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Efficient Noise Measurement with Energy Constrained IoT Nodes

A Case Study on Working Environment Quality

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Science and Technology

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Problem description:

Noise is an unwanted disturbance, especially in a working environment for focused work. The noise distributions in diverse contexts are distinct, and this constitutes a need for different approaches in each context. The objective for measuring will also affect the technique for noise measurement.

In this thesis, the focus is on noise measurement in working environments. An objective for measuring noise in such a context could be to qualitatively characterise the working environment. The university campus is used as the subject of analysis, due to its availability and relevance related to working environments.

The objective of this thesis is to gain insight into which user requirements apply to a working environment, and how to measure noise efficiently while fulfilling these requirements. More specifically, the aim is to translate user requirements into technical requirements for data. Once we know which metrics are relevant, we can investigate how to adjust the sampling rate and transmission rate in order to measure noise more efficiently, while still maintaining the acceptable accuracy. If we can sample and transmit less data and still get valuable information, it could be advantageous to implement adaptive sensing in working environments.

The main tasks in this thesis includes 1) designing a system for sampling of noise in working environments, 2) defining user requirements and deriving technical requirements, 3) data analysis and simulation of various possible sampling techniques, 4) propose a model for noise measurement in working environments.

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Abstract

Noise is undesirable sound that can be both annoying and harmful to humans. An increasing amount of studies report the many negative health effects of noise, both physical and mental. These findings have led to an interest in noise monitoring, to measure and regulate noise in various contexts. The noise in each context will be different, and thus require different strategies for noise measurement. Stakeholders in a context want to make decisions about noise, and they need reliable information to base the decisions on. The information must be accurate *enough* for them to make the right decisions, but at the same time we want to save as much cost as possible to get this information. In terms of noise measurement, we need to find out which metrics that represent the information the stakeholders need, and how little we can sample noise to get accurate enough values of these metrics.

In this master thesis, we research noise in working environments through a case study. The main research goal is to find an efficient and accurate way to measure noise in working environments. First, we define a set of *user requirements* through a literature review, to represent the needs of stakeholders in a chosen working environment. Second, we translate these user requirements into *technical requirements* through a literature review. We define a suite of existing metrics to describe the quality of a working environment, and we also define a new metric which is tailored to working environments. These technical requirements represent the information on which the stakeholders will make decisions. Finally, we investigate how *efficient* we can measure noise using these technical requirements. We compare the effect of several simulated sampling rates on accuracy, through a simple statistical analysis in a single-case mechanism experiment.

The main findings show that there is a significant potential for down-sampling in working environments. The ability to reduce the sampling rate will vary for different contexts with different stakeholder needs, and the noise measurement must be tailored accordingly. Nevertheless, our results indicate that it is generally possible to obtain an acceptable accuracy with a sampling rate between 1-7.5 minutes. This is a substantial improvement on cost from a full sampling rate; respectively 30-225 times more efficient. These findings highlight the potential for adaptive noise monitoring. An interesting topic for further work is to define the properties of an adaptive system, and investigate how efficiency and accuracy could be improved from a static sampling strategy in various contexts.

Sammendrag

Støy er uønsket lyd som kan være både irriterende og skadelig for mennesker. En økende mengde studier rapporterer om de mange negative fysiske og psykiske helseeffektene av støy. Disse funnene har ført til en økt interesse for støyovervåking, for å måle og regulere støy i ulike kontekster. Støyen i hver kontekst vil være ulik, og dermed kreve forskjellige strategier for støymåling. Interessenter i en kontekst vil ta beslutninger relatert til støy, og de trenger pålitelig informasjon de kan basere beslutningene sine på. Informasjonen må være nøyaktig nok, samtidig som vi ønsker å redusere kostnaden knyttet til å skaffe denne informasjonen så mye som mulig. Skal vi måle støy må vi finne ut hvilke metrikker som representerer denne informasjonen, og hvor lite støydata vi kan samle inn og fortsatt få nøyaktige nok verdier av disse metrikkene.

I denne masteroppgaven ser vi på støy i arbeidsmiljøer, gjennom en studie på et utvalgt arbeidsområde. Målet er å finne en effektiv og nøyaktig måte å måle støy på i slike miljøer. Først definerer vi et sett med *brukerkrav* gjennom en litteraturstudie, som skal representere interessenters behov. Deretter oversetter vi brukerkravene til *tekniske krav* gjennom enda en litteraturstudie. Vi definerer et sett med eksisterende metrikker for å beskrive kvaliteten på arbeidsmiljøet, og vi definerer også en ny metrikk som er tilpasset et arbeidsmiljø. Disse tekniske kravene representerer informasjonen som interessentene skal ta beslutninger basert på. Til slutt undersøker vi hvor *effektivt* vi kan måle støy ved å bruke disse tekniske kravene. Vi sammenligner effekten flere simulerte samplingsfrekvenser har på nøyaktighet gjennom en enkel statistisk analyse.

De viktigste funnene viser at det er et betydelig potensial for å redusere samplingfrekvens i arbeidsmiljøer. Evnen til å redusere samplingsfrekvensen vil variere for ulike kontekster med ulike interessentbehov, og måling av støy må tilpasses hvert tilfelle. Likevel viser våre resultater at det generelt er mulig å oppnå en akseptabel nøyaktighet med en samplingsfrekvens mellom 1-7,5 minutter. Dette er en betydelig forbedring av kostnadene fra en full samplingsfrekvens; henholdsvis 30-225 ganger mer effektiv. Disse funnene fremhever potensialet for adaptiv støyovervåking. Et interessant tema for videre arbeid er å definere egenskapene til et slikt adaptivt system, og undersøke hvordan effektivitet og nøyaktighet kan forbedres fra en statisk samplingstrategi i ulike kontekster.

Preface

This thesis is submitted as the final requirement of my 5-year MSc in Communication Technology at the Department of Information Security and Communication Technology (IIK) at the Norwegian University of Science and Technology (NTNU). The main work was carried out between January and May 2019.

I would like to give a special thanks to my professor and supervisor Frank Alexander Kraemer for his support, guidance and encouragement throughout this semester. I would also like to thank my co-supervisor Faiga Alawad for her valuable input and contribution, and Pål Sturla Sæther for providing and helping with the technical equipment used in this project. This would not have been possible without their support.

On a personal note, I would like to extend my deepest gratitude to my boyfriend, for keeping me sane through this process. You provided me with all the love, care and support I needed to finish this thesis in time. I would also like to thank my family for believing in me and always being there when I need you. And not least, thank you for reading through my thesis and giving me feedback on my work.

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List of Acronyms

API Application Programming Interface.

CQI Composite Quality Indicator.

END Environmental Noise Directive.

IDE Integrated Development Environment.

IEC The International Electrotechnical Commission.

IEEE Institute of Electrical and Electronics Engineers.

IIK Department of Information Security and Communication Technology.

IoT Internet of Things.

ISO International Standards Organization.

MSE Mean Squared Error.

NEA The Norwegian Environment Agency (Miljødirektoratet).

NPL Noise Pollution Level.

NTNU Norwegian University of Science and Technology.

RMSE Root Mean Squared Error.

SCME Single-Case Mechanism Experiment.

SNR Signal-to-Noise Ratio.

SPL Sound Pressure Level.

SQL Structured Query Language.

TSDB Time Series Database.

UDP User Datagram Protocol.

WASN Wireless Acoustic Sensor Network.

WSN Wireless Sensor Network.

Chapter 1

Introduction

In the following sections we present the motivation, scope, relevance and goals of the project, as well as the main contributions and thesis structure.

1.1 Motivation

Noise is a phenomenon that most of us have to deal with throughout our lifetimes. It can be defined as unwanted or harmful sound, and it is increasingly recognised as one of our greatest social problems. The consequences of short-term and long-term noise exposure are gradually being uncovered. Figure 1.1 shows an overview of some identified consequences of noise exposure. Numerous studies have argued that noise has a negative impact on public health, including sleep disruption, annoyance, cognitive impairment, increased stress and blood pressure, hearing loss, and impact on mental health [11, 12, 1]. Indeed, previous studies have reported that long-term exposure of noise can increase the risk of hypertension, heart attack and other cardiovascular diseases, diabetes and chronic sleep disturbance, which can lead to further problems [13, 14, 15, 16, 11]. Additionally, recent evidence suggests that urban noise levels worldwide consistently exceed the recommended noise limits, resulting in irreversible sensorineural noise damage [17]. Not only do these noise-induced problems affect the exposed human beings, but they also increase health care costs if remained untreated [18].

Furthermore, noise can interfere with concentration at work or school. A substantial amount of studies have shown that noise leads to cognitive impairment in children, including negative effects on reading and memory [11, 19]. This effect has been shown to apply to adults in working environments as well [20], emphasising the impact of noise throughout the life of human beings. The open-plan office is a well-established design for workplaces and learning environments. They are often filled with disturbing speech, noise from machines like printers and telephones, doors slamming, people moving or walking by, etc. Such noise has proven to be significantly

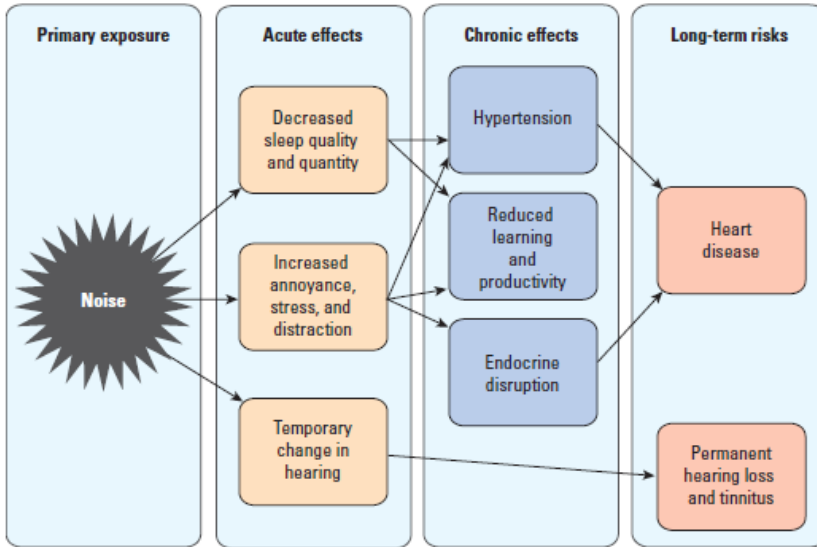


Figure 1.1: Select health effects of noise. Taken from [1].

disturbing for concentrated work, resulting in reduced task performance and learning outcome [20, 21, 22, 19]. In addition, people working in industry and construction commonly experience hazardous noise at the workplace. Although the number of affected is decreasing due to increased use of hearing protection and noise reduction measures, many end up with reduced or complete loss of hearing due to occupational noise [23].

People living in large urban areas are generally exposed to excessive noise around the clock, reducing their quality of life [11, 24]. Urban noise includes for example noise from road traffic, airports, railways, industry, concerts, restaurants and clubs, and construction work. Increasingly more people are moving into big cities every year, resulting in higher noise levels for a growing number of individuals. The Environmental Noise Directive (END), also known as Directive 2002/49/EC [25], was implemented in 2002 to assess and manage noise in urban areas for Member States. The directive covers several areas regarding environmental noise: determination of exposure; information accessibility for the public; noise prevention and reduction where necessary; and noise quality preservation in good areas. The existence of such a directive indicates a global noise problem that requires attention.

1.2 Problem Scope

The importance of the present noise problem is clear. The growing amount of research on noise measurement emphasises the lack of good ways to measure and identify noise

in a variety of contexts. Moreover, the related work in the field do not systematically address the design choices of their methods. This implies the need for a *system* tailored to the needs in a given context. Hence, the properties of such a system will change based on the purpose of the noise measurement. The system needs to be both efficient and accurate *enough*, based on what information we are looking for and what decisions we have to make based on this information.

What does tailored noise measurement involve? If we want to know what the noise level in an area is at all times, we must measure and transmit continuously throughout the whole period of interest. If we only want to know if we ever exceed a limit, it may be enough to measure now and then until a higher level is detected. If the high level persists, we can then monitor more frequently and trigger an alarm if the level is exceeded. Then, we need to make a decision on whether to change something to avoid such alarms in the future. When we measure traffic, we may be most interested in the peaks of noise, while we may be more interested in the background noise in working environments. In an office we can study the noise in a time frame of the 8 hour working day, while in residential areas we may look at the whole day and night.

If we know what we are interested in learning and what decisions we have to make, we can customise the noise measurement accordingly. Consequently, we measure noise more efficiently and accurately for our need and make good decisions. The chosen context in this thesis is working environments where concentrated work is performed. In a working environment we may have to make a decision on whether to work in an area at certain times or not. In this case, we probably want to know if it usually is noisy Monday mornings, for example. If the area is very noisy through long periods of time, we need to decide about making changes to the working area. We may need to install more noise reducing padding, move a disturbing printer or other mitigating measures. In either of these two cases, *continuous* noise measurement would be required to know how the noise distribution develops over time.

Internet of Things (IoT) is growing at an exponential rate and is more accessible than ever before. As a result, there is potential for using IoT to measure noise continuously and real-time in areas exposed to noise. An advantage of IoT is the automation of data collection, which reduces the human intervention needed. Furthermore, wireless machine-to-machine communication allows for high accuracy and a great flow of information. Another advantage is the ability to perform calculations in the IoT node. Thus, the amount of data sent from a node can be reduced. Moreover, the type of information sent can be tailored to each need. Additionally, noise measurement by IoT can reduce costs, making it suitable for continuous noise measurement. An extensive amount of recent research uses IoT technology for noise measurement systems in order to face today's challenges and

needs [26, 27, 28, 29, 30, 31]. This is further addressed in Section 2.2.

