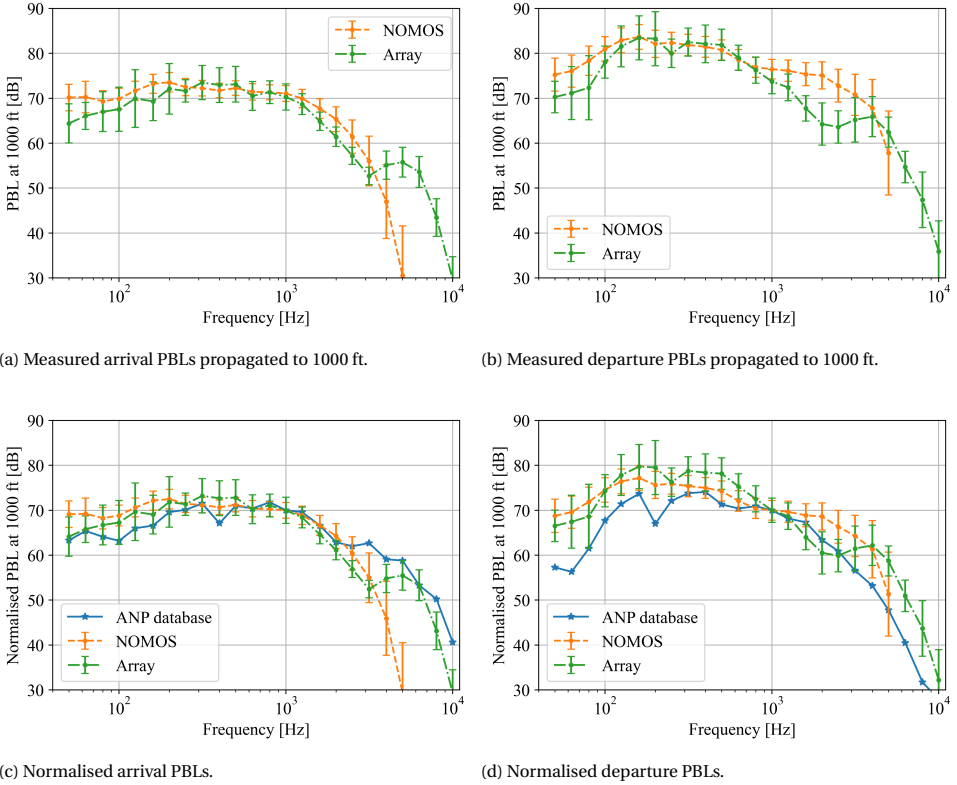


Figure 6.3: Averaged measured B737-800 PBLs and their standard deviation compared to the standard ANP spectral class before and after standardisation.

When looking at the averaged measured PBLs of the close and long-range measurements before normalisation in (a) and (b), a few things are noted. For the B738, the PBLs in the mid-frequency range show a close match between the NOMOS and array measurements. This is not the case for the A330, where the close-range array measurements show lower PBLs than the long-range NOMOS measurements when both are propagated to 1000 ft. For both aircraft, the departure measurements are less consistent than ar-

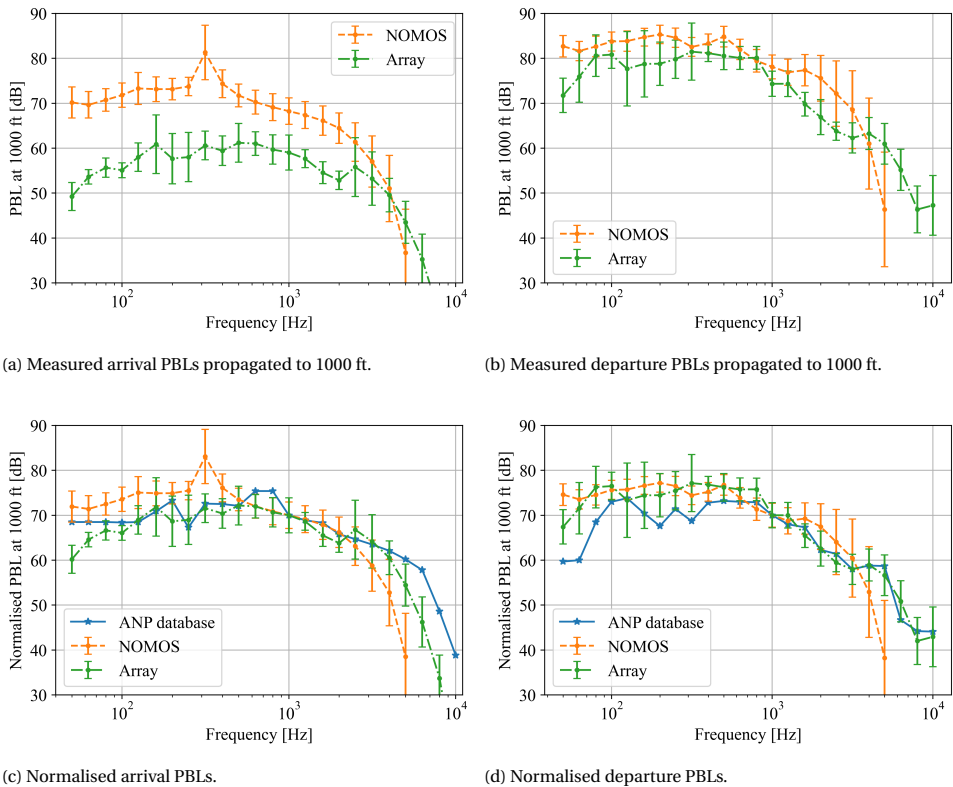


Figure 6.4: Averaged measured A330 PBLs and their standard deviation compared to the standard ANP spectral class before and after standardisation.

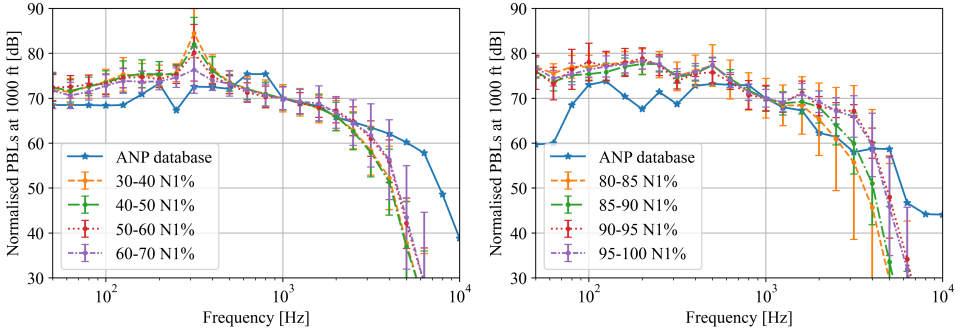
rivals, i.e. a larger standard deviation is seen in the PBLs of both array and NOMOS measurements. Departure operations commonly have more irregular flight paths, weight and thrust profiles than arrival operations, which follow a fixed descent angle. These deviations in operational conditions can cause a larger variation in measured noise levels. Specifically in the NOMOS measurements, the standard deviation of the PBLs grows with increasing frequency. This is likely due to the low signal-to-noise ratios for long distances.

For comparison of the two measured spectral shapes with each other and the ANP spectral classes, the measured data is normalised as seen in (c) and (d). For the B738, the array measurements show, for both operations, a drop followed by a peak around 3500 Hz. This could be due to engine liners, as this is the first harmonic of a typical blade passing frequency (BPF) of the CFM56-7B engines. When looking at the overall trend of the array and NOMOS departure measurements, it seems that the ANP spectral class underestimates the lower frequency band levels. This is in line with research results where semi-empirical models under-predicted the noise levels at low frequencies [49].