Despite the advantages of IoT systems, there also exist some restrictions regarding noise monitoring. First, the nodes consumes a great deal of energy when measuring and transmitting data. If the node is programmed to read noise data continuously, the energy consumption will be high. Additionally, WiFi is costly in terms of energy, and most nodes have strictly limited battery capacity. Consequently, they may depend on a continuous power supply to measure and transmit data continuously. Second, most IoT nodes have limited computation and storage capacity. Thus, it can be challenging to perform complex analysis in the nodes, and to store large amounts of data.

Several studies investigate the topic of adaptive sensing and sound-source identification and classification using machine learning [32, 33, 34]. These systems are frequently used in urban areas, because of the varying noise distribution in such contexts. With a broad variety of noise sources and changing distributions of noise, there may be a potential for more accurate and efficient noise measurement by the use of these adaptive systems.

The design and development of adaptive systems is beyond the scope of this thesis. Nevertheless, an aim of this research is to highlight possible advantages of adaptive sampling in working environments. Our hypothesis is that adaptive sampling can help address the existing challenges of IoT noise measurement. Further work on the topic is required to determine if such a solution is feasible.

This thesis takes the form of a case study of the noise in a working environment for focused work at NTNU. Several recommendations and regulations for noise in working environments exist, and a considerable amount of research has been published in the field. However, it is still unclear how noise should be measured efficiently and accurate in this context. This research offers some important insights into how noise can be measured in working environments if we know what information we want to learn. The aim is to contribute to the growing amount of research on noise by exploring the use of IoT systems and the possibilities for adaptive sampling in working environments.

1.3 Research Questions

Given this broader context, the objective of this thesis is to characterise the quality of working environments for focused work with regard to noise, as efficient as possible, based on a chosen set of metrics. In order to decide if a working environment is *good*, we need to know the user requirements applying to the area. In other words, we must decide what we are interested in knowing. The user requirements affect the

way we have to sample, transmit, and analyse data in order to learn the information we need. Moreover, there is a trade-off between the accuracy of the information we get and the amount of energy we have to spend to acquire it. The balance between them must be decided carefully.

With this in mind, we address three research questions in this thesis. In accordance with the case study, we define the context as *working environments for focused work*. RQ1 and RQ2 lay the foundation for the main research question, RQ3:

- **RQ1:** What are the user requirements with respect to noise for working environments for focused work?
- **RQ2:** How can these user requirements be translated into technical requirements for noise measurement?
- **RQ3:** How do the requirements affect the sampling- and transmission-rate in working environments for focused work, in terms of efficiency and accuracy?

Figure 1.2 shows an overview of the scope of the thesis. The left side of the figure represents RQ1, while the right side represents RQ2. The square in the middle represents the ideal sampling system found by RQ3. The dotted square represents the scope of this thesis.

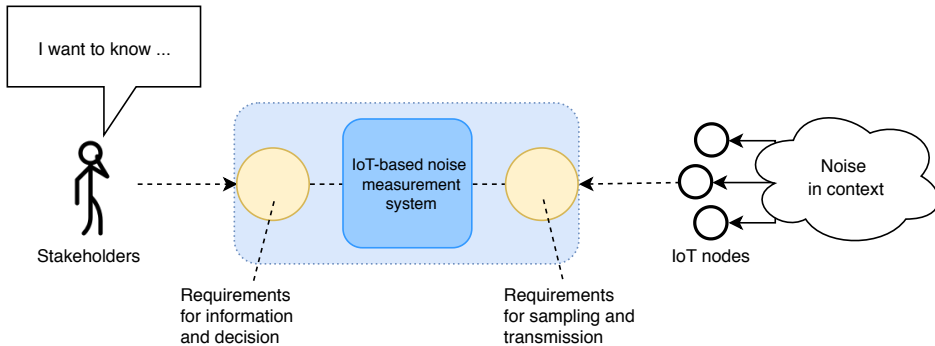


Figure 1.2: Thesis scope. Finding the ideal noise measurement system from user requirements and technical requirements.

1.4 Contributions

Given this problem scope, the main contribution of this thesis is the insight into the effect of when IoT sensors sample less data and therefore use less energy. The

comparison of the accuracy and cost of different static sampling rates show that there is a great potential for down-sampling in the chosen working environment, given the defined requirements. Our results in this thesis indicate that it is possible to save great amounts of energy by utilising an adaptive sampling approach. This supports the motivation of further work on adaptive noise monitoring.

1.5 Outline

The overall structure of the thesis takes the form of eight chapters, including this introductory chapter. The remaining chapters proceed as follows:

- Chapter 2 - Background and Related Work: Addresses the theoretical background and related work in the field of study. It presents key concepts, documents and terms in noise measurement, as well as the technical specifications for the designed system.
- Chapter 3 - Methodology: Thoroughly presents the methodology of the thesis, including main tasks, utilised methods and knowledge questions that will be answered.
- Chapter 4 - User Requirements for Noise Measurement: Introduces the chosen working environment and its stakeholders and goals. Moreover, it presents the user requirements in working environments, derived from related literature and regulations. Namely, RQ1 is assessed in this chapter.
- Chapter 5 - Technical Requirements for Noise Measurement: Presents the technical requirements based on the user requirements, in the form of a suite of metrics; thereby assessing RQ2.
- Chapter 6 - Design of a Simple Noise Measurement IoT System: Presents the designed and implemented simple system for IoT noise measurement, and key limitations.
- Chapter 7 - Trade-Off Analysis: Discusses several sampling approaches, and the efficiency and accuracy of the techniques. The different approaches are compared through a trade-off analysis. This chapter deals with RQ3.
- Chapter 8 - Discussion and Further Work: Discusses the research approach, the main findings and validity of the results. Finally, it discusses main limitations and future work in the field of study.

Chapter 2

Background and Related Work

In this chapter we present the relevant theoretical background and related work for the subsequent chapters. Furthermore, we introduce the technology used for designing the simple IoT noise data collection system.

2.1 Acoustics and Noise

In this section we present the fundamental background of acoustics and noise, along with relevant standards, laws and regulations.

2.1.1 General Acoustics

Sound can be defined as the auditory sensation evoked by oscillations in pressure [35, p. 20]. Figure 2.1 shows an overview of some important terms regarding sound. The amplitude of a sound wave represents the loudness of the sound, and is the magnitude of an oscillation, also called the energy of a wave. The frequency of a sound wave represents the pitch of the sound, and is expressed in hertz (Hz). A frequency of 1 Hz equals one oscillation per second. Both the amplitude and the frequency are used to measure sound.

When measuring noise, the quantity *decibel* (dB) is commonly used. It is a dimensionless and logarithmic unit for the sound level. It is based on the ratio of a reference quantity and a measured quantity. The unit of the quantities is usually power, intensity or pressure. The decibel formula is defined by [35, p. 23] as:

$$L = 10 \log_{10} \left(\frac{A}{B} \right) \text{ dB} \quad (2.1)$$

where B is the reference level and A is the measured level. L is the sound level expressed in dB. If the quantities A and B are expressed in power, L is called the Sound Power Level (PWL) or L_W . If they are expressed in pressure, L is called the

Sound Pressure Level (SPL) or L_p . Since the sound pressure is measured more easily than the sound power, most noise measuring equipment are built to measure the SPL [35, p. 24]. Thus, when the sound level is mentioned in this thesis, we refer to the sound pressure level.

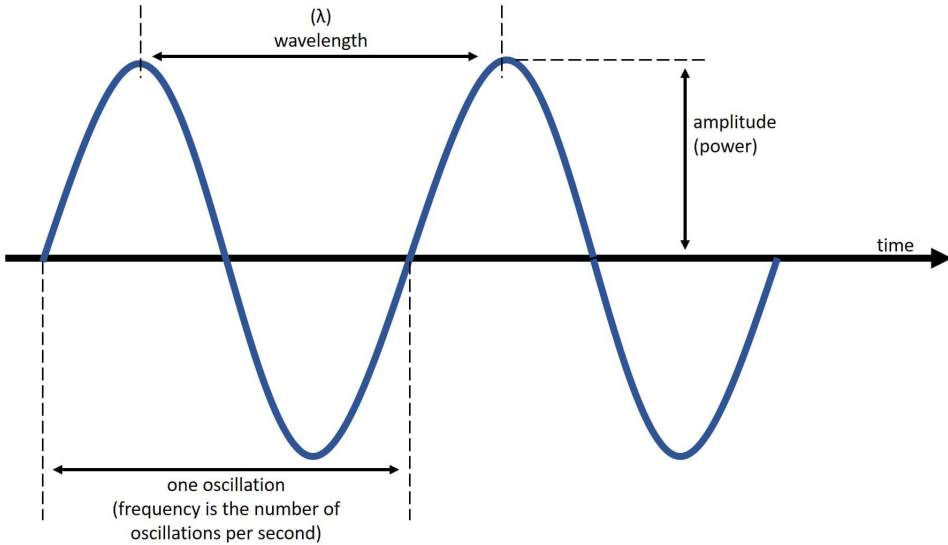


Figure 2.1: The difference between amplitude, wavelength, oscillation and frequency of a sound wave. Taken from [2].

Since dB is logarithmic, a change of 10 dB will for most humans be subjectively sensed as a doubling or halving of the sound volume. In terms of sound energy, an increase of 10 dB equals a tenfold increase. A doubling of the sound energy equals a decibel increase of approximately 3 dB, which is barely noticeable for most humans. This means that if you are exposed to a sound of 30 dB for 1 hour, this equals the energy exposure you get from 33 dB during 30 minutes. This is called a *3 dB exchange rate* [35, p. 73], and it is often applied to noise limits. Sometimes a 4 or 5 dB exchange rate is applied, but this is less common.

The difference between a background noise level and a signal is called the Signal-to-Noise Ratio (SNR), or S/N. It indicates how much useful information there is compared to unwanted information, and the higher the number the better. The signal can for example be a noise we are interested in, or speech. In terms of speech, it indicates to what degree a listener can obtain the meaning of sentences and words. The level where the SNR is adequate for a listener is called the *threshold of intelligibility*, and it lies at around 12 dB for background levels between 35 and 110 dB [35, p. 587].

2.1.2 Weighting Filters

The raw sound measurements are not always enough to analyse the noise and get the information we need. The following weightings are defined in the standard IEC 61672-1:2013 [36].

Frequency-Weighting

Frequency-weighting is a standard way of electronically filtering noise, to adjust the measured sound to a curve. An advantage of using frequency weighting is that it characterises the sound with a single number [35, p. 27]. Since the human ear is less sensitive to low and high frequencies of sound, a frequency weighting called *A-weighting* is commonly used to adjust the measured sound to represent what the human ear hears.

A-weighting is a standard curve which shape is similar to the response of the human ear. The human ear is most sensitive between 500 Hz and 6 kHz, and A-weighting ranges from 20 Hz to 20 kHz, which approximates to this sensitivity. A-weighted decibels are expressed in terms of *dBA* to indicate the weighting. Indicators measured using A-weighting is often expressed with a sub-scripted A, such as $L_{Aeq,T}$ presented in Section 2.1.5.

It is common to use A-weighting to measure environmental and industrial noise. Most sound level meters have an option to apply this weighting to measurements. Furthermore, A-weighting is used in many regulations and standards on noise. Assuredly, it makes sense to use A-weighting for this thesis on noise in working environments.

There also exists a frequency weighting called C-weighting, which is commonly used to measure peaks of noise. The C-weighted decibels are expressed in *dBc*, and indicators measured using C-weighting is often expressed with a sub-scripted C. An example of such an indicator is $L_{Cpeak,T}$ presented in Section 2.1.5. The equipment presented in Section 2.3.1 does not support C-weighting, and it is therefore not applied in this thesis.

Furthermore, recent work has suggested that a more accurate way of calculating loudness is the Zwicker method [37]. The model calculates the psycho-acoustic annoyance perceived by people, using the Zwicker algorithm. The loudness perceived with both ears is commonly called *binaural loudness*.

Time-Weighting

Time-weighting is also called the response of a sound level meter. It is the speed of which a sound level meter responds to changes in noise levels. Historically, this

exists due to the use of sound level meters with analogue needles. The standardised time constant defined the speed of the needle movement, ensuring comparable measurements for different equipment. There are commonly two possible time-weightings on sound level meters: SLOW and FAST. Figure 2.2 shows the difference in response of the two modes when a change in sound level occurs.

The SLOW mode is called *S-weighting*, and the time constant is 1 second. It is typically used to determine an average or slowly changing average value of observed sound [35, p. 47]. For this thesis, the SLOW mode in the noise sensors was used.

The FAST mode is called *F-weighting*, with a time constant of 125 milliseconds. This is typically used to estimate the variability in the observed sound, if we are interested in the limits [35, p. 47].

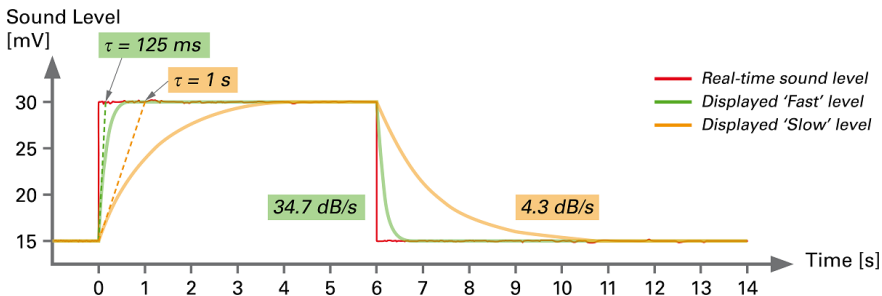


Figure 2.2: Response of FAST and SLOW time weightings to a change in sound level. Taken from [3].

2.1.3 Common Noise Levels

Table 2.1 shows some decibel levels for common noise sources. The distance to the source is given in meters, when it is relevant. In a library, in example, we assume that the level represents the noise we experience when we are standing in the room. Bear in mind that the subjective perception will vary for different people. These examples represent common perceptions of noise, but they are not finite definitions.

The threshold of human hearing is defined at 0 dBA. A normal conversation can vary from 50 to 70 dBA, but 65 dBA is regarded most common. If exposed to noise over 85 dBA over some time, humans are prone to hearing damage. At 140 dBA all frequencies are painful, and this level is extremely damaging to hearing for even short exposure times. Humans can experience immediate death from an exposure of around 200 dBA.

Table 2.1: Common sound sources (with distance in meters where relevant) and corresponding decibel levels.

Source	dBA
Threshold of human hearing	0
Normal breathing (1m)	10
Whispering (1m)	30
Quiet library	40
Large office, busy street (90m)	60
Normal conversation (1m)	65
Vacuum cleaner (3m)	70
Heavy traffic, noisy restaurant	85
Truck (10m), shouted conversation (1m)	90
Chainsaw (1m)	110
Rock concert (5m), threshold of discomfort	120
Jet engine (50m)	130
Threshold of pain	140
Gunshot (0.5m)	160
Explosion (close)	190

2.1.4 Standards

International Standards Organization (ISO) and The International Electrotechnical Commission (IEC) have published a variety of standards on noise. Table 2.2 presents an overview of the relevant standards applying to this thesis.

ISO 1996-1:2016 provides definitions of relevant basic quantities for measuring noise. These are used extensively throughout this research, especially for discussing noise indicators in Section 2.1.5 and Section 5.4.

IEC 60050-801:1994 defines acoustic vocabulary used throughout this thesis, and is important for understanding acoustic terms.

ISO 11690-1:1996 discusses how to tackle noise problems in workplaces in section 7 of the standard. More specifically, it presents recommended noise limits for different kinds of workplaces. This is relevant for defining the user requirements in Chapter 4. Another relevant standard for chapter Chapter 4 is ISO 12913-1:2014. It provides a conceptual framework of soundscape, thus helping to understand the acoustical

Table 2.2: Standards regarding noise.

Key	Title	Ref.
ISO 1996-1:2016	Acoustics - Description, measurement and assessment of environmental noise - Part 1: Basic quantities and assessment procedures.	[38]
ISO 11690-1:1996	Acoustics - Recommended practice for the design of low-noise workplaces containing machinery - Part 1: Noise control strategies.	[39]
ISO 12913-1:2014	Acoustics - Soundscape - Part 1: Definition and conceptual framework.	[40]
ISO 37120:2018	Sustainable cities and communities - Indicators for city services and quality of life.	[41]
IEC 61672-1:2003	Electroacoustics - Sound level meters - Part 1: Specifications.	[36]
IEC 60050-801:1994	International Electrotechnical Vocabulary (IEV) - Part 801: Acoustics and electroacoustics.	[42]

environment.

IEC 61672-1:2013 gives performance specifications for three types of sound measuring equipment. The standard specifies two performance classes, Class 1 and 2, that mainly differ in the acceptance limits. Class 1 is more strict than Class 2, and the equipment in Section 2.3.1 is classified as Class 2.

ISO 37120:2018 is a rather new standard, which defines how to measure a city's performance on quality of life through a set of indicators. Section 8.8 in the standard introduces noise pollution as a supporting indicator for many core indicators. The standard states that the noise pollution shall be expressed as the percentage of the population affected by noise pollution, using the indicator L_{den} with a limit of 55 dBA. Levels above this is considered polluted areas that must be reported. This standard is relevant for the user requirements in Chapter 4.

ISO 532-1:2017 [37] specifies a method for estimating the loudness and loudness level of sounds, based on the Zwicker algorithm. This method is good for rating the loudness of complex sounds, as it concerns psycho-acoustic parameters. These parameters are recognised as fitting for assessing subjective irritation of noise. Due to restrictions in the noise measurement equipment presented in Section 2.3.1, this method is not included in this research.

Table 2.3: Noise indicators and descriptions.

Indicator	Description
L_A	The A-weighted instantaneous sound pressure level.
$L_{AE,T}$	The A-weighted sound exposure level (SEL) for a time interval T.
$L_{Aeq,T}$	The A-weighted equivalent continuous sound pressure level, where T is the time interval duration. The time-averaged level.
$L_{A2,T}$	A-weighted sound pressure level exceeded for 2% of the time interval considered. The peaks of noise.
$L_{A5,T}$	A-weighted sound pressure level exceeded for 5% of the time interval considered. The peaks of noise.
$L_{A10,T}$	A-weighted sound pressure level exceeded for 10% of the time interval considered. The peaks of noise, often used for traffic noise.
$L_{A50,T}$	A-weighted sound pressure level exceeded for 50% of the time interval considered. The average/median noise.
$L_{A90,T}$	A-weighted sound pressure level exceeded for 90% of the time interval considered. The background noise level.
$L_{A95,T}$	A-weighted sound pressure level exceeded for 95% of the time interval considered. The background noise level.
$L_{A10,T} - L_{A90,T}$	Difference between the A-weighted sound pressure levels exceeded for 10% and 90% of time interval T. The soundscape variability.
$L_{day,T}$	Equivalent continuous sound pressure level when the reference time interval is the day. T defines the day, normally 12h or 15h.
L_{den}	Day-evening-night-weighted sound pressure level. $T = t_{day} + t_{evening} + t_{night} = 12h + 4h + 8h = 24h$.
$L_{Amax,T}$	Maximum A-weighted sound pressure level, in time interval T.
$L_{Amin,T}$	Minimum A-weighted sound pressure level, in time interval T.
$L_{Cpeak,T}$	The C-weighted peak sound pressure level. The maximum absolute value of the instantaneous sound pressure during an interval T. Not to be confused with $L_{Amax,T}$.

2.1.5 Noise Indicators

There are several ways to analyse noise in order to gain insight into the characteristics of the noise. An overview of some noise indicators is presented in Table 2.3, as specified in ISO 1996-1:2016 [38]. T is the time interval the indicator is calculated for, and must be determined by suitability for the context.

Since the decibel scale is logarithmic, it is not possible to calculate the arithmetic mean of noise levels during a period to obtain the average noise level. The average

noise level is useful when the noise level varies during an interval, and is the most used indicator for environmental noise. The A-weighted equivalent continuous sound pressure level, $L_{Aeq,T}$, uses the principle of equal energy. The indicator gives the steady noise level that has equal energy as the varying noise levels during a time interval T. The formula for calculating the $L_{Aeq,T}$ is given in [38] as:

$$L_{Aeq,T} = 10 \log_{10} \left[\frac{\frac{1}{T} \int_{t_1}^{t_2} p_A^2(t) dt}{p_0^2} \right] dB \quad (2.2)$$

where $p_A(t)$ is the instantaneous A-weighted sound pressure at running time t, and p_0 is equal to 20 μ Pa (micropascals). In this thesis we calculate the $L_{Aeq,T}$ from several $L_{Aeq,1s}$ values that the equipment provide, instead of raw sound pressure values. This is calculated using a different formula, where we take the anti-log of each $L_{Aeq,1s}$ value i , and add them together before we divide by the total number n of values:

$$L_{Aeq,T} = 10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n 10^{\left(\frac{L_{Aeqi,1s}}{10} \right)} \right] dB \quad (2.3)$$

If the L_{Aeq} is calculated for a whole day, it is denoted as $L_{day,T}$, where T generally is a time period of 12 hours (07-19) or 15 hours (07-22). If the noise level is calculated for a 24 hour period, we call it the day-evening-night (den) weighted sound pressure level. The indicator is denoted L_{den} . It is the addition of day, evening and night periods; usually 12 hours (07-19), 4 hours (19-23) and 8 hours (23-07), respectively. The evening and night periods are adjusted with a weighting, because people often are more sensitive to noise during these periods. This penalty increment is 5 dB for the evening period, and 10 dB for the night period.

To investigate the extremes of a time interval T, the maximum and minimum time-weighted and frequency-weighted sound pressure levels can be calculated. They are denoted $L_{ASmax,T}$ and $L_{ASmin,T}$, when A-weighted and S-weighted. The time-weighting-subscript is omitted in this thesis, since all values are S-weighted. $L_{Amax,T}$ is the greatest A-weighted sound level within an interval T, while $L_{Amin,T}$ is the smallest level within the same interval.

Noise can also be measured in percentile levels, to identify the time-varying character of the noise. The indicator is then described by the statistical distribution during a time interval T. It is commonly known as the *N percentage exceedance level*,

and is defined in [38] as the “time-weighted and frequency-weighted sound pressure level that is exceeded for N % of the time interval considered”. In this thesis we calculate the percentile levels based on the $L_{Aeq,1s}$ sound pressure values provided by the equipment. It is denoted with a subscript of the weightings, percentage level and the time interval. For example, the A-weighted and S-weighted noise level exceeded for 10% during 1 hour is written as $L_{AS10,1h}$. Since we only use the S-weighted measurements in this thesis, the subscript for the time-weighting is omitted from the notation.

The greater the percentile we use, the higher the percentage exceedance level will be. Thus, $L_{A10} > L_{A50} > L_{A90}$ for the same time interval. From Table 2.3, $L_{A2,T}$, $L_{A5,T}$ and $L_{A10,T}$ all indicate, to varying extents, the highest levels of fluctuating noise. L_{A10} is commonly used to measure traffic noise, because of its high correlation with individual events. The indicators $L_{A90,T}$ and $L_{A95,T}$ exclude these noise events, and only include the general background noise. $L_{A10,T} - L_{A90,T}$ is often used to indicate the variability of the noise, also called the *noise climate*. The final percentile indicator mentioned in Table 2.3, $L_{A50,T}$, is the median of the noise levels. It can also be used in some cases as an indicator for background noise [43].

The sound exposure level (SEL) quantifies the accumulated exposure to noise, and is defined in [35] as:

$$L_{AE,T} = L_{Aeq,T} + 10 \log_{10} \left[\frac{T}{T_o} \right] \text{ dB} \quad (2.4)$$

where T is the duration of exposure in seconds, and T_o is the reference duration $T = 1s$. It highly correlates with discrete sound events, normalising the equivalent noise to 1 second. Thus, noise with different interval lengths can be compared. This is an alternative to the L_{Amax} and L_{A10} indicators, which all describe noise events. These indicators must not be confused with the peak sound pressure, $L_{Cpeak,T}$. It is used in several regulations, and is the C-weighted true peak of the sound pressure wave. More specifically, it is the greatest absolute instantaneous sound pressure during a time interval T [42].

2.1.6 Laws, Regulations and Guidelines

EU Directives

The European Union created Directive 2002/49/EC in 2002, called the END [25]. The purpose of this directive is to identify the levels of noise pollution and to trigger reducing actions. The EU sets two demands for affected parties; every five years they must prepare and publish noise maps and noise management action plans for areas meeting specified criteria. This directive also applies to Norway, and one of the affected areas is the city of Trondheim, with more than 100,000 inhabitants. It is

the polluter that is responsible for conducting noise level measurements in the area they pollute. The Municipality of Trondheim is the responsible party when it comes to collecting noise data from different sources of pollution, and they also create a noise map of the city that is accessible to the public [44]. This noise map is based on simulations from traffic flow and the environment around. The directive does not apply to work places, but it still provides interesting information regarding noise. The main indicators considered in this directive are L_{den} and L_{night} . Supplementary noise indicators may be used for some cases.

Directive 2003/10/EC [45] defines European limits for noise levels in working environments, with the objective to protect workers from risks to health and safety due to noise exposure. The directive define indicators to be used for analysis: peak sound pressure; daily noise exposure level; weekly noise exposure level. Exposure limit values and exposure action values are defined for all indicators. The values for the daily noise exposure are expressed by $L_{\text{EX,8h}}$, and defined as follows: the lower exposure action value is 80 dBA; the upper exposure action value is 85 dBA; and the exposure limit value is 87 dBA. The *3 dB exchange rate* can be applied to these limits to convert them to different time intervals. Additionally, the directive presents several obligations of employers during the noise assessment. This includes keeping the assessment up to date, determination of risks, reducing exposure where necessary, and providing hearing protection for vulnerable employees.

Norwegian Law

There are several laws and regulations in Norway regarding noise. We introduce the most relevant ones in this section.

Regulations concerning limit values for noise (Forskrift om grenseverdier for støy) [46] sets minimum requirements for noise levels in populated areas. If the day equivalent noise level exceeds 35 dB(A), mapping and investigation shall be done. If the day equivalent noise level exceeds 42 dB(A), measures shall be made to reduce the noise.

The Pollution Regulation (Forurensningsforskriften) [47] sets minimum requirements for indoor noise levels in order to promote human health and well-being. The regulation aims to prevent and reduce harmful effects of noise exposure, and applies to educational institutions. It states that if the average indoor noise level during the day and night is above 42 dB $L_{\text{Aeq,24h}}$, reducing measures shall be made. Indoor noise shall be mapped down to 35 dB $L_{\text{Aeq,24h}}$.

The Working Environment Act (Arbeidsmiljøloven) [48] presents requirements regarding the working environment. General requirements include that the working environment shall be fully satisfactory when judging factors that may influence

employees' physical and mental health. In addition, emphasis shall be placed on preventing injuries and diseases, for planning and arranging of work. Requirements regarding the physical working environment include that factors relating to noise shall be fully satisfactory, with regard to the employees' health, environment, safety and welfare. In addition, employees shall be protected against injuries from machines and other work equipment.