For the A330 measurements, different shapes of spectra are found for the two mea-

surements and the ANP database. The arrival NOMOS measurements show a sharp peak at 300 Hz, while the array measurements and ANP database show a small peak at around 200 Hz. At higher frequencies, both measured spectra are lower than the ANP database. For the departure measurements, the array measurements show, especially for frequencies above 1000 Hz, a good agreement with the spectral class of the ANP database. Similarly to the B738, the PBLs at low frequency are underestimated by the ANP database.

An analysis to find the potential origin of the differences is performed. From the NOMOS audio files, the BPF could be found and used to analyse the engine setting $N1\%$. The method of extracting $N1\%$ from NOMOS audio files is explained in chapter 4. To find the influence of this engine setting on the measured spectrum, the PBLs are sorted by $N1\%$ in Figure 6.5. Two things can be seen. During arrival operations, visible in Figure 6.5a, the peak around 300 Hz flattens out at a higher engine setting while at higher frequencies (around 3 - 4 kHz), these higher engine settings produce more noise. For the departure noise measurements, visible in Figure 6.5b, the PBLs of the lower frequencies are not affected by a change in engine setting. Similarly to the arrival measurements, higher engine settings produce more noise for frequencies larger than 2 kHz. Given the limited effect of $N1\%$, there must be other factors than $N1\%$ that cause the mismatch between spectral class and the measured spectra.



(a) Normalised arrival PBLs of the A330 split into engine setting. (b) Normalised departure PBLs of the A330 split into engine setting.

Figure 6.5: Measured and normalised PBLs from the NOMOS system split out by engine setting.

6.3.2. EFFECT ON DOC 29 PREDICTIONS

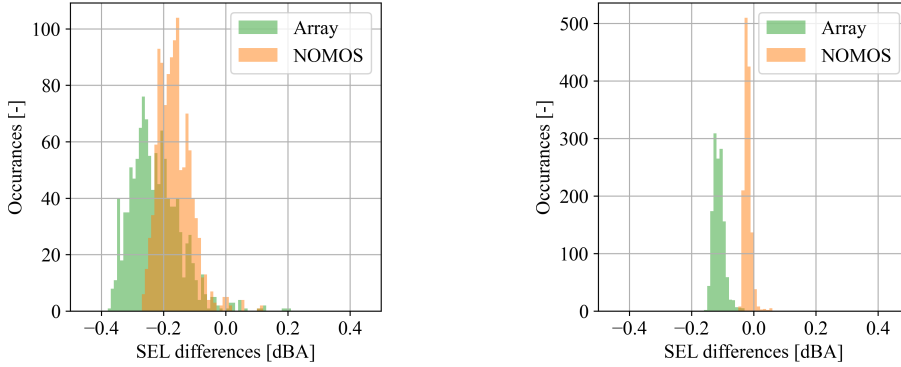
The Doc 29 model is used to predict noise levels of aircraft flyover events on the ground. Outputs are the maximum A-weighted noise level $L_{A,max}$ and the Sound Exposure Level (SEL). To analyse the effect the spectral class has on the weather correction, the measured (and normalised) PBLs are implemented as a new spectral class in Doc 29 (replacing $L_{n,ref}$ in Equation 6.1) to predict a new $L_{A,max}$ and SEL. These values are compared to the ANP spectral class based values. The difference in SEL values is plotted in Figure 6.6 and Figure 6.7 according to

$$\Delta L_{A_{spec}} = L_{A_{measurement}} - L_{A_{ANP}} \quad (6.3)$$

where $L_{A_{measurement}}$ is the A-weighted noise level ($L_{A,max}$ and SEL) predicted by Doc 29 using the normalised measured spectrum. $\Delta L_{A_{spec}}$ quantifies the effect of using a different spectrum, where ΔL_A (Equation 6.1) is the weather correction.

When comparing the data sets of the B738 and the A330 flights modelled with the standard and measured spectra, a slight shift in the levels is observed in Figure 6.6 and in Figure 6.7, respectively. For both aircraft, a primarily negative ΔL_A is seen, caused by a larger absorption when using the measured spectra for both departure and arrival operations. The newly modelled noise levels are thus lower at the locations of the NOMOS NMTs. This higher absorption is mainly caused by the higher lower frequencies. The array spectrum generally results in lower modelled noise levels than when using the NOMOS spectrum.

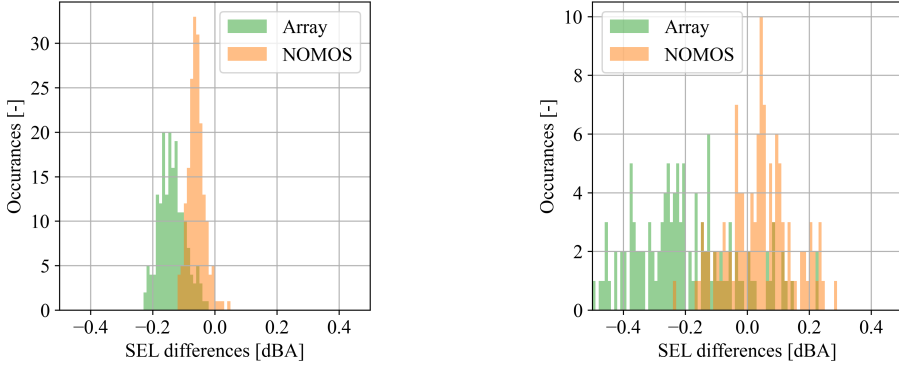
As a final step, the noise predictions are also compared to the $L_{A,max}$ and SEL measured by NOMOS. Although the average of the modelled $L_{A,max}$ and SEL values changes, the differences between modelled and measured values remain similar. The standard deviation of these differences is unaffected by the use of updated spectral classes. This analysis is not shown in this contribution.



(a) Arrival operations modelled with NOMOS and array-(b) Departure operations modelled with NOMOS and array-derived spectra.

Figure 6.6: Effect of applying measured spectra of B738 on Doc 29 SEL predictions.

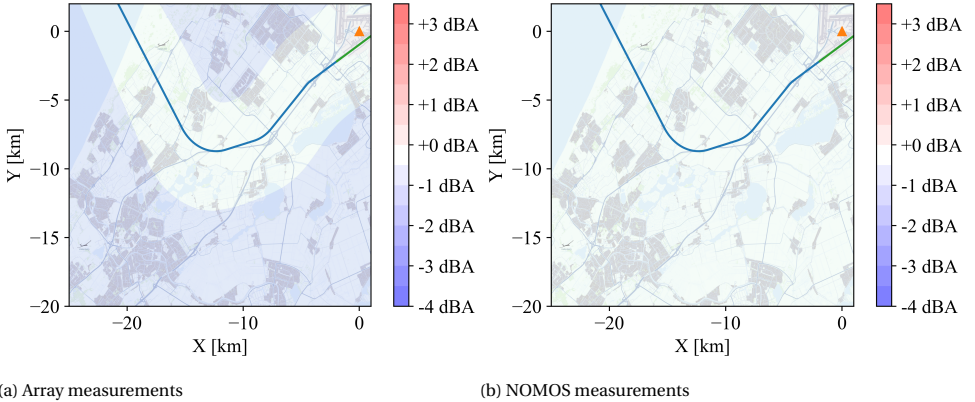
Best-practice models, such as Doc 29, are often used to model the impact of aircraft noise over large areas using contours. To analyse the effect of a change in ANP spectral class on these contours, the measured spectra are used to model the noise of a departure operation of the B738 at Schiphol Airport. In Figure 6.8, the change in noise level predicted on the ground is shown when the measured spectra are used instead of the ANP spectral class. The weather condition during this simulation is a winter day; 5 °C, 1013 kPa and 80% relative humidity. The effect of the close-range array measured spectrum is small, up to -0.9 dBA. The effect of the long-range NOMOS measured spectrum is smaller, up to -0.5 dBA. Note that these values are not encountered in Figures 6.6 and 6.7 due to the smaller distances between the NOMOS NMTs and the aircraft considered during the measurements. These results are similar to what is seen in Figure 6.6b, where the use of the array-derived spectrum has a larger effect than the NOMOS-derived spec-



(a) Arrival operations modelled with NOMOS and array-(b) Departure operations modelled with NOMOS and array-derived spectra.