The Workplace Regulation (Arbeidsplassforskriften) [49] states that workplaces and work stations shall be designed so that the individual work stations are protected from noise and vibrations. The alertness of the employees should not be reduced due to noise, and conversations should not be interfered by noise. Sound absorbing materials and shields should be used if necessary, and noise from technical devices such as printers should be taken into account when designing the workplace.

Regulations concerning Action and Limit values (Forskrift om tiltaks- og grenseverdier) [9] defines three different work groups based on type of work. Each group is assigned a lower action value for noise exposure, which shall not be exceeded. The groups and their limits are shown in Table 2.4. For groups I and II, the noise made from the worker's activity is not included in the assessment. Additionally, the regulation defines limit values for noise, regarding all groups. The limit for the daily noise exposure level, $L_{Aeq,8h}$ is set to 85 dB. The limit for the peak sound pressure level, $L_{C,peak}$, is set to 130 dB.

Table 2.4: Lower action values for working conditions in three groups. Definitions taken from [9].

Group	Definition	Lower action value
Group I	Working conditions where there are high demands for continuous concentration or a need for conducting unstrained conversations, and in mess rooms and recreation rooms	$L_{Aeq,1h} = 55$ dB
Group II	Working conditions where it is important to conduct conversations or with persistently high requirements for precision, speed and attention	$L_{Aeq,1h} = 70$ dB
Group III	Working conditions involving noisy machinery or equipment that are not covered by working groups I or II	$L_{Aeq,8h} = 80$ dB

Regulations concerning the performance of work, use of work equipment and related technical requirements (Forskrift om utførelse av arbeid) [50] extends the *Regulations concerning Action and Limit values* by adding that endeavours shall be made by the employer to reduce the noise exposure to at least 10 dB below the lower

action values in Table 2.4.

International regulations and recommendations

Other countries in Europe have set recommended limits for noise in workplaces, including Denmark, Austria and Germany. Four noise groups are defined in Denmark, where group 3 concerns work requiring attention and effortless conversation [51]. This group has a recommended noise limit of 45-50 dBA. Group 4 concerns work requiring no disturbing noise, and this group has a recommendation of an "even lower level" than group 3, without specifying a specific limit.

The German Association of Engineers defines three groups with different recommended noise limits [52]. The group applying to concentrated work, involving "mainly intellectual work", has a recommended noise limit of 55 dBA. Additionally, the German Social Accident Insurance (DGUV) association has published a recommendation [53] in accordance with ISO 11690-1:1996 [39], which states that for work which includes specific demand for concentration, noise should not exceed 45 dBA. Similarly, Austria defines three groups [54]. The group applying to concentrated work has a recommended noise limit of 50 dBA. The group for simple office tasks has a limit of 65 dBA.

2.2 Noise Measurement

In this section we introduce related work on noise measurement. First, we present three techniques for noise measurement: manual, simulated and IoT system measurements. Second, we give an overview of technical details from a selection of research, including conventions on sampling rate, intervals, time-span of measurements and indicators used.

2.2.1 Manual Noise Measurement

Manual noise monitoring involves using calibrated sound level meters, or other similar equipment. It is also known as "in situ" measurement. The main utilisation of this type of measurement today is the case where we need to know the noise level in a specific area for a specific time. Examples of such scenarios are responses to neighbour complaints, and checking levels at cinemas, concerts and restaurants, or noise from construction sites. Additionally, it has been used as a part of more complex methods for measuring noise pollution [55]. Besides, manual monitoring was the utilised method in older research, in lack of other methods [56, 57, 58] The manual method is also commonly used to verify simulations of noise as described below.

Measuring noise manually can be costly and time-consuming. Consultants may need to be hired, the representative time and place for the noise measurement must

be carefully chosen, the equipment must be correctly calibrated, among other things. As a result, annoying or even hazardous noise problems are not always dealt with in the correct manner, if dealt with at all. Moreover, employees, residents and other affected parties don't always know what rights they are entitled to, and the threshold may be high to request action. Thus, manual noise monitoring is not an advantageous choice for working environment noise monitoring.

2.2.2 Simulation of Noise

An alternative to manual monitoring is the simulation of noise. This technique is often used to predict noise, especially for traffic noise in cities. The results are then used to create noise maps, like the map from The Municipality of Trondheim [44]. The prediction models are commonly based on traffic data, short-term monitoring data, data sets from geographical information systems (GIS), among other things [59, 60, 61, 62]. It is a more economic solution than manual measurements, but the models are often tailored to a specific city and context. As a result, the model is not directly applicable to a new city with other characteristics, even if the traffic density is the same [63]. Although prediction models for traffic are getting better, it is still less accurate than real-time monitoring.

As mentioned above, these prediction models are sometimes verified by a shorter period of manual monitoring, data of which is compared to the simulated results [64]. The data from the manual monitoring is often accompanied by number of passing and type of vehicles, if traffic is involved [60, 61, 59]. Several studies investigating short-term versus long-term measurements have reported that such short-term measurements can be representative for the long term [65, 10]. This applies especially if we have a rather constant distribution of noise, such as highways or major roads do [66].

However, other studies show that this is not always the case [67]. Other variables should be taken into consideration for more accurate prediction, such as road types, land usage, distribution of population, among other things [68, 69, 70]. This claim is supported by studies on models for traffic noise prediction, reporting that the existing models aren't always suitable for predicting traffic noise, highlighting the uncertainty by high noise variability [71, 66, 72, 73]. Similarly, a recent study on construction noise prediction reported corresponding results [74]. Recent research has included neural networks in their models to improve the accuracy of predictions, but states that further work is required [75]. Thus, when selecting prediction models, caution must be applied.

The lack of prediction models for fields other than traffic may indicate unsuitability in those contexts. The noise in working environments is varying, and simulation of noise is therefore not the best choice of method.

2.2.3 IoT Systems

In this section we explain what the term IoT means, and how it has been used in a select amount of research on noise measurement.

Internet of Things

IoT stands for Internet of Things, and is generally referring to the embedding of Internet connectivity into physical everyday objects. These devices can then communicate with others, and be monitored and controlled remotely. Institute of Electrical and Electronics Engineers (IEEE) has an initiative called the IEEE IoT Initiative [76], and they have made an effort to create a good definition of IoT among all the different, often unclear, definitions that exist. Based on a thorough review of state-of-the-art definitions and architectural models, the initiative highlights nine features of IoT:

- Interconnection of things
- Connection of things to the internet
- Uniquely identifiable things
- Ubiquity
- Sensing / actuation capability
- Embedded intelligence
- Inter-operable communication capability
- Self-configurability
- Programmability

With these features in mind, the initiative provides two different definitions of IoT based on the size and complexity of the system at hand. The first definition, for small environment scenarios, is as follows:

An IoT is a network that connects uniquely identifiable “Things” to the Internet. The “Things” have sensing/actuation and potential programmability capabilities. Through the exploitation of unique identification and sensing, information about the “Thing” can be collected and the state of the ‘Thing’ can be changed from anywhere, anytime, by anything. [76, p. 73]

The second definition is for large environment scenarios, where a substantial amount of interconnected devices deliver complex services across different administrative domains. The definition is as follows:

Internet of Things envisions a self-configuring, adaptive, complex network that interconnects “things” to the Internet through the use of standard communication protocols. The interconnected things have physical or virtual representation in the digital world, sensing/actuation capability, a programmability feature and are uniquely identifiable. The representation contains information including the thing’s identity, status, location or any other business, social or privately relevant information. The things offer services, with or without human intervention, through the exploitation of unique identification, data capture and communication, and actuation capability. The service is exploited through the use of intelligent interfaces and is made available anywhere, anytime, and for anything taking security into consideration. [76, p. 74]

It is important to note the difference between IoT systems and Wireless Sensor Networks (WSNs). The terms are often used interchangeably, but they are not the same. The difference is defined by IEEE IoT Initiative [76] as follows:

A WSN is a spatially distributed network of autonomous sensors that monitor physical or environmental conditions, such as temperature, sound, pressure, etc. and cooperatively pass their data through the network to a central location. The WSN is built of “nodes” – from a few to several hundreds or even thousands, where each node is connected to one (or sometimes several) sensors. The scope of WSN is the coordinated collection of data.

On the other hand, an IoT system’s scope goes beyond this, in a way, where smartness can be added to the objects so that they can do the work of actuation to achieve a certain goal without human intervention. On top of that unique identification of “Things” and their connection to the Internet is another necessary feature of IoT that doesn’t pertain to WSN.

Generally, WSN can be one part of IoT in that sensors used in an IoT system can be networked to achieve a coordinated result. [76, p. 72]

Thus, the term IoT covers a broader scope than WSN, which can be a type of IoT system. A WSN system measuring noise is often referred to as a Wireless Acoustic Sensor Network (WASN). The following section covers both IoT and WSN systems.

IoT Noise Measurement

There is an inconceivable amount of possible system solutions using IoT, and the justification of the chosen methodology is rarely addressed in the research. In this section we aim to give an overview of state-of-the-art research related to IoT noise measurement, to give a clearer understanding of how IoT is used in this field of study. Then, in the succeeding section, we present the technical details of measurement for a selection of studies.

Several actors are offering commercial solutions [77, 78, 79, 80], but these can be very costly and are not always tailored to the exact needs of the users. Unfortunately, these actors do not reveal any implementation details of their systems, making it difficult to get insight into their system. Some researchers use mobile phones as nodes in their systems [81, 82, 83], but these do not always give accurate results, especially due to the variation in location of devices. For this reason, they are excluded from this thesis.

A considerable amount of literature has been published recently on urban IoT systems, due to an increasing interest in the potential of smart cities. Such systems can for example be utilised to detect important urban events [84], monitor a city's sustainability and livability (quality of life) [85], for smart health care (s-health) [86, 87], for smart car parking [88], and for noise monitoring for a variety of purposes.

Much of the current literature on IoT noise measuring systems pays particular attention to traffic monitoring. A likely explanation is that traffic noise accounts for a large proportion of environmental noise in cities. For example, Bartalucci et al. [89] designed and implemented a smart noise monitoring system for urban areas characterised by road traffic restrictions, in order to regulate traffic noise in these areas. Wang et al. [90] developed a WSN for collecting traffic noise data, which they subsequently used to create a neural network that simulated traffic noise for 100 roads.

Numerous studies have the objective to investigate the suitability of a system for urban noise measurement, and to evaluate the noise environment. This is often in relation to the introduction of the END [25], as an alternative data collection procedure. The END require member states to publish noise maps every 5 years, which increases the demand for an uncomplicated and economical way to generate these maps. Santini et al. [91, 92] focus on the assessment of environmental noise pollution in urban areas, with the aim to highlight the potential and qualitative considerations of a WSN used to generate noise maps. Additionally, they developed TinyLAB, a tool for data collection, processing and visualisation of WSN data.

In regards to noise mapping, Murphy and King [93] have looked into method-

logical issues and policy implications of member state implementations of the END. There is a lack of a standardised noise calculation model, resulting in a difficulty in comparing studies directly. Furthermore, after the introduction of the annual L_{den} indicator several issues have emerged. Due to the difference in calculation methods, conversion methodologies has been developed to simplify the compliance with the EU standard. The authors state that discrepancies as a result of these conversions are likely to arise. The precision of the L_{den} indicator is also an issue, since such an annual measure offers little description of the nature of noise. This includes short term variations in noise levels, yet they are generally considered more annoying by the public. Also, meteorological conditions are not always accounted for in the applied methods. On the issue of noise mapping, the authors judge comparison of produced noise maps to be extremely difficult. This is due to the usage of different commercial software packages with varying capabilities, unknown spatial interpolation techniques for compilation of the maps, and differing visual representations such as graduated or delineated colouring display methods. They recommend that appropriate standards and policies are developed, and suggest creating a common calculation software package that should be freely available to the end users.

Comparatively, Mioduszewski et al. [94] compare two noise assessments in Gdansk. One assessment was from a noise map created from simulation, whereas the other was from a noise monitoring system, from 14 of 40 stations. They concluded that the actual noise level generally was higher than the predicted noise level from the noise maps. They highlight the necessity of monitoring non-acoustical parameters precisely, if more accurate predictions are to be made. This evidence suggest that the common methods of collecting data and generating noise maps no longer is sufficient for reflecting actual noise characteristics in urban environments.

In order to measure noise easily, efficiently and accurately, there is a need for continuous, real-time systems that can automate the noise measurement procedure. There are currently several ongoing projects addressing this challenge. In the following paragraphs we present a selection of projects to illustrate the variety in focus and methodologies in the field of research.

A project called SENSEable [95, 96] created a WASN in Pisa, with the objective to include citizens to participate in urban noise monitoring. They provide a low-cost real-time noise mapping system, available to the public online [97]. Paulo et al. [98] created a quasi-real-time WSN system producing noise maps and event maps from urban noise. The objective of the project was to build a system that could analyse the city soundscape continuously. It is based on the FIWARE platform, and reports a vast amount of noise indicators. The system was implemented as a pilot project on a university campus with success.

Farrés [99] deployed a WASN platform in Barcelona, a city which has a high acoustic complexity. The main objective was to evaluate sound levels in challenging areas real-time, in order to provide quicker decision making and response times. The WASN consists of a main network and a complementary, low-cost network, which deploys different kinds of sensors. Similarly, Mietlicki et al. [100] implemented an urban WASN and platform in Paris through the project RUMEUR, with the aims to investigate the noise distribution, mitigating noise and making information accessible to the public. The main focus is on noise from roads, rails and aircrafts. The platform provides real-time noise maps for a comprehensive part of the city, through 45 long-term and 350 short-term measurement nodes [101].

Segura-Garcia et al. [102] designed a WASN for a small city in Spain, in order to address the challenge of real-time mapping systems for noise pollution monitoring. The system is based on Raspberry Pi nodes, with an omnidirectional condenser microphone each, and a OpenCPU based data collection system. They created a spatial geo-statistical model that estimates noise levels in the city, to use in combination with the WASN to predict the equivalent sound pressure levels (L_{Aeq}) in order to create noise maps. The study focuses on noise from traffic, and records a number of qualitative and quantitative variables relating to this during the measurements. Based on five three-hour time periods of the day, a fitted model is proposed for each period. Four of five models are validated through a spatial statistical analysis.

A project called CENSE [103, 104] aims at producing more realistic noise maps than those by the END, through a dense network of low-cost sensors combined with simulated data. Their focus is on the quality of input data, and uncertainty of output data. They provide a new methodology for characterising urban soundscapes, including sound recognition and assessments of perception.

The DYNAMAP Life+ project [105] is aiming to develop a system for dynamic noise mapping, that represents the real-time noise impact of road infrastructures. There has been published a vast amount of research on this project, continuously reporting the progress [106]. In a preceding paper [107], which describes the system in detail, they state the importance of being able to generate cost-effective, easily updated and easy-to-read noise maps that are available to the public, following the END. They designed a low-cost WASN that can detect anomalous events not related to traffic automatically, and remove them from the data set for higher accuracy. In their recent work [108], they continue developing the noise event detector. Moreover, they address the trade-off between accuracy and cost of spatial and temporal sampling for different types of roads in [109]. A cluster categorisation of roads is conducted based on the 24-hour distribution of noise, in addition to other non-acoustical characteristics such as vehicle flow. The authors report two main road behaviour clusters, which helps localising the most representing sites to place noise sensors.

The SONYC project [110, 32] addresses noise pollution in New York City through a real-time, low-cost WSN, combined with input from the public, machine learning and analysis for more effective mitigation. The system can recognise individual sound sources real-time and detect violations of the noise code through machine listening. It currently consists of 56 Raspberry Pi-based sensors with a calibrated MEMS microphone each. Each node sample continuous SPL measurements, along with audio snippets of 10 seconds at random intervals for the machine listening solution. Data is uploaded to a server at one-minute intervals. They are working on a three-dimensional visualisation framework called Urbane, allowing for fast computation and visualisation of multiple data streams. The agenda of the project is to eventually deploy the system worldwide.

A common focus for studies on IoT is cost-effectiveness. IoT systems can potentially have high costs, both in hardware components and in energy consumption. Hakala et al. [111, 112] implements a low-cost WASN that can be deployed both indoor and outdoor, for measuring environmental noise. Polastre et al. [113] developed a module for WASNs, with minimal power consumption as the main objective. Manvell [114] compares the cost and accuracy of several sound sensor technologies, with focus on usability and suitability in different purposes. Basten and Wessels [115] discuss advantages and disadvantages of a number of developed acoustic sensor networks. They compare cost, scalability, flexibility, reliability and accuracy in their overview, and analyse one selected approach in depth.

Bertrand [116] presents an overview of applications and trends in WASNs, and the main challenges that remain. Acoustic monitoring is addressed as one of the applications that could benefit from using WASNs. Quintana-Suárez et al. [31] created a wireless acoustic sensor for the use in Ambient Assisted Living (AAL), with the aim of low cost and high performance. They composed it of a Espressif ESP32 micro-controller board and an omnidirectional microphone, after considering three different micro-controller platforms. One of the considered, but not chosen platforms was the Libelium Wasp mote platform [117], which is used in the present thesis and described in Section 2.3.1. Overall, these studies highlight the need for cost-effective, scalable, and accurate noise measurement systems. Environmental noise monitoring will almost certainly become increasingly applied and demanded in the future.

Some studies have taken into account other aspects than just the common noise indicators. Especially, the human perception of noise has become increasingly important. Kang et al. [118] developed a model to generate predicted noise maps representing an individual's perception of the acoustic environment. In addition to calculating the main statistical indicators, they included the individual responses to noise from a set of participants. They defined six categories of perception: pleasant, annoying, calm, chaotic, eventful and monotonous. The model was able to predict

noise with acceptable accuracy for contexts with homogeneous noise distributions.

Through the IDEA project [119], the authors implemented a system for noise monitoring with the aim to approach the human perception as closely as possible. They take into account salience of sound and feature extraction to identify sounds that attract human attention. Noriega-Linares et al. [30] describes the development of an acoustic sensor device for evaluation of binaural loudness. Such psycho-acoustic parameters are better for describing subjective annoyance of noise than the the equivalent sound pressure level, as stated in [37].

Similarly, Segura-Garcia et al. [27] include several binaural psycho-acoustic parameters in their work. The objective of the study is to evaluate the spatial distribution and evolution of indoor and outdoor urban acoustic environments, through the implementation of a WASN. The system is based on Raspberry Pi, and calculations are made in the node and published to a cloud-based storage, before they are processed. The two contexts of study are indoor offices and an outdoor area near a highway. The indoor environment includes student working environments. The authors propose a spatial statistical annoyance model, that is validated by spatial and temporal analysis. However, the authors offer no explanation in either research for the choice of sampling methodology for the data that was a basis for the models.

Marsal-Llacuna et al. [85] highlighted the need for a summarising indicator to give information about a city's sustainability level. They propose a construction of synthetic indices for visualising the Smart Cities initiative, and stress the need for real-time indicators for improved results on smart monitoring.

Few studies have made IoT systems for working environments. Most of such systems are commercial, due to the business potential of smart buildings. A couple of the above studies used offices and similar working environments as a context to test their systems, without the intent to create the system for that purpose. Studies on working environments are commonly looking at air conditioning noise or building services, since these noises can be disturbing. However, those studies are mostly based on *in situ* measurements.

Most of the addressed studies in this section are failing to address the choice of methodology for data collection. In the following section, we provide an overview of some technical details of a selection of research. The aim of the overview is to give some clarification of the state-of-the-art conventions in the field.

2.2.4 Technical Specifications of Noise Measurements

In this section we present details of the technical methods used in noise measurement research. This includes sampling rates, time intervals, time-span of measurements, and what indicators that are studied. The choice of these technical details are generally not addressed in a systematic way, despite the growing amount of research on the topic of noise. An overview of a selection of research is shown in Table 2.6, and discussed further in the subsequent sections.

Number of Points

The number of sampling points used affects the amount of collected data. Furthermore, the points can cover overlapping areas resulting in a correlation of the collected data, or they can cover discrete areas. Sometimes, the number of available nodes in a project is less than the desired sampling areas. Thus, the nodes must be moved geographically, and sample noise in a periodic way.

Sampling Rates

We define sampling rate as the time between samples are taken. Sampling rates can be continuous or periodic. Continuous measurements indicate an insignificantly short time between measurements. Periodic measurements have a greater amount of time between each measurement. The two methods are sometimes combined, making the sampling more complex. For example, if a measurement is made for 10 minutes every 3 hours it is continuous within those 10 minutes, but otherwise periodic. In this thesis we define the sampling rate as 3 hours in this case, and the time interval for the indicator as 10 minutes.

The choice of sampling rates varies greatly, as shown in Table 2.6. The more frequent the sampling rate, the better the accuracy of the measurement. It could seem like the convention is to use a continuous, or almost continuous, sampling rate. Then, they rather adjust the time intervals the indicators are calculated based on.

Time-Span of Measurements

The time-span of a study's data collection can be long-term or short-term. It indicates the amount of data that has been collected as a basis for the research. The time-span affect the accuracy of the results, but higher accuracy generally require a higher cost.

The END [25] requires that selected indicators are calculated on the basis of an average year, to accurately represent the noise emission in an area. Although, it states that member states can apply methods for determination of long-term indicators. Collecting data for a full year is cumbersome and costly, resulting in member states using short-term indicators as an estimation of long-term indicators.

Garg et al. [10] looked into this practice, comparing the accuracy of short-term monitoring strategies with long-term noise monitoring strategies in major cities of India. The authors present a SWOT (strengths, weaknesses, opportunities and threats) analysis of three different strategies: long-term (yearly); short-term (weekly or monthly); temporary (days). An excerpt from the SWOT analysis is shown in Table 2.5. It shows that short-term monitoring can replace long-term monitoring in some cases, where the distribution of noise is uniform.

Table 2.5: SWOT analysis of short-term vs long-term noise monitoring. Excerpt from [10].

Strategy	Strength	Weakness	Opportunity	Threat
Long-term	Low uncertainty for average yearly value	Highly expensive and cumbersome	Generating noise maps; easily calculate annual uncertainty	Equipment calibration and maintenance; require central point for reporting and analysis
Short-term	Less expensive; re-use equipment for different sites	Moderate uncertainty; not fulfilling noise directives	Areas with steady traffic density; can replace long-term for some cases	High uncertainty when high variability in traffic; error ± 1 dBA < 90% probability
Temporary	Economical; less time consuming; moderate uncertainty with right approach	Serious error when varied traffic density; easily affected by anomalous events	Random strategy can be a good substitute for saving cost and time	Doubtful accuracy in some cases

In this research we adopt the three strategy categories presented in Table 2.5. We define them as follows: long-term measurements have a duration of minimum a year; short-term measurements have a duration of minimum a week; temporary samplings have a duration of less than a week; often less than a day.

Table 2.6 shows that most research concerns short-time and temporary strategies. Many of the temporary samplings were conducted during less than a day. Most of the selected research in the table were conducting temporary samplings, indicated by a T. A likely explanation for this convention is the cost involved with longer time spans.

Time Intervals

The time intervals used in a measurement is the basis for characterising the acoustic environment. More specifically, it is the duration of which chosen indicators are calculated for. Continuous measurements can be aggregated into 15 minute or 1 hour intervals, for example. If the sampling rate is low, the time interval may contain few samples to calculate the indicator from.

Brocolini et al. [120] discusses the choice of different time intervals of noise measurements, with the objective to find the minimal duration to give a representative result. They conclude that a sampling period of 10 minutes is a sufficient duration in almost all their tested contexts. In order to cover all the tested contexts, a duration between 10 and 20 minutes was sufficient. However, the variability of the noise will affect the required duration of such time intervals, and longer intervals than these may be needed.

Correspondingly, a guideline from The Norwegian Environment Agency (Miljødirektoratet) (NEA) suggests that a basis interval of 10 minutes should be sufficient for measuring noise from industry [121]. If the variability in noise levels is great, they recommend measuring 10 minute intervals several times, with at least 1 hour between them. For daytime, the recommended number of repetitions is minimum 5; for evening and nighttime the number is 3.

The most common time intervals shown in Table 2.6 is 1 hour, 15 minutes and 10 minutes. A majority of the state-of-the-art research do not mention the utilised time interval, only the indicator that was calculated. Others fail to address the choice of a utilised time interval. Thus, comprehending the choice of time intervals is a current challenge.

Indicators

Different indicators are used to describe the characteristics of noise. Many of the indicators presented in Section 2.1.5 has been applied in the research presented in Table 2.6. As we can see in the table, there is a great variety of utilised indicators. Very few justify their choice, but some are motivated by legality.

The END [25] requires the use of L_{den} and L_{night} , which is based on L_{Aeq} . Thus, most research on environmental noise and noise maps utilises these indicators. Bartalucci et al. [89] analysed the technical specifications of several smart, low-cost acoustic systems, and stated that all case studies used the indicators L_{Aeq} , L_{A10} , L_{A50} , and L_{A90} . From Table 2.6 we see that many of the projects employ the same indicators.

A growing amount of research employ the Zwicker method [37] and looks into binaural loudness. Many also include the L_{Amax} and L_{Amin} , to cover the extremities of the noise distribution.

Table 2.6: Technical details of research. The context and objective of the study, number of nodes used (if number of measurement points and available nodes are different, it is given as [no of points/no of nodes]), sampling rate and duration, time-span of the measurement (short-term [S], long-term [L], temporary [T]), and which indicators were measured. If several experiments were conducted in a paper, the details from each are given as [d1 & d2]. [N/A] indicates a missing detail in the research.

Ref.	Context	Objective	N° of points	Sampling Rate	Time-Span	Indicators
[32]	Urban	Implementation of WASN, source identification	56	Continuous	L	L_A
[96]	Urban	Implementation of WASN, noise map	2	1 s	L	L_{night}
[99]	Urban	Evaluate noise levels, noise map	99/25 & 11	Continuous	L	$L_{Aeq,1min}$, L_{AFmax} , $L_{Aeq,15min}$
[100]	Aircraft & Urban	Analyse noise pollution dynamics, noise map	350 & 45	1 s	S & L	L_{Aeq} , L_A
[102]	Urban	Implementation of WASN	78/39	3 h	S	$L_{Aeq,10min}$
[95]	Urban	Implementation of WASN, noise map	8	1 s	S	$L_{Aeq,1h}$, $L_{Aeq,month}$, L_{den} , L_{night}
[122]	Campus	Implementation of noise mapping system	735	1 min	S	L_{Aeq} , L_{peak} , L_{max} , L_{min} , $L_{n(percentiles)}$
[123]	Urban	Analyse noise pollution dynamics	3	1 h	T	SNR, $L_{Aeq,10min}$
[118]	Urban	Prediction, noise map	8/1	Continuous	T	L_{Aeq} , L_{min} , L_{max} , L_{A10} , L_{A50} , L_{A90}
[27]	Office & Urban	Evaluate annoyance model	4 & 5	1 s	T	SPL, binaural loudness & sharpness
[111]	Traffic	Implementation of WASN	3 & 5	Continuous	T	L_{Aeq} , L_A
[90]	Traffic	Simulation	35	N/A	T	$L_{Aeq,1h}$
[109]	Traffic	Categorisation of roads	58	N/A	T	$L_{Aeq,1h}$, L_{day}
[124]	Residential	Evaluate annoyance of traffic noise	75	Continuous	T	$L_{Aeq,15min}$
[30]	Residential	Design of sensor	1	5 s	T	$L_{Aeq,1h}$, L_A , L_{den} , L_{max} , L_{min} , L_{A10} , L_{A90} , binaural loudness

2.3 Technology

In this section we introduce the technology and tools used in the designed and implemented system for noise monitoring, presented in Chapter 6.