Figure 6.7: Effect of applying measured spectra of A330 on Doc 29 SEL predictions.

trum. The use of the measured spectra thus results in a smaller noise footprint.



(a) Array measurements

(b) NOMOS measurements

Figure 6.8: Changes in modelled footprints of SEL values of a departing flight of the B737-800 for using measured spectral data versus ANP spectral class.

6.4. DISCUSSION

The measured source PBLs are found to differ from the standard spectral class. Also, a difference is found between the close-range (array) measurements and long-range (NOMOS) measurements. An important cause for these differences is probably that these measurements are taken at different flight phases. In addition, even though the NOMOS NMTs are equipped with a class 1 microphone, the measurement conditions (unmonitored with possible background noise and/or reflections) are less favourable. Nevertheless, they allow for building a large dataset and can give insight into the differences in the spectra for changing operating conditions, such as engine settings.

For both analysed aircraft, changing the standard spectral class to the measured ones had a limited effect on the modelled SEL of flights around Schiphol airport. The influence of the used spectral class on the modelled noise levels can be significant for very short distances, but dampens out quickly. The changes in contour caused by differences in the lower frequency PBLs tend to influence the larger distances. Although the changes in modelled level become significant (up to 1 dBA), the total noise level at these locations is low ($SEL < 40$ dBA) and outside of the scope of best-practice noise modelling. Thus, the current method of using the ANP spectral classes is deemed accurate enough for the Doc 29 model.

As a final step, the effect of assuming a flat spectrum is investigated. A uniform spectrum with PBLs of 70 dB for every frequency band is used to model the contour in Figure 6.9. The effect of using a uniform spectrum on the weather correction is higher than when the measured spectra are used, especially close to the runway. There, at the top right of Figure 6.9, SEL differences of more than 3.5 dBA are found. This is due to the high PBLs (70 dB) at high frequencies compared to the PBLs in the ANP database (see Table 6.1). Further away from the runway, the high frequencies dampen out, and the contour looks similar to Figure 6.8b. Even though the used standard source spectra are not perfect and have a limited effect, using a spectrum is still better than none at all as it does influence noise calculations significantly close to the flightpath.

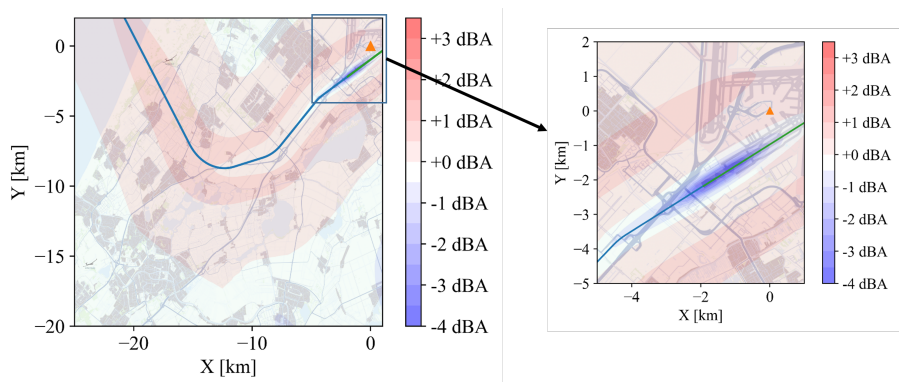


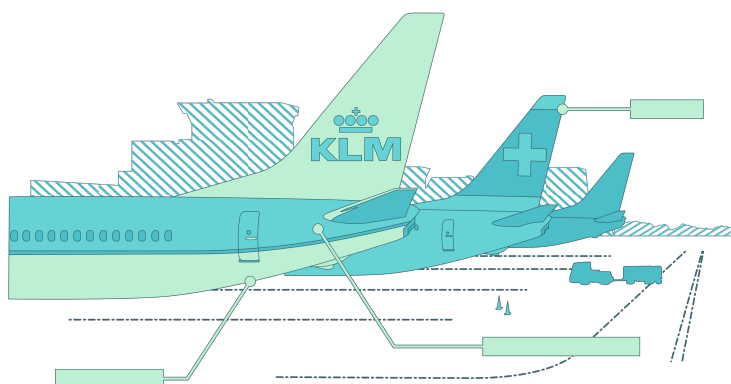
Figure 6.9: Changes in SEL footprint when a uniform spectrum is used for a departing flight of the B737-800.

6.5. CONCLUSION

All aircraft have different noise emission characteristics. These differences are visible in the acoustic spectrum and influence the propagation of sound through the atmosphere. With changing weather situations and thus changing sound propagation, knowledge about the emitted noise spectra of each aircraft is important to accurately quantify the effect of the changing atmosphere on the received levels. In this research, the noise spectra of the B737-800 and the A330-300 are measured and compared to their respective standard spectral class from the Aircraft Noise and Performance (ANP) database. Two types of measurements are used, i.e. at close range (200-500 ft), using an acoustic

array, and at long range (500-3000 ft), using the NOMOS measurement system. The measured spectra are then applied to the Doc 29 aircraft noise model for the calculation of the weather correction.

Differences between the two measurement types and the aircraft's respective spectral class are found. Despite that, differences in Doc 29 calculated Sound Exposure Levels (SEL) are limited to 0.2 dBA for arrivals and 0.1 dBA for departures on average for the predictions of the NMT stations considered. For larger distances from the track, larger differences up to 1 dBA are found. However, total noise levels are low for these larger distances. For the situations considered in this contribution, it can be concluded that the spectral class from the ANP database can be applied.



VALIDATING AND COMPARING THE SONAIR AND DOC 29 AIRCRAFT NOISE MODELS

Previous chapters focused on the Doc 29 noise model, as this is the standard in Europe. However, more alternatives have become available, such as the sonAIR aircraft noise model created by the Swiss Federal Laboratories for Materials Science and Technology (Empa). Their goal was to fill the gap between best practice approaches for long-term averages on one side, and highly detailed, computationally expensive models on the other side. The model, further described in section 7.2, is based on backpropagating flyover measurements from an extensive measurement campaign around Zürich Airport. However, no independent large-scale validation study for sonAIR has been conducted at airports outside Switzerland yet. The results, discussed in section 7.3, demonstrate that sonAIR provides more reliable predictions of noise levels on the single flight event level than Doc 29, especially for larger distances from the flight path.

A previous version of this chapter has been published in the conference proceedings and presented at the 30th AIAA/CEAS Aeroacoustics Conference Rome 2024 [106]. Research following this paper resulted in updated N1-to-thrust conversions that now have been applied in this chapter.

7.1. INTRODUCTION

There are various models that have been developed for the purpose of noise predictions, each with its own strengths and limitations, where a differentiation can be made between physics-based and (semi-)empirical models [94]. Physics-based models, or theoretical models, are based on physics describing the noise emission and propagation. (Semi-)empirical noise prediction models are based on noise measurements.

In Europe, the European Civil Aviation Conference (ECAC) Doc29 modelling approach is the current best-practice modelling approach, which has been previously compared with measurements [68, 75]. This is a semi-empirical method which makes use of Noise-Power-Distance (NPD) tables, which provide a noise value for an aircraft at a certain distance, given its thrust setting.