2.3.1 Libelium

Libelium [117] is a wireless sensor network platform provider. Libelium has a great deal of resources online: several guides and examples for programming using the Waspnote Pro Integrated Development Environment (IDE); documentation and technical guides for the Waspnote equipment; a forum for users, among other things. Their technology is open-source, and is intended to be easy to use. For this reason, it is a good option for IoT projects.

Libelium’s product line Waspnote Plug & Sense! [125] enables a plug-and-play approach, using the “black box” concept for their equipment. Consequently, the user is only required to create a program to perform the desired tasks, and upload the code to the equipment.

The equipment used in this thesis consists of two components; a Libelium Waspnote Plug & Sense! Smart Cities Pro [126] and a Libelium Noise / Sound Level Sensor [127]. They are connected as shown in Figure 2.3. Both are described in detail below.

Smart Cities Pro

The Smart Cities Pro mainly consists of a micro-controller board, an USB plug for power and data transmission, several socket plugs for sensors, an integrated SD card and an integrated battery. Moreover, there exists an optional external battery module that can be connected, or the device can be charged using solar panels. In addition, the device is sealed with warranty stickers. Thus, the Smart Cities Pro box should not be physically opened.

The Smart Cities Pro board can be programmed using the Waspnote IDE [128], which supports a C++-based language. The structure of the code, as described in the programming guide [129], consists of two basic functions: `setup()` and `loop()`. `Setup()` is run once on start-up, while `loop()` runs continuously. The initialisation is done in `setup()`, while the executing logic of the device is done in `loop()`. Furthermore, several libraries are available through the Waspnote Application Programming Interface (API).

To upload the program to the board, the user attaches an USB cable from the computer to the USB socket on the device. Thereupon, the upload button in the IDE is pressed and the code is compiled and uploaded. The program is then immediately



Figure 2.3: Equipment from Libelium. Waspote Plug & Sense! Smart Cities Pro with antenna (right) and Noise / Sound Level Sensor (left). Two other sensors are connected to the right side of the Smart Cities Pro in the illustration, but they are not used in this project. Taken from [4].

run by the device, and loops until it is powered off. Debug messages can be printed to the console in the IDE as long as the device is connected to the computer.

The device has a radio module providing Wi-Fi capabilities. The network standard used is IEEE 802.11b/g/n, with a frequency of 2.4 GHz. The enclosed antenna provides a range of 500 meters. The Wi-Fi PRO module supports both TCP and UDP, HTTP and FTP, among other protocols. It can connect to any standard router configured as an AP (access point), or send data directly to a web server.

Several sensor probes can be connected to the device simultaneously using the sockets. They are easily screwed into their allocated positions. Accordingly, the user can read out measurements from the sensors. In this thesis, only one sensor is used:

the noise level sensor.

Noise Level Sensor

The Noise Level Sensor probe has an omni-directional microphone that measures the noise level in decibels. In order to function, the sensor is depending on a power supply from an USB cable. The sensor follows the specifications of the IEC standard 61672 [36]. Furthermore, it has been calibrated in a test laboratory for accuracy, and a test report from the calibration is issued for every sensor.

The indicator measured is the A-weighted L_{Aeq} , and its time period can be configured for two different modes; FAST mode (125 ms) and SLOW mode (1 second). The accuracy of the sensor is ± 0.5 dBA, corresponding to the Class 2 devices in IEC 61672 [36]. The range of the sensor is 50 dBA to 100 dBA, and the microphone sensitivity is 12.7 mV / Pa. The frequency range is 20 Hz to 20 kHz, similar to the human hearing.

2.3.2 InfluxData

InfluxData [130] is a time series data platform provider, and we use their tools for data management. Their platform is built upon the TICK Stack [5], which is a set of open source projects: Telegraf, InfluxDB, Chronograf and Kapacitor. The architecture is shown in Figure 2.4. Only InfluxDB and Chronograf is used in this project.

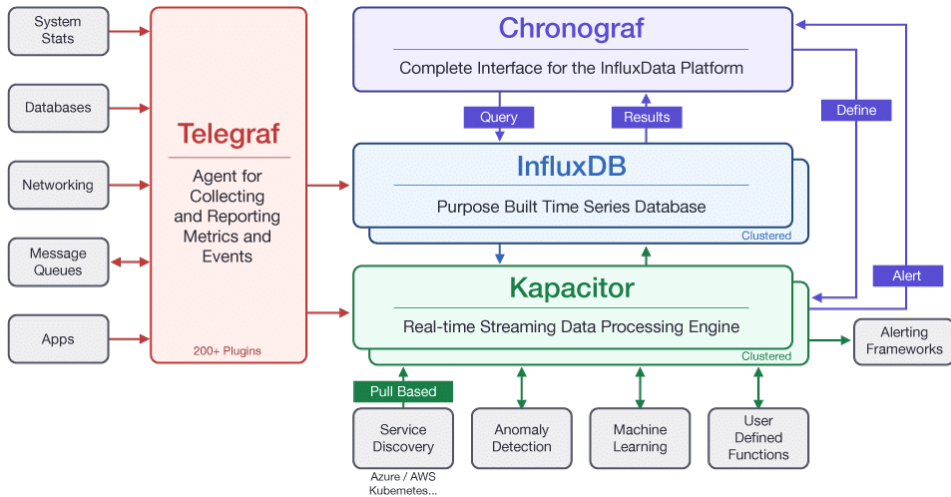


Figure 2.4: Architecture of the open source InfluxData platform, based on four open source projects collectively called the TICK Stack. Only InfluxDB and Chronograf is used in this thesis. Taken from [5].

InfluxDB

InfluxDB is a Time Series Database (TSDB) created by InfluxData. A TSDB is optimised for time-stamped data, and for measuring change over time [131]. It supports data life cycle management, performing operations on whole time series, conditional filtering based on time ranges or value ranges, time-stamp data compression, among other things.

Using a TSDB for an IoT project is advantageous, because of the capacity to handle great loads of data. If an IoT device measure a value every other second for a week, it would result in 302,400 measurements to store and manage. If we have five sensors, this adds up to 1,512,000 measurements. Even for such simple scenarios, the data amount quickly grows to become unmanageable if the right tools are not utilised.

Data is written to the database using the line protocol format [132], which has the following structure:

```
measurement-name,tag_set field_set timestamp
```

Both the tags and the fields are key-value pairs, and there is no limit to the amount of these in each measurement. Tags are optional, but recommended since they are indexed. The time stamp is in nanosecond-precision Unix time, and is an optional element. If no time stamp is given, it is set to the time the data is written to the database. The following is an example of such a line protocol:

```
weather,location=no,season=spring temperature=15 154929427104066029
```

InfluxDB queries are based on Structured Query Language (SQL), but with extended functionality tailored to time series data. The query language is called InfluxQL, and it is uncomplicated to start using for people familiar with SQL.

Chronograf

Chronograf is a visualisation tool that works “out of the box” with InfluxDB. Building a dashboard for InfluxDB is straightforward, both for local and remote databases. The user interface allows for effortless monitoring and setup of alerts and automation rules. There are several templates that simplify querying of the data. Figure 2.5 shows an example of a Chronograf dashboard.



Figure 2.5: View of the Chronograf dashboard. A query is submitted to InfluxDB, and a graph is plotted from the results. The time interval can be adjusted in the top right corner.

Chapter 3

Methodology

In this chapter we present and describe the utilised methodology. The title of this thesis indicates a *case study* on working environments, which we have limited to the domain of focused work. We do not have the time and resources to study the quality of all such working environments. Thus, we study a chosen working environment for focused work at the campus of NTNU called Koopen, which is presented more thoroughly in Section 4.1. Our aim is to generalise the results for other working environments for focused work with a similar noise distribution as Koopen.

A high-level overview of the methodology is shown in Figure 3.1, including research questions, main tasks and how the methodology is applied. The thick arrows represent the main flow of the methodology, while the thin arrows show the method that is used to conduct the given tasks for each step in the methodology.

Design science is the enveloping method, and we use three literature reviews and a case-based experiment in order to answer knowledge questions. We present the design science method and the main objective with this thesis more thoroughly in Section 3.1.

The first step in Figure 3.1 is to get an overview of the state-of-the-art research on noise monitoring. This is necessary to frame the scope of the thesis. Then, we answer RQ1, which involves defining user requirements for noise in working environments for focused work by the means of a literature review.

Based on these requirements, we proceed by answering RQ2 through another literature review. This involves selecting relevant metrics from related work, and composing a suite of metrics for noise monitoring that can help fulfil the user requirements. Moreover, we define new metrics based on the existing metrics, that can give additional information about the noise in working environments for focused work. We present these three literature reviews further in Section 3.2.

These technical requirements are then used in a case-based experiment to answer RQ3. We design a simple, “dumb” IoT system for noise monitoring in order to collect data for the experiment. We process and analyse the collected noise data to investigate the impact a simulated down-sampling has on the accuracy of the data. We explain the steps of this method in depth in Section 3.3.

Finally, we validate the results from this methodology and discuss the findings in a design science perspective. All the steps above form the product of this thesis, and we tie the results together in this last step.

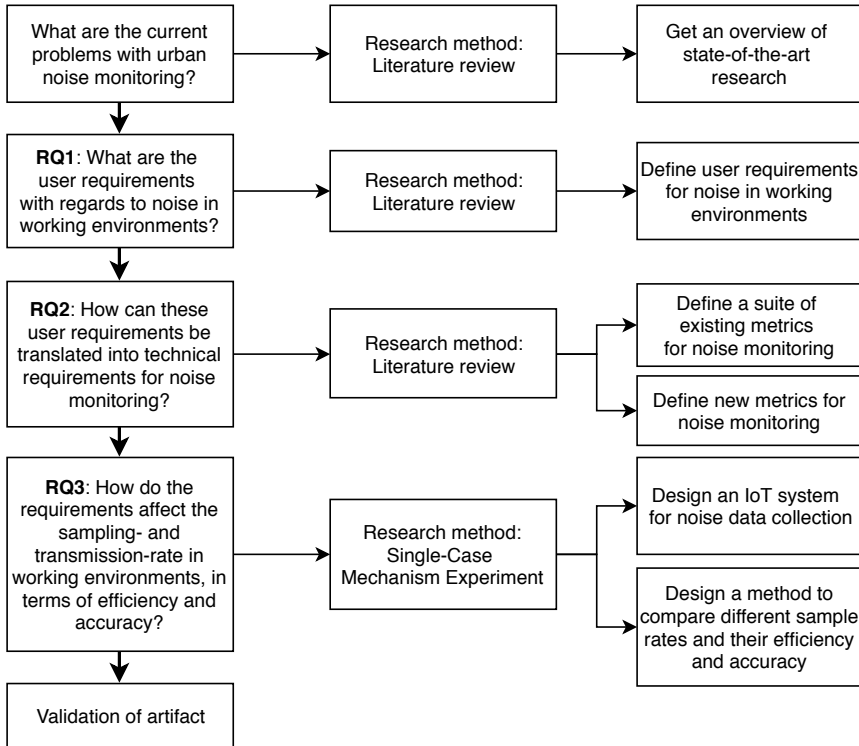


Figure 3.1: Overview of methodology. Research questions, methods & main tasks.

3.1 Design Science

In design science, the purpose is to design and investigate an artifact in context, with the focus on the interaction between the artifact and the problem context [6]. This methodology is well suited for this thesis; the context is working environments for focused work, and the artifact is *how noise is measured*. The artifact in this case is an abstract one: an imaginary, non-existing concept of how to measure noise in a specified context. The actual development of the real system is not part of this

thesis. Further in the thesis, we call the artifact a *system* for noise measurement. The aim is to improve something in the context; in this thesis we want to improve the measurement of noise in working environments. This represents a higher-level improvement goal of the research.

The aim with this methodology is not to find one single best solution, but rather to propose and study possible solutions to the problem of noise in working environments. Such solutions are commonly referred to as *treatments* in design science. In order to design our system, we need to answer a series of knowledge questions. They help define the system, by requirements such as user requirements, technical requirements and accuracy requirements. Consequently, we use an iterative process that consists of answering knowledge questions and adjusting the designed system accordingly. This process is illustrated in Figure 3.2, which shows a framework for the design science process.

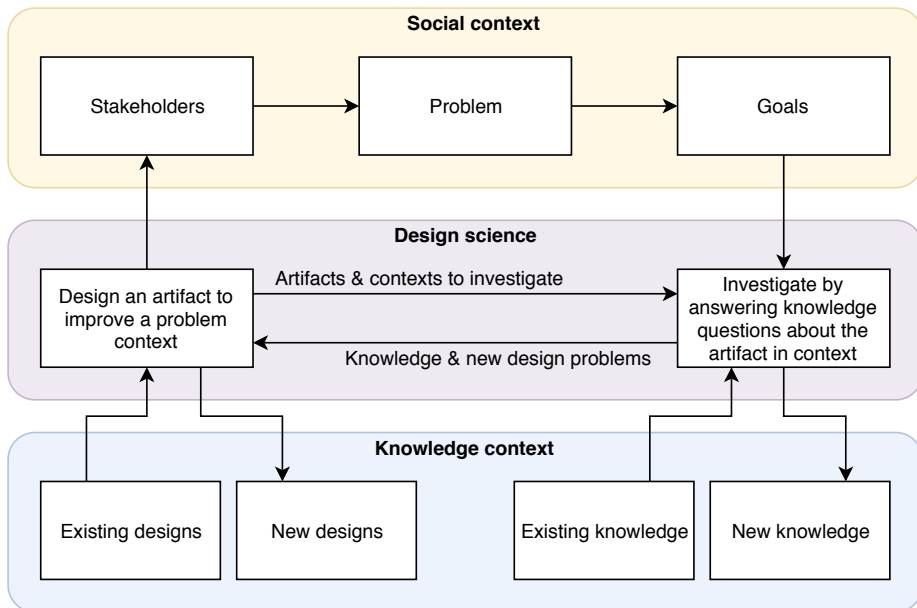


Figure 3.2: A framework for design science. Adapted from [6, p. 7].