Alternatively, the sonAIR aircraft noise model was created by the Swiss Federal Laboratories for Materials Science and Technology (Empa). Their goal was to fill the gap between best practice approaches for long-term averages on one side, and highly detailed, computationally expensive models on the other side. The model is based on backpropagation of flyover measurements from an extensive measurement campaign around Zürich airport. The model is able to simulate single noise events with a high level of detail, but also can perform noise mapping for airports [6]. However, no independent large-scale validation study for sonAIR has been conducted on airports outside Switzerland.

This study aims to apply and validate the sonAIR noise model using noise data from Schiphol airport, by comparing its performance to measurements (NOMOS) and the current best-practice modelling approach (Doc 29) around the Netherlands' largest airport. The Doc 29 methodology is explained in chapter 2. In this chapter, the sonAIR methodology is explained in section 7.2, including a description of the implementation for this research. Validation results are discussed in section 7.3. Finally, conclusions are drawn, and an outlook is given in section 7.4.

7.2. SONAIR AIRCRAFT NOISE MODEL

The sonAIR aircraft noise model consists of two parts: an emission model and a propagation model. Each model is formulated for 24 1/3-octave bands, with a frequency range from 25 Hz to 5 kHz. The emission model is specific to each aircraft type. The emission models were established based on an extensive measurement campaign at Zurich Airport. The noise measurements at numerous microphone positions, along with flight data from the Aircraft Condition Monitor System (ACMS) and meteorological data, provided the input data for the backpropagation of the recorded noise to the source. Based on these inputs, linear regression models were established for each 1/3-octave band. The emission models are split into an airframe and engine noise model, whereas the total emitted noise is a sum of both. For most aircraft types, a so-called reduced model was generated, which, compared to the most detailed sonAIR models, does not account for configuration.

Depending on the sound path from source to receiver, the propagation is calculated in two modes. The first calculates direct sound assuming a homogeneous atmosphere. In the second mode, for more complex propagation situations, usually at shallow sound

incidence angles, the noise propagation model sonX is used [107]. It accounts for atmospheric absorption, ground effect, foliage attenuation, reflections and the influence of vertical gradients of wind, temperature, and relative humidity. In the following sections, the sonAIR model is discussed in more detail.

7.2.1. MODEL INPUTS

The sonAIR model requires six input parameters for the reduced model and an additional three variables for the advanced emission model. An elaborate explanation of the sonAIR input parameters is given in Zellmann et al. [50]. A brief description is presented in this section. An overview of all input parameters can be seen in Figure 7.1.

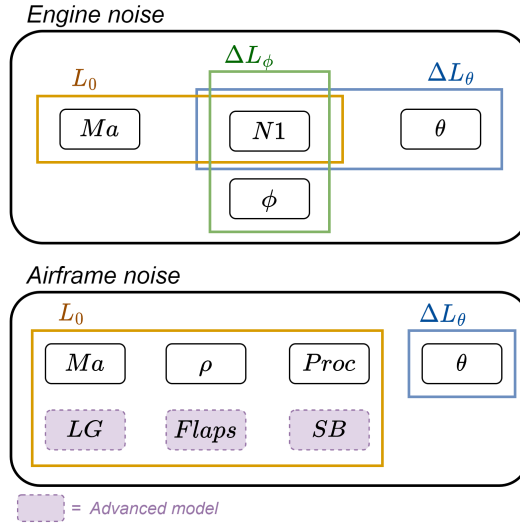


Figure 7.1: SonAIR input parameters

For modelling the engine noise, the rotational speed of the engine's low-pressure fan N1 in % is one of the main inputs. This parameter strongly correlates with the engine noise and can be derived from noise recordings when ACMS data are not available, e.g. the thrust setting [107]. To determine the relation between N1 and the sound pressure level (SPL), an engine run-up test was performed on an Airbus A330-300 with the TRENT772B engine [50]. The SPL was measured at a distance of 170 meters from the aircraft, at four locations: 15° , 50° , 90° and 120° respectively, with 0° corresponding to the nose of the aircraft. The results provided a second-order polynomial for each 1/3-octave band.

The second input parameter, the Mach number, influences both the engine noise and the airframe noise levels and is used to account for speed-dependent sound sources. For engine noise, a linear relation is used, i.e., $L_{em,eng} \propto Ma$. A logarithmic relation is derived for airframe noise: $L_{em,afm} \propto \log_{10}(Ma)$, which represents the physics of airframe noise better than a linear relation. The air density ρ is used as the atmospheric parameter. The air pressure p and temperature T were omitted because of the close

relation between the three, which might lead to multicollinearity.

The directivity of aircraft sound emission is described in spherical coordinates. The engine noise differs along the polar angle θ and the azimuth angle ϕ , whereas the airframe noise model is independent of the latter. Finally, a binary variable is used to indicate the procedure of the aircraft. The procedure input (*Proc*) is either departure or arrival.

For the advanced emission models, the aircraft configuration is described by three variables: landing gear (*LG*, 0: retracted, 1: deployed), flap handle position (*Flaps*, depending on aircraft type) and speed brakes (*SB*, 0: not deployed, 1: deployed).

7.2.2. REGRESSION MODEL

Before regression models are created, the dataset is split into two subsets. The first subset contains data for idle engines ($N1 \leq 40\%$) and the second subset contains all data for engines on-load ($N1 > 40\%$). The former includes only approaches, the latter both approaches and departures. This separation of the dataset allows for the creation of two different regression models: one for airframe noise and one for engine noise. The airframe noise model consists of a source term (L_0) and a radiation term (ΔL_θ):

$$L_{em,afm}(f) = L_{0,afm}(lMa, l\rho, Flaps, LG, SB, Proc) + \Delta L_{\theta,afm}(\theta), \quad (7.1)$$

with $lMa = \log_{10}(Ma)$ and $l\rho = \log_{10}(\rho/\rho_0)$. This transformation of input variables is done to ensure a linear relation with L_{em} . The reduced and advanced models have different variables in the airframe model, while the engine model is the same for both. The engine noise model also consists of a source term (L_0) but has two radiation terms (ΔL_θ and ΔL_ϕ) to account for the noise directivity of the engine and is given by

$$L_{em,eng}(f) = L_{0,eng}(Ma, N1) + \Delta L_{\theta,eng}(\theta, N1) + \Delta L_{\phi,eng}(\phi, N1). \quad (7.2)$$

7.2.3. MODEL VERIFICATION

In Zellmann et al. [50], the performance of the model is evaluated using the coefficient of determination R^2 and the root mean square error $\hat{\sigma}_E$. Two aircraft were selected for a detailed evaluation, the Airbus A320 and the Embraer E170. In general, a good correlation was found for the regression models, with R_{total}^2 between 0.7 and 0.8 approximately. The engine model performs best, with R_{eng}^2 above 0.8 for almost all frequency bands. The airframe model performs worse, with R_{afm}^2 values between 0.2 and 0.6; however, it peaks in frequency ranges in which airframe noise is significant. The root mean square error $\hat{\sigma}_E$ shows similar behaviour for both aircraft, with values between 4.5 dB (low frequencies) to 3 dB (mid to high frequencies).

These results lead to the belief that sonAIR is a suitable model for predicting and assessing aircraft noise. The relevance of the model will increase if it is tested and validated for more aircraft types and airports.

7.2.4. MODEL VALIDATION

In a validation study by Jäger et al. [6], over 20,000 noise events around Zurich and Geneva airports were simulated and compared to measurements. The reduced and advanced models were evaluated separately. Overall, the advanced models perform well,

with almost all aircraft types having a mean difference and standard deviation below values of ± 1 dB and 2 dB, respectively. The reduced models show an average increase in standard deviation of about 0.7 dB when compared to the advanced models. This difference may be due to the models using less information (no ACMS data), both during creation and simulation.