The social context consists of stakeholders, their problem in the context and their goals. In this case, the context is working environments for focused work and a goal can be to perform concentrated work in the working environment. This part is covered further in Section 4.1. The knowledge context consists of existing knowledge on noise, noise monitoring, working environments, among other things. This part is covered in Chapter 2, Chapter 4 and Chapter 5 in this thesis through the literature

reviews. The design science process involves using input from the social context, existing knowledge and designs to produce new knowledge and new or improved designs through a design cycle.

This thesis represents one iteration through such a cycle, illustrated in Figure 3.3. The outcome from this iteration is a validated artifact design, which in this case is the abstract system for noise measurement. The step of treatment implementation is not conducted in this thesis, because it is part of a larger engineering cycle that is out of scope. The design cycle incorporates several empirical cycles, which are conducted when we need to answer knowledge questions. In Figure 3.1 the questions represent such cycles.

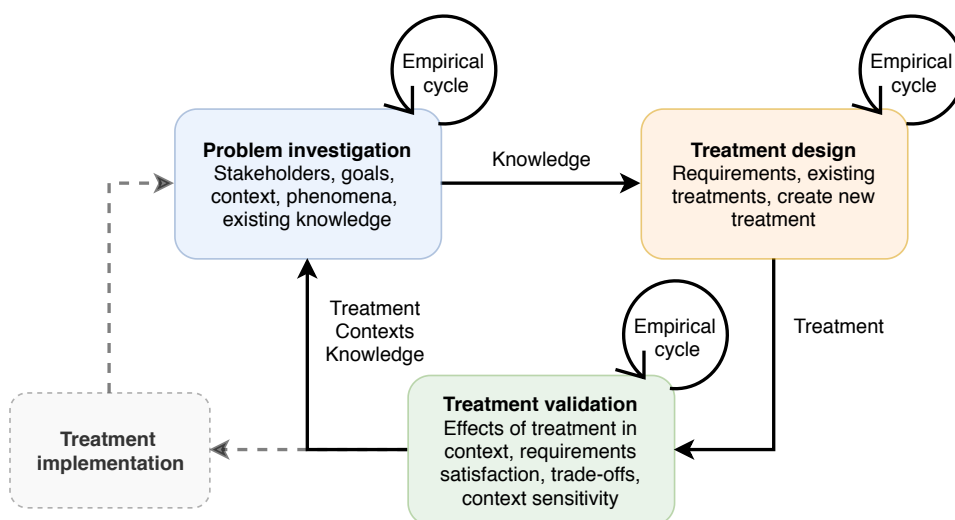


Figure 3.3: The design cycle. Adapted from [6, p. 28].

Our research questions give us an indication of what knowledge questions we need to answer. RQ1 and RQ2 implicates a design problem, while RQ3 is a more explicit knowledge question. To make it clearer, we decompose these research questions into several knowledge questions, which we will answer throughout this thesis in order to design our system for noise measurement:

RQ1: What are the user requirements with respect to noise for working environments?

- What do people find disturbing while they work?
- What actions are people required to perform while working?

RQ2: How can these user requirements be translated into technical requirements for noise measurement?

- What metrics represent the phenomena that people find disturbing while they work?
- What metric values represent the level of which people are able to work?
- What suite of metrics represent the soundscape in which people can perform the required work tasks?
- What are the accuracy requirements for the metrics?

RQ3: How do the requirements affect the sampling- and transmission-rate in working environments, in terms of efficiency and accuracy?

- How much can we down-sample, and still meet the accuracy requirements?
- Which metrics are more suitable for down-sampling?
- How efficient is the down-sampling of the metrics?

As presented in Figure 3.1, this thesis addresses two design tasks, to design the final artifact. First, we consider the design of an IoT system. This is not the main design task, and the IoT system is not the artifact in this thesis. It is merely a part of the validation step to predict how the artifact behaves in a working environment for focused work. The IoT noise sampling system acquires the data set to be used in the second design task from a selected working environment. The equipment is chosen based on availability, and consists of IoT technology from Libelium [117]. Five *Wasp mote Plug & Sense! Smart Cities Pro* [126] with Wi-Fi capabilities and five *Noise Level Sensors* [127] was used in combination with an *InfluxDB* [131] instance running on a virtual server. The IoT system is described further in Chapter 6.

Second, we conduct a Single-Case Mechanism Experiment (SCME) to compare different sampling rates and their efficiency and accuracy. In this step, we simulate a down-sampling of the collected data. This is done to predict how the sampling rate and transmission rate of a system can be manipulated in order to provide improved noise measurement. It represents the logic of the system; considering the accuracy of down-sampled measurements against the cost of sampling with a given rate. This method and its validation is explained further in Section 3.3, and is part of the artifact we design in this thesis.

Finally, we validate our results in order to show that our designed system, including the answers to our research questions, will contribute to the stakeholder goals when implemented in a working environment. The validation is done to predict how the artifact will interact in the context. The validation is performed before the implementation of the artifact, and represents the final step of this thesis.

3.2 Literature Reviews

Before designing the artifact, we conduct literature reviews. As stated by [133], an objective with the literature review is to provide general patterns in the previous work, and to identify key issues and gaps in the research area. To gain this knowledge, we found inspiration in the steps provided by [134]. The process consists of: selecting a review topic; searching the literature; gathering, reading and analysing the literature; writing the review; and providing references. Where it was possible, we used primary sources of information. This process was approximately followed for all three literature reviews. Despite our best effort to conduct broad and comprehensive literature reviews, there is still a risk of bias. If we have failed to consider important contradicting work, our results will be affected accordingly.

To get a deeper understanding of the state-of-the-art research in the field, we first conducted a literature review on topics such as urban noise monitoring, health effects of noise, IoT noise monitoring systems and WASNs. This method was a logical choice for this purpose, based on conventions in the field and the utility of a literature review when making comprehensive summaries of related work. The findings from this literature review are presented in Section 2.2 in Background and Related Work. This served as a foundation when we framed the research scope and defined the research questions.

Then, to define user requirements in Chapter 4 we conducted a literature review on topics such as office noise, noise in other related working environments and learning environments, and effects of noise on humans. It was essential for understanding what constitutes a “good” working environment, and what phenomena that causes disturbance when people do focused work. There also exist other methods available for this purpose, which we could have used. For example, it could have been interesting to conduct interviews with the users of the chosen working environment to define the user requirements. Then, we would have based the user requirements on real user needs in the context. However, this method was not chosen due to restrictions in time and resources. The user requirements are not the main contribution in this research, and we chose to rather prioritise the technical part of the thesis.

Finally, we did a third literature review to define the technical requirements in Chapter 5. We needed to understand how to translate the user requirements into measurable metrics, and how the values of these metrics would affect people. We chose this method because of the extensive research that has been performed in the field. The review covered topics such as subjective perception of loudness and annoyance, the performance and selection of metrics in different contexts, and analyses of sampling methodologies. Additionally, the literature review laid the foundation for defining new, composite metrics for noise measurement in working

environments for focused work. These technical requirements were then used as an analytical basis in the case-based experiment.

3.3 Single-Case Mechanism Experiments

SCMEs is a methodology within design science where we test a mechanism in a single case with a known architecture [6]. The aim is to investigate the cause-effect behaviour of the object of study; how a difference in an independent variable X has an effect on a dependent variable Y [6]. It is thus concurrently a single-case causal experiment. We chose this method because it fits well with our need to perform a trade-off experiment on cost and accuracy through a case study.

This method possess several limitations. The external validity is affected when we choose to do a case study on a single case; our results are less likely to be generalisable for other cases. As suggested by Willis [135], a single case study analysis' external validity is dependent on the selection of a proper case, the purpose of the case study, and the aim of generalisation. Another concern highlighted by Willis is the reliability and replicability of such a case study [135]. In this thesis, we have made a great effort to disclose all relevant information related to our data collection, data analysis, reasoning and potential errors and bias to improve the reliability and replicability. We regard these limitations as necessary trade-offs for this thesis, considering the limited time and resources at hand. The advantageous aspects of a case study outweigh these limitations, especially the resource economic aspect.

In this thesis, the single case is the noise in a selected working environment, and the investigated variables X and Y are the sampling rate and the accuracy, respectively. We reduce the data set collected by the IoT noise monitoring system, in order to simulate a reduction of the sampling rate, which is our independent variable. Each simulated sampling rate represents a cost for the noise monitoring; the more often we sample, the more expensive it is in terms of energy. We then do a trade-off analysis by comparing the accuracy of each simulated reduction and the cost of sampling, using a set of calculated metrics.

SCMEs require an experiment protocol and an experiment log. The experiment protocol should contain the description of the research context, the statement of the research problem, and the specification and validation of the research design. The experiment log should contain documentation of events during execution of the research, and details of the data analysis. Figure 3.4 illustrates the steps of the methodology.

For each step, [6] provides a checklist to use as a guideline when conducting the research. The checklist for each step can be found in [6, p. 247], and it is used

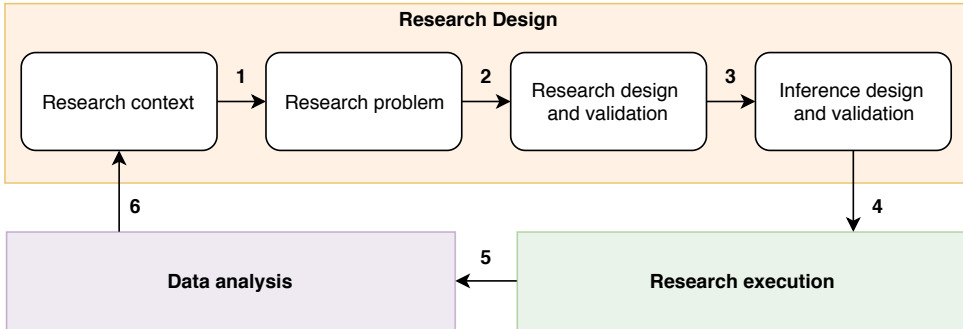


Figure 3.4: The steps of a single-case mechanism experiment.

selectively during the research process. The steps are presented briefly below.

Research Context

The research context step consists of knowledge goals, improvement goals and current knowledge. This was thoroughly covered in Chapter 1 and Chapter 2, but a brief summary is provided here. The knowledge goals is what we want to know from this research. In this thesis we would like to know if it is possible to measure noise more efficiently, and with sufficient accuracy, in working environments for focused work by applying the designed artifact. The improvement goal is part of a higher-level engineering cycle on noise measurement. The goal of that cycle is to improve noise measurement in urban environments, and we chose working environments for focused work as one possible urban environment to improve. We present the current knowledge in the field in Chapter 2, and cover acoustics, noise measurement, IoT and the technology required to perform the experiments.

Research Problem

The research problem consist of the conceptual framework, knowledge questions and sample population. We presented the knowledge questions above, as decomposed research questions. The conceptual framework is a set of concept definitions, which are used to define the structure of an artifact and the context [6]. We use the framework to frame the research problem, describe phenomena and analyse their structure [6]. It comprises the information presented in Chapter 2, the user requirements and the technical requirements we define.

The population in our case is the noise level samples that are collected in working environments for focused work using IoT systems. We took the samples from the real, continuous noise in the environments, and we define these samples as our new reality. The method for data collection is more thoroughly presented in Chapter 6.

Research Design and Validation

Research design and validation consists of objects of study, sampling, treatment design and measurement design. Validation of these items are based on the repeatability, inference support and ethics.

The object of study is the entity where the phenomena occur from which measurements are taken [6]. In our case, the object of study is the noise produced in the working environment for focused work. All noise that is present in the area is part of the working environment, and thus relevant objects of study. The people working in the environment, which we assume produce part of the noise, were informed of the data collection and provided with contact information if they had any questions or complaints. The validity of the objects of study is thus supported.

The sampling frame for the objects of study is the period of which the data collection was conducted. It consists of nine consecutive weeks in February, March and April 2019. If there are incomplete periods in the data set, these are removed. The remaining data set is then used as the study sample. Since this sample is tested under idealised conditions in a relatively small scale, it will not provide a realistic representation of the theoretical population. Thus, the results will most likely not be generalisable for all working environments.

The treatment design includes the choice of treatments, treatment instruments and how they are to be applied. Our treatments are several simulations of down-sampling, which will be performed using a Python script. We do these simulations on separate instances of the noise data set, which then is used in the measurement. The treatments are applied in Chapter 7.

The measurement design is the construction of how the down-sampled data is to be analysed. This includes what variables and metrics to compare, which are decided in Chapter 5. Measurements generate data from which we will draw inferences. In our case, this data will be used to discuss whether we are able to down-sample noise measurements and still get qualitatively good results. The measurements are conducted in Chapter 7.

Inference Design and Validation

In a case-based method such as SCME, we follow the inference steps illustrated in Figure 3.5 to draw conclusions. The inference design and validation consists of descriptive inference design, abductive inference design and analogic inference design.