The land cover data was identified as the most influential input parameter. Especially in urban areas, a coarse grid may not differentiate between, e.g. a park and (highly reflective) buildings, which can lead to deviations.

An interesting discovery is the seasonal effect on the model accuracy. It is found that the model is quite accurate during the summer months, but underestimates the noise levels in winter. Jäger et al. suspect that this may be (partially) due to the fact that all measurements used to set up the model were conducted during spring and summer [6].

In a comparison study by Meister et al. [77], sonAIR is compared to two other aircraft noise prediction models, FLULA2 and AEDT. It is concluded that sonAIR outperforms these two models when ACMS data is available. For simulations without ACMS data, all three models gave similar results. Additionally, sonAIR performs better for detailed single flight simulations.

In another initial small-scale validation performed by Jäger et al. [108], sonAIR was compared to measurements around Schiphol airport in collaboration with Delft University of Technology. A total of 74 overflights were measured, using a microphone array consisting of 32 microphones. The results show a mean difference of -0.4 dB, with a standard deviation of 1.1 dB. These measurements were performed close to the runway, nevertheless, it demonstrates the applicability of sonAIR to different airports.

7.2.5. SCHIPHOL IMPLEMENTATION

In this research, two main sources of data are consulted. First, an airline provided ACMS data for a selection of flights. This is information from on board the aircraft, which updates every second. Second, NOMOS provides radar track data and measurement data. The radar track data is updated every four seconds. Measurement data is available for both flights with ACMS tracks and flights with radar tracks. To limit the scope of the research, the focus is on one aircraft type and only departure operations. The aircraft type that was identified as most interesting and relevant is the Boeing 737 Next Generation series (B737NG). This series entails the 737-700, 737-800 and 737-900. This aircraft is used frequently at Schiphol airport, thus input data is widely available. Unfortunately, only the reduced sonAIR model is available for this aircraft type. For the ACMS dataset, there is a mix of B737, B738 and B739 data, while the radar data used is only B738.

DATA SOURCE MODEL

The first required model input data, the N1, could be derived directly from the ACMS flight data. For the flights with only radar tracks, N1 was determined following the method as described in chapter 4. In this method, N1 is estimated by finding the fan tone in the spectrogram of an acoustic measurement. Through positional data, described in latitude, longitude and altitude, the Mach number and polar and azimuthal angle are determined. This data is included in the ACMS tracks and the radar tracks.

DATA NOISE PROPAGATION

Noise propagation calculations for sonAIR were carried out in *BASIC* mode, which does not account for meteorological conditions. To correct for this, the methodology as described in Appendix D of Doc29 Volume 2 [20] was used. This entails a correction for meteorological conditions that are different from the specified standardised atmosphere. This methodology makes use of the calculation corrections for atmospheric absorption as described in SAE-ARP-5534 [39]. Meteorological conditions were obtained from the Royal Netherlands Meteorological Institute [44]

Two more inputs are required: a height map and a landcover map, which are used to calculate sound reflections. The height map of the Netherlands is available via the Netherlands' Cadastre, Land Registry and Mapping Agency [109]. The landcover file was downloaded and adapted through Statistics Netherlands [110].

MEASUREMENT DATA

The acoustic measurement data were retrieved from the NOMOS software. The main metrics used in this research are the Sound Exposure Level (SEL or L_{AE}) and the maximum noise level ($L_{A,max}$), as both are commonly used to compare measurements with noise predictions. The measurement data also entail noise level time histories and frequency spectra for 1/3-octave bands from 16 Hz to 16 kHz. The dataset used for this study is similar to the one used in chapter 5, with the exception that for this research, only measurements with wind conditions under 8 m/s were used. Other requirements, i.e. no rain, elevation angle $\beta > 60^\circ$ and $L_{A,max} > 70$ dBA are the same. Due to the limited dataset for the ACMS data, these requirements are waived, and all available measurements are used. A total of 110 measurements are used coupled to ACMS data, and 2331 measurements coupled to radar data.

7

7.3. RESULTS

The simulated results give the noise levels for each desired source-receiver combination. An example noise level time history can be seen in Figure 7.2, where both models are compared to NOMOS data. The 10 dBA downtime line indicates the section of the curve which is used to calculate the SEL. For this example, it can be seen that the sonAIR curve is approximately the same shape as the NOMOS curve. The NOMOS curve is less smooth than the model curves. Doc 29 exhibits a wider curve, with longer rise and fall times of L_A . This is typical for the found measurements.

7.3.1. MODEL PERFORMANCE OF NOISE CALCULATIONS

In this research, noise events are compared on an individual basis, mainly on their SEL and $L_{A,max}$. Results are presented as mean differences, calculated by

$$\Delta L = L_{model} - L_{measured} \quad (7.3)$$

where a negative ΔL indicates an underestimation of the noise levels by the model. The mean differences are expressed by mean values (μ) and the corresponding standard deviation (σ). The correlation ρ between model results and measurements depicts the agreement between the datasets, where 1 is perfect correlation. The results of the two datasets for both models are given in Table 7.1.

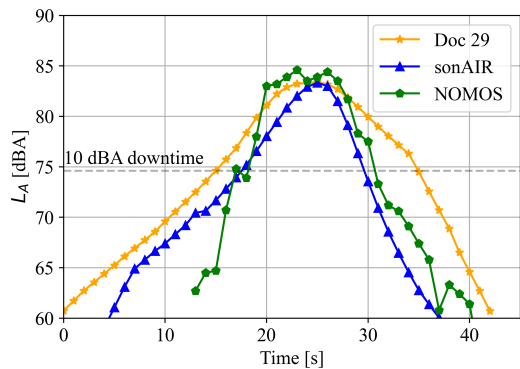


Figure 7.2: Example noise level time history for B738 departure

Table 7.1: Results of the sonAIR and Doc 29 models in comparison with measurements for the ACMS and radar datasets.

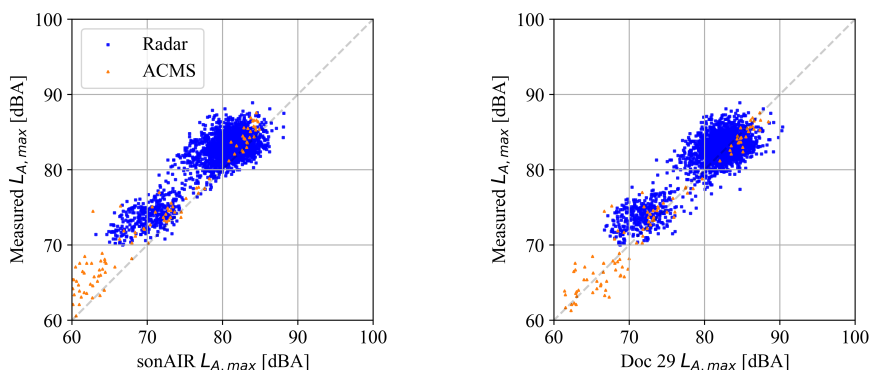
Model	Dataset	$\Delta L_{A,max}$			ΔSEL		
		μ [dBA]	σ [dBA]	ρ	μ [dBA]	σ [dBA]	ρ
Doc 29	ACMS	-0.76	3.69	0.93	-0.48	5.03	0.85
	Radar	-0.79	2.29	0.85	-0.85	1.66	0.88
sonAIR	ACMS	-2.46	2.17	0.97	-0.46	1.77	0.97
	Radar	-2.29	2.24	0.87	-1.14	1.59	0.89

These results are visualised in Figure 7.3 and Figure 7.4 for $L_{A,max}$ and SEL, respectively. Both models underestimate SEL and $L_{A,max}$. The sonAIR model shows a larger underestimation of $L_{A,max}$ compared to Doc 29, with mean values around -2.3 dBA. For SEL, the underestimation is smaller, approximately -1.1 dBA, which is consistent with previous findings by Jäger et al. [6]. This bias is explained by the emission model being grouped for the B737 series rather than individual subtypes, leading to inaccuracies for larger aircraft such as the B738. For $L_{A,max}$, additional underestimation arises from atmospheric turbulence effects not included in sonAIR, which add about one decibel deviation. Despite this, sonAIR demonstrates good precision and capability to predict single-flight noise events, as indicated by its consistently lower standard deviations and higher correlations with measurements than Doc 29.

Spatial differences were also observed. NMT 34, located further from the runway, showed better agreement with sonAIR predictions, with $\Delta SEL = 0.05 \pm 1.33$ dB, compared to NMTs closer, like NMT 40. This indicates that sonAIR is particularly reliable at lower noise levels and larger distances.

The improved accuracy of sonAIR with respect to Doc 29 becomes clearer when analysing the ACMS dataset. This dataset includes measurements at lower elevation angle and noise levels. In the Doc 29 data, you specifically see large deviations in the low-noise areas. SonAIR manages to more accurately predict these low-noise events. Due the more elaborate directivity in the source noise and the sound propagation calculations, sonAIR

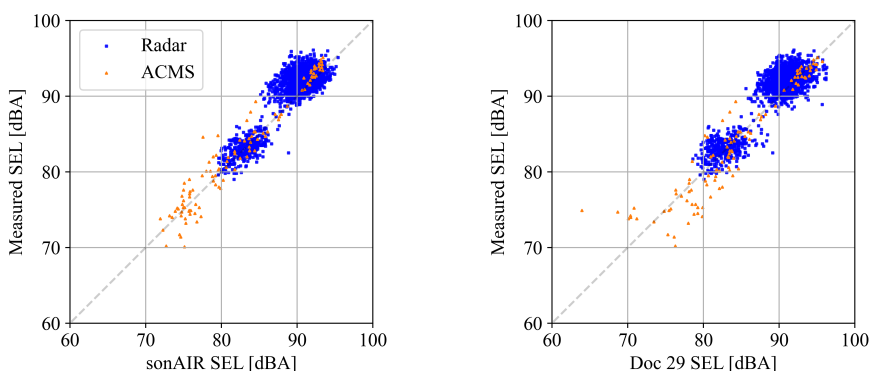
shows great promise for noise predictions in low-noise regions.



(a) sonAIR

(b) Doc 29

Figure 7.3: Comparison of measured $L_{A,max}$ and the sonAIR and Doc 29 model for the ACMS and radar datasets.



(a) sonAIR

(b) Doc 29

Figure 7.4: Comparison of measured SEL and the sonAIR and Doc 29 model for the ACMS and radar datasets.

7.3.2. CALCULATION SENSITIVITY ON INPUT PARAMETERS

The B738 radar data results were used to analyse the relation between input parameters and noise levels. The plots comparing the average N1 during the event to the SEL for each event can be seen in Figure 7.5. For all events, the minimum distance between the aircraft and the NMT is taken and put into bins of 300 meters. A relation is found between the estimated N1 and the modelled SEL for the two models and the measured SEL. The p-value of all relations is smaller than 0.05 except for the 0-300 m distance bin, which is 0.1 due to a limited amount of measurements.

The main observation is the big difference in slope between the Doc 29 model predictions and the measurements. The average slope is 0.31 dBA per N1 for Doc 29 in com-

parison to 0.12 for the NOMOS measurements. This is over three times larger. The mean slope of the sonAIR model is 0.19 dBA per N1 thus lying closer to the measurements.

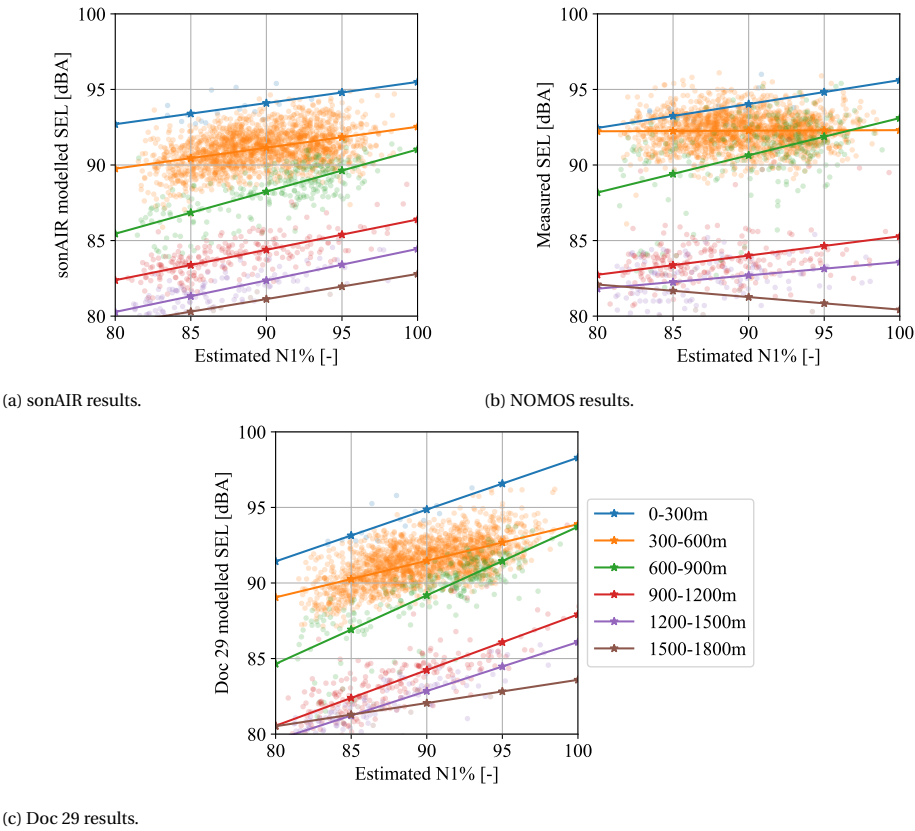


Figure 7.5: Relations between the estimated N1 and the modelled and measured SEL for different distance bins.

In sonAIR, the relation between N1 and engine noise is modelled by a quadratic function, which assumes noise levels to increase with N1. A similar assumption is made in Doc 29, albeit for a linear increase with thrust. This linear increase of noise with N1 is evaluated in Figure 7.5 and it is found that the current Doc 29 model overestimates this dependency, as found in chapter 5. For the N1 range of 80-100%, an increase of 2.4 dBA is measured, while the model predicts a 7.4 dBA increase. The relation found in the sonAIR model matches the measurements more closely, although still, a small overestimation of 0.06 dBA per N1 is visible.

For the example plot of the larger range of N1 values (20% - 100%) in Figure 7.6 (adapted from Zellmann et al. [50]), it can be seen why a quadratic relation was assumed for sonAIR. For this N1 range, it seems to be a good and robust fit. Looking at N1 values above 80% only, this fit might lead to the above-mentioned overestimation, as low N1 values are weighted strongly. To better represent the N1-noise relationship in this range,

a different regression approach might be more suitable.

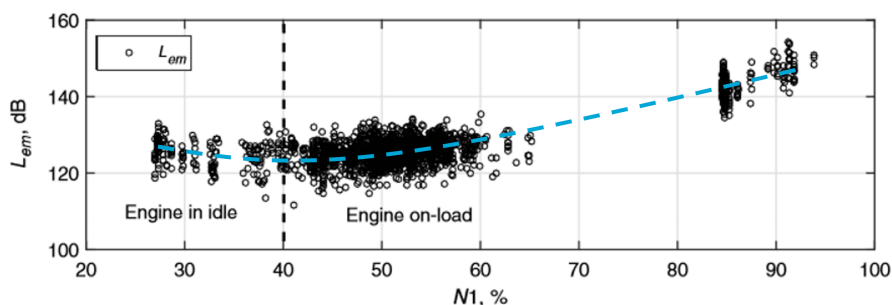


Figure 7.6: N1 versus emitted noise for the A320 at 100 Hz. (Adapted from Zellmann et al. [50])

7.4. CONCLUSIONS

In this research, the sonAIR noise model was compared to NOMOS measurements and the current best-practice modelling approach, Doc 29, for the Boeing 737 Next Generation series at Schiphol airport. The results demonstrate that sonAIR provides more precise predictions of noise levels on the single flight event level than Doc 29. Additionally, this study shows agreement with results from a previous validation study in Zürich, thereby confirming the applicability of sonAIR to another airport. SonAIR specifically outperformed Doc 29 for noise predictions at larger distances and lower elevation angles, showing promise to be better suited for estimating noise exposure in low-noise areas. The comparison highlights the influence of simplified source descriptions and propagation assumptions in Doc 29 and provides insight into where future model improvements are most needed.

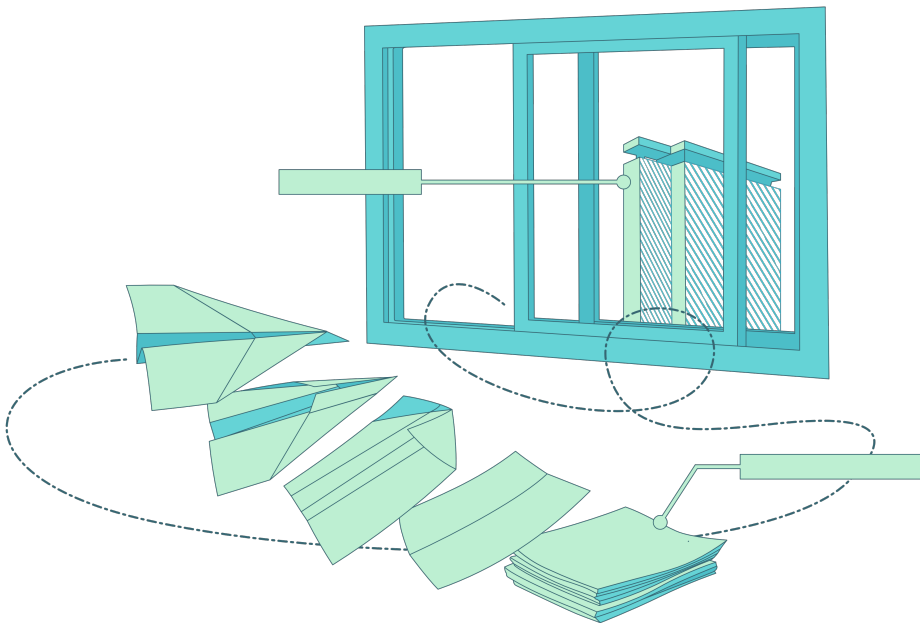
Although sonAIR provides more precise predictions than Doc 29, improvements can still be made as we see an underestimation for 1 and 2 dBA for SEL and $L_{A,max}$, respectively. Further measurements to update and refine the emission models are recommended, including separate models for aircraft subtypes, to improve the accuracy of noise predictions.

Unfortunately, this study is limited to departure measurements. As a result, the potential benefits of sonAIR's detailed airframe noise modelling could not be fully evaluated. This feature is expected to be particularly valuable for arriving aircraft, where airframe noise becomes a dominant contributor to the overall noise emission. Future validation using arrival measurements is therefore recommended. Furthermore, the analysis should be extended to additional aircraft types to assess the versatility of sonAIR and support its application to full-year airport noise assessments.

8

CONCLUSIONS AND RECOMMENDATIONS

This final chapter presents the overarching findings of this thesis, made to improve best-practice noise modelling with acoustic measurements. It also provides a list of recommendations for future research.



8.1. CONCLUSIONS

This thesis set out to improve the accuracy of aircraft noise predictions produced by the noise model Document 29 (Doc29) of the European Civil Aviation Conference (ECAC) by systematically reviewing the input and comparing its outputs with noise measurements around Amsterdam Airport Schiphol. Because best-practice models underpin regulatory decision-making, they must be both accurate and transparent. In chapter 1, this overarching aim was divided into three sub-objectives, for which the conclusions are discussed below.

1. Validate standard Doc 29 predictions at the single-event level and for yearly averages, and assess the causes of differences with measurements

In terms of validation at an annual level, modelled and measured noise levels generally fall within the intended 1–2 dBA margins (chapter 3), indicating that Doc 29 can reproduce long-term exposure reasonably well in its standard configuration. Nonetheless, systematic biases were identified: an underestimation of L_{den} and an overestimation of L_{night} . These discrepancies between model and measurements increase with distance from the airport, particularly in low-noise regions where measurement accuracy decreases. Even though the model performs within the expected limits, the causes of the discrepancies were further researched.

First, the year-round measurements are analysed. The influence of undetected flights and background noise on measured L_{den} was quantified, revealing differences of up to 2 dBA in low-noise areas. When averaged over all Noise Monitoring Terminals (NMT) from the Noise Monitoring System (NOMOS) and eight operational years, these effects resulted in a -0.8 dBA adjustment to L_{den} . The analysis in chapter 3 also highlighted substantial differences in the assumed operational inputs used by the model compared with actual flight performance.

To reduce these discrepancies, chapter 5 validated the single-event Doc 29 model using accurate operational inputs (as developed under Objective 2) and stringent measurement conditions. The resulting underestimation of Sound Exposure Level (SEL) by approximately 1 dBA suggests that operational variability tends to average out, although this finding is based on a limited set of aircraft types and relatively short propagation distances.

It is important to expand the knowledge of the noise model limitations. That is why a benchmark comparison with the sonAIR model (chapter 7) is performed. This model, which separately evaluates source and propagation effects, showed a similar 1 dBA underestimation for departures, but with lower variability. SonAIR outperformed Doc 29 at larger distances and lower elevation angles, demonstrating its potential to better represent noise exposure in low-noise regions.

Overall, the validation efforts show that while Doc 29 is adequate for annual averages in high-noise exposure areas, its robustness depends critically on data completeness and on how well assumed operations reflect reality. In general, an underestimation is observed across operations, suggesting that assumptions embedded in performance profiles and source emissions are consequential at the single-event scale.

2. Obtain accurate model input based on historical operational data and validate it with flight data

Reliable model assessment requires accurate operational input. Current Aircraft Noise and Performance (ANP) procedures rely heavily on assumed altitude, speed, and thrust profiles, yet actual flight behaviour can deviate substantially, as shown in chapter 3. To address this, chapter 4 focused on deriving thrust from the engine setting $N1\%$, which can be obtained from onboard flight data or inferred from downsampled NMT audio. While $N1\%$ can be directly used in sonAIR (chapter 7), it is not directly compatible with best-practice models, where thrust is internally computed and sensitive to ambient conditions.

Mapping $N1\%$ to thrust is non-trivial because it depends on aircraft speed, temperature, and pressure. Using simulated data from the Gas turbine Simulation Program (GSP), chapter 4 demonstrated a practical method to translate audio-derived $N1\%$ into operationally plausible input sets compatible with the ANP framework. This results in accurate thrust input to be used in further noise research, reducing the large model input discrepancies seen in chapter 3. Furthermore, this pipeline represents a concrete step toward reducing model uncertainty without requiring proprietary airline data. This use of more open-source data increases the transparency into aircraft noise modelling.

3. Identify the limitations of the model and estimate their effect by individually assessing model components against measurements

With input uncertainty reduced and measurement conditions controlled, individual Doc 29 model components were evaluated. These components consist of Noise Power Distance (NPD) tables and correction factors, with this thesis focusing on the two most influential elements: NPD tables and source spectra used for atmospheric corrections.

Current NPD tables group broad aircraft subtypes and apply single correction factors. This can lead to systematic underestimation of the thrust–noise relationship for departures. Constructing NPD tables directly from measurements (chapter 5) improved predictive accuracy by approximately 25%, assuming propagation and correction factors are adequately representative. This indicates that current source descriptions are too coarse and that measurement-derived relationships can meaningfully reduce error. Furthermore, source directivity is only partially represented in Doc 29 due to large simplifications, limiting the accuracy of the predictions across different ground observation angles.

Propagation effects are embedded in the NPD tables and adjusted for non-ISA conditions. Doc 29 uses a simplified homogeneous-atmosphere attenuation model with source spectra approximated by third-octave bands normalised to 70 dB at 1 kHz. chapter 6 showed that within this simplified framework, the exact choice of source spectrum is less important than the neglected physics of non-homogeneous meteorology and lateral/ground interactions.

The sonAIR model better captures directionality and distance-dependent behaviour under varying conditions. This model, however, has its limitations as it has

a higher computational cost and incomplete aircraft coverage. That means it cannot yet replace Doc 29 as it can not calculate all aircraft flying around the airport, but it can complement it and help identify more robust noise estimates.

Taken together, this thesis advances the validation and improvement of best-practice aircraft noise models through detailed analysis of noise measurements around Schiphol Airport. Doc 29 can meet the required 1–2 dBA accuracy for annual and single-event predictions, but its simplified assumptions about engine settings, configuration, directivity, and propagation limit its ability to represent the full complexity of aircraft noise. These limitations become particularly evident at long distances and low elevation angles, where discrepancies with measurements grow.

While Doc 29 remains suitable for estimating average noise exposure, its outputs must be interpreted with caution when used for route optimisation or evaluating the impact of individual flights. The improvements provided in this thesis support more transparent noise assessments, helping ensure that modelling outcomes better reflect the interests of both policymakers and affected communities.

8.2. RECOMMENDATIONS

The results of this thesis point to concrete steps for improving the accuracy and transparency of best-practice aircraft noise modelling. Although Doc 29 can reproduce annual exposure within its intended accuracy range, the analyses in this thesis show that several assumptions embedded in the model remain significant sources of uncertainty. Addressing these limitations will be essential for improving both scientific understanding and the reliability of noise assessments used in policy and operational decision making. The main recommendations highlighted from this thesis focus on improving the aircraft performance model input, investigating the effects of model assumptions on noise predictions and finally improving measurement quality for validation purposes.

MODEL INPUT IMPROVEMENT

The largest source of uncertainty identified in this thesis concerns the operational inputs used by Doc 29. Flight procedure assignment, in particular, remains insufficiently transparent and often diverges from actual flight behaviour. Because annual noise exposure is highly sensitive to these assumptions, future work should prioritise developing open-source, well-documented procedure assignment methods that clearly communicate how altitude, speed, and thrust profiles are selected and how these choices influence predicted noise levels. Large, multi-airline datasets are needed to capture the diversity of operational practices, especially since preliminary analyses showed that aircraft types behave distinctly different from each other and the standard modelled procedures.

Improving thrust estimation is equally important. Arrivals remain especially challenging as thrust patterns are difficult to estimate from open-source data. The method developed in this thesis to derive thrust from acoustically measured $N1\%$ offers a promising direction, particularly when combined with GSP-based simulations. Future research should verify this approach across a broader range of aircraft types, atmospheric conditions, and operational configurations. Such work would not only reduce reliance on proprietary airline data but also strengthen the reproducibility and transparency of noise modelling.

MODEL ASSUMPTIONS AND CORRECTION FACTORS

A second set of recommendations concerns the assumptions embedded in Doc 29's modelling framework. Current NPD tables combine source noise and propagation effects into a single dataset and primarily reflect thrust-dependent behaviour. The findings in this thesis show that NPD tables underestimate the thrust–noise relationship for departures and that measurement-derived NPDs can reduce prediction error by approximately 25%. Extending this approach to more aircraft types and operational conditions would significantly improve model accuracy.

Several physical effects are also insufficiently represented. The deployment of landing gear and high-lift devices during arrivals introduces noise components not captured in standard NPDs. Similarly, aircraft noise directivity is only partially included and inconsistently applied to the different noise metrics. Incorporating both longitudinal and lateral directivity, tied to engine setting and configuration, would improve predictions across a wider range of observer positions.

Propagation modelling remains another major limitation. Doc 29 assumes a homogeneous atmosphere and applies simplified lateral attenuation corrections. It currently neglects physics, such as non-homogeneous meteorology, wind gradients, and ground interactions, which become increasingly important at long distances and low elevation angles. Future work should therefore explore more advanced propagation models, potentially drawing on the modular structure of sonAIR, which separates source and propagation effects and better captures distance-dependent behaviour. Although sonAIR is not yet suitable as a regulatory replacement, it provides a valuable framework for identifying and quantifying model limitations.

MEASUREMENT QUALITY AND USE

The quality and interpretation of noise measurements also require attention. Background noise limits the reliability of measurements in low-noise regions, where both model and measurement discrepancies grow rapidly with distance. Because many existing NMTs are located for public information rather than scientific validation, expanding the monitoring network with low background noise locations dedicated to research would substantially improve the quality of validation data. The high rate of undetected flights identified in this thesis further underscores the need for improved detection algorithms. Approaches such as adaptive thresholds or acoustic aircraft fingerprinting could reduce missed events and strengthen the empirical basis for model assessment.

As mentioned, the current use of measurement systems such as NOMOS is mostly for information to communities around the airport. This thesis shows the potential of using the measurements for validation and identifying model limitations. Yet care should be taken when using them for policy applications like the enforcement of noise limits. When NMTs are used as enforcement instruments, operational behaviour can shift to avoid monitors, redistributing noise rather than reducing it. A more constructive use of measurements is to support model improvement, verify the effectiveness of operational changes and mitigation strategies, and to communicate exposure and uncertainty transparently to the public. Clear reporting of typical model errors, such as the 1–2 dBA annual margins and the larger uncertainties in low-noise regions, helps build trust in how noise is assessed. It also ensures that policymakers and communities understand both the capabilities and the limitations of the tools used to evaluate aircraft noise.

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List of journal papers:

3. van der Grift, R. C., Snellen, M., & Amiri Simkooei, A., *Challenges of Comparing Measured and Modelled Annual Aircraft Noise Levels*. Manuscript under review at Journal of Transportation Research Part D: Transport and Environment. (Chapter 3)
2. van der Grift, R. C., Snellen, M., & Amiri Simkooei, A. (2025). *Aircraft Noise Model Improvement by Calibration of Noise-Power-Distance Values Using Acoustic Measurements*. CEAS Aeronautical Journal. <https://doi.org/10.1007/s13272-025-00902-6> (Chapter 5)
1. van der Grift, R. C., Snellen, M., & Amiri Simkooei, A. (2025). *The Effect of Using N1% as Input for Aircraft Noise Modelling*. Transportation Research Part D: Transport and Environment, 142, Article 104710. <https://doi.org/10.1016/j.trd.2025.104710> (Chapter 4)

List of conference proceedings:

6. van der Grift, R., Jayanthi, A. S., Snellen, M., & Amiri-Simkooei, A. (2025). *Analysing the effect of undetected flights in the comparison of measured and modelled aircraft noise*. In Proceedings of Forum Acusticum / EuroNoise 2025 (pp. 5607–5614). European Acoustics Association. <https://doi.org/10.61782/fa.2025.0129>
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