The first step is descriptive inference, which concerns the presentation of data into aggregate forms such as tables and graphs that are easier to understand. It includes data preparation into a processable form, data interpretation into descriptions of

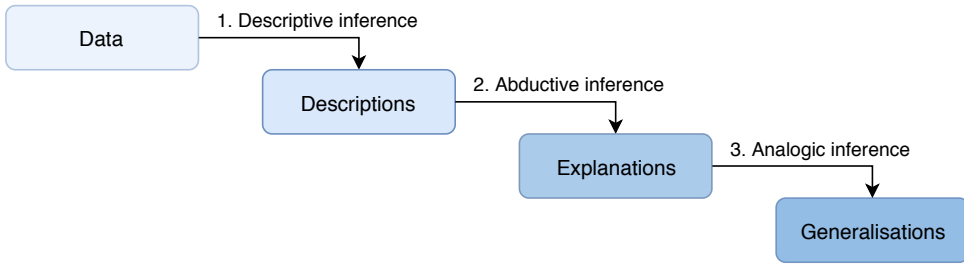


Figure 3.5: The steps of case-based inference. Adapted from [6, p. 117].

data, and description of data which gives statistical summaries of data [6]. The description validity is assured since we confirm that no information has been added to the original data we collected. In this thesis, we collect data into a database, which can then be queried in order to extract the data we need for calculations. We remove incomplete data periods, caused by errors in the data collection. This is necessary, since we are calculating average values over selected time periods. If there are only a few data points in a data set for a time period, it would give us inaccurate results. Selected statistics are calculated, such as error mean and variance. The results are presented graphically in Chapter 7.

The next step is abductive inference, which is the process of producing possible explanations of our results, and what data we might need to give those explanations [6]. A common type of reasoning within abductive inference is the causal inference. If one type of down-sampling performs better than the others, what could be an explanation? We conduct a controlled experiment where we only change one variable, which is the sampling rate. If the accuracy changes when we change our variable, we know that it must be the sampling rate reduction that is the cause of the change. Thus, we assume that our inference has a high internal validity.

The last step is the analogic inference, which aims to generalise the results from the object of study to other objects with similar architecture. In this thesis, our goal is to generalise for working environments with similar noise distribution as our case. We assume that when the architecture of the object is similar, similar phenomena will be produced by similar mechanisms [6]. The ability to generalise depends on how representative the noise in the chosen working environment is of the noise in the population, how similar the down-sampling is to sampling in the population, among other things. Due to restrictions in time and resources, we do not expect a high external validity. We will not generalise for noise in other contexts such as traffic or suburban areas, or working environments with a very different noise distribution.

Research Execution

The research execution addresses what happened during execution. This includes the collection of the noise data through the IoT system, and the application of down-sampling to the data. Unexpected events, failures and errors are also included. This step is covered in Chapter 6 and Chapter 7.

Data Analysis

Data analysis consists of applying the defined inferences. This includes descriptions of data from the descriptive inference, explanations from the abductive inference, generalisations from the analogic inference and answers to knowledge questions. Chapter 7 addresses this step, and Chapter 8 discusses the results and provides a summary of conclusions.

Research Context

Finally, we close the circle by discussing the implications for the context. This includes presenting new knowledge, need for further research, and the contribution to the knowledge goals and improvement goals of the research. This is covered in Chapter 8.

In this chapter we described the methodology used in this research, which consists of three literature reviews and a single-case mechanism experiment. In the subsequent chapters we present the results of these methods, including the definition of user requirements, technical requirements and the analysis of the simulated down-sampling of collected data.

Chapter 4

User Requirements for Noise Measurement

What makes a good working environment? Factors such as air quality, temperature, light and comfort will affect the experience of the working environment, but in this thesis we focus on the factor *noise*. In this chapter we present a definition of working environments and the chosen working environment. We then discuss related work and regulations on working environments, before we present a set of user requirements for further use. The requirements define user needs and which tasks users want to perform. These requirements define the part of *what we want to know* about the noise, which relates directly to RQ1.

4.1 The Working Environment

A working environment is a place where a task is completed. It consists of the physical geographic location and the immediate surrounding environment. It includes factors such as air quality, noise level, and physical equipment. In this thesis, we consider the noise level factor of a selected working environment for focused work.

A working environment for focused work can refer to the workplace of corporate employees, students, self-employed people, among others. Norwegian University of Science and Technology (NTNU) is a university with a great variety of working environments for both students and employees. They range from isolated offices and cubicles to open-plan offices and reading halls. One of the working environments is called Koopen, and in this section we present that area and its stakeholders as the chosen context of this thesis.

4.1.1 Koopen

Koopen is an area used by students at NTNU, primarily those attending the five year master's degree programme Electronics Systems Design and Innovation. Figures 4.1 and 4.2 show the working area. It consists of a variation of working stations allowing for many forms of learning. It is mainly composed of large tables for group

work. The room holds up to 80 people, and when tutoring is scheduled it is usually filled to its maximum capacity.

The ceiling is high, and apparently there has not been made any physical measures to improve the acoustics of the room. Consequently, the noise levels is perceived as quite loud when the room is occupied by many people. There are some shielding walls around the area, and some sofa blocks in the centre to separate work stations. Nevertheless, since the whole building has multiple open work areas that is used, the surrounding environment contributes with some additional noise.

Koopen was chosen for this case study because of its convenience and availability. The area is easily accessible if physical adjustments are required, and it is simple to get a visual overlook several times a day. Additionally, it is an interesting area to study as it enables a new, innovative form of learning called Team-Based Learning (TBL) [136]. This research contributes to an emerging field within education, by highlighting the importance of the noise factor in such working environments.



Figure 4.1: Koopen area in the Electro-building at NTNU. Taken from [7].

4.1.2 Stakeholders

A stakeholder of a problem is defined as “a person, group of persons, or institution affected by treating the problem” [6, p. 35]. *Treating* here refers to finding a solution to the problem. The solution need not be the most optimal one. Identifying the stakeholders is essential, since stakeholders have goals that affect the requirements of a solution of the problem. A stakeholder goal is defined as “a desire for which the stakeholder has committed resources” [6, p. 38]. Such resources can be money, time, energy, among other things.



Figure 4.2: Students working in Koopen. Taken from [8].

The main stakeholders in Koopen are the students using it as a working environment. The area is used for individual work, group work and to attend classes and lectures held there. The main goal of a student in Koopen is to study. Studying involves reading, writing, performing mental arithmetic tasks, discussing with co-students if necessary, among other things. In order to achieve this goal, Koopen must be a good working environment for students. Chapter 4 will go into what *good* means in this context.

Different students can have different goals, causing conflicts. If one student's goal is to read a book, and another student's goal is to discuss a problem in a group with other students, these two students' goals are conflicting. The first student requires silence in order to concentrate and read the book, and the other student is producing noise in order to fulfil his or her goal. Both of their goals cannot be fulfilled at the same time, and thus Koopen cannot be a good working environment for both of them at the same time. This is a challenge regarding working environments that needs to be addressed. By defining the user requirements in an unambiguous manner, such conflicts can be reduced. Yet, this may involve choosing between stakeholders.

Other stakeholders are any teachers using the area for lectures, and any student assistants helping with academic exercises and assignments. For these stakeholders, a goal may be to facilitate good learning in this environment. Koopen is apparently sometimes used for testing new learning methods such as TBL, and from this perspective Koopen must be a good place for group work. This goal may conflict

with some of the student goals.

The operator of the Koopen area, the Department of Electronic Systems (IES), is also a stakeholder. The department used resources building the area, thus it is reasonable to assume that they want Koopen to be used. Correspondingly, Koopen will need to be a good area to work in, in order to be used. This stakeholder goal therefore matches the above goals.

4.1.3 Use Cases

The schedule of Koopen is shown in Figure 4.3. The whole brief is enclosed in Figure A.1 in Appendix A. Some slots are reserved for courses, including both lectures and exercise sessions. In these time slots, TBL, group work and project work are conducted. In the remaining time slots, students can work as they desire. Thus, a variety of activities are performed in Koopen during a normal week. Between classes there are normally a 15-minute break, from the whole hour (xx:00) until 15 minutes past (xx:15). This activity variation will most likely influence our results, since the distribution of noise probably will be varying for the different activities. Because of the limited time and resources, we will only study the working environment as a whole. However, it could have been interesting to research the differences for the distinct activities.

	mandag	tirsdag	onsdag	torsdag	fredag
08:15			TTT4270	TTT4260	TTT4270
09:00					
09:15					
10:00					
10:15					
11:00					
11:15	TFE4172				
12:00					
12:15		TFE4172			
13:00					
13:15	TFE4260				
14:00					
14:15			TTT4146		
15:00					
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16:00					
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17:00					
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19:00					
19:15					
20:00					

Figure 4.3: Weekly schedule for Koopen, spring 2019. See Appendix A.

4.2 Hazardous Noise

As presented in Section 2.1.6, Directive 2003/10/EC defines European limits for noise levels in working environments. They base their limits on the hazard involved, more specifically the risk of hearing damage or other related health issues. The limits in the directive are defined to reduce hearing damage, and a hazard-free working environment should be the highest priority in any institution. However, for the focus of this thesis there is a need for additional lower noise limits in order to support concentrated work and an environment for learning.

4.3 Annoyance

An important aspect of concentrated work is the degree of annoyance. Several studies investigating annoyance have been carried out on working environments, indicating that it significantly affects the performance of work-related tasks.

A publication by the World Health Organisation (WHO) [11] on the health impacts of environmental noise included annoyance as one of the health effects. They estimated *disability-adjusted life years* (DALYs)¹ lost from environmental noise to be 654,000 years for annoyance in the EU member states and other western European countries. Consequently, this rates annoyance as one of the main burdens of environmental noise.

[12] highlights the health effects related to environmental and occupational noise. Two of the considered effects are annoyance and performance, related to occupation and school. Annoyance was rated the main psycho-social effect from exposure of occupational noise, based on population. They define annoyance as a “feeling of resentment, displeasure, discomfort, dissatisfaction, or offence when noise interferes with someone’s thoughts, feelings or actual activities” [12, p. 126]. The authors state that non-acoustical factors also influence the feeling of annoyance, of which it is difficult to understand the impact. Such factors could be the avoidability, predictability and subjective attitude toward the noise. Additionally, the character of the noise has an impact; for more constant sources such as fans, the annoyance is generally lower.

[137] looked into the effects of low-frequency noise on humans, which is commonly found in background environmental noise. *Low-frequency* is defined as frequencies below 250 Hz. They report that such noise often is judged as louder and more annoying than other noises with the same SPL, especially when coming from artificial sources. Moreover, annoyance is increased from rattle and vibration from low-

¹DALY: “The sum of the potential years of life lost due to premature death and the equivalent years of ‘healthy’ life lost by virtue of being in states of poor health or disability” [11, p. xiii]

frequency noise, for example as resonance in the body. [138] found that the main factor of annoyance is noise loudness. As a result of annoying noise, 61% of workers reported loss of concentration, 45% reported loss of productivity, and 31% reported difficulties in telephone conversation.

4.4 Cognitive Performance

In addition to being annoying, noise can affect the cognitive performance of humans. The concentration required to complete focused tasks is disturbed by noise, resulting in decreased performance. This has been reported by numerous studies, both in children and adults.

4.4.1 Children and Learning

[12] reports that noise can decrease attention to a task, evoke learned helplessness, change the strategy choice related to a task, among other things. The authors refer to studies of school children, which indicate that the exposure to high traffic noise impair the cognitive performance. Especially, the reading comprehension and long-term memory seems to be affected.

In a review of the effects of noise on children at school [139], the authors conclude that children are clearly affected by the noise. More specifically, the performance is decreased and the children experience annoyance. This was supported by their further work on the topic [140, 141]. In their more recent work [19], they took a closer look at noise in open-plan classrooms in primary schools. The study reported that noise in such areas is higher than in conventional classrooms, and that control measures are required to reduce distraction and annoyance caused by noise.

Similarly, [142] investigate the annoyance and effects of noise in student working environments. Both students aged 13-15 years old and teachers were included, and they found a significant correlation between rated annoyance and effect on schoolwork in students. The most annoying noise sources were identified as chatter from other students and scraping sounds from the furniture.

4.4.2 Working Environments

For the case of adults in working environments, we find comparable results to those presented above. [143] looks into the effects of the physical environment on job performance, and reports that noise is the most common source of discomfort and reduced productivity in open plan offices. She finds that functionally uncomfortable work spaces, such as noisy areas, is drawing energy from workers that would otherwise be spent on work. In her further work [144], she states that office workers are consequently dissatisfied with open-plan offices, partially because of disturbing noise

levels. Due to increased density in offices and collaborative work, the efforts to control office noise has been weakened.

Similarly, [145] investigate the indoor environmental quality of office work spaces, including acoustic conditions. The studied area comprised of open and closed work spaces and classrooms. All acoustic attributes were found to be significant contributors to the satisfaction of the overall acoustic condition. Furthermore, the noise in the open-plan offices were significantly higher than in the closed offices, and workers in the closed offices were on average more satisfied with their work space.

Another study on open-plan offices [146] focused on unattended background speech as a source of distraction. They concluded that room acoustic design decreasing the speech intelligibility did not sufficiently decrease the distraction caused by nearby speech. Speech still had undesirable effects on cognitive performance, both for short term memory and working memory tasks.

In the same manner, [20] investigates the effect of background noise on office-related tasks, namely memory regarding written material and arithmetic tasks. Speech was found to be severely disturbing for these two tasks, independently of the meaning of the irrelevant speech. General office noise was also rated as disturbing for performing both tasks. A study on acoustic satisfaction in open-plan offices [21] also highlights speech as the major noise problem, and emphasise the difficulty in masking such noise. These studies show that when performing intellectual work, there is a need for a quiet space in order to avoid disturbance, annoyance and reduced quality of the work performed.

4.5 Legislation

An important aspect of the user requirements is the legal rules that apply to working environments. The fundamental document is Directive 2003/10/EC on hazardous noise, as presented above. Another essential document is The Working Environment Act presented in Section 2.1.6. In addition to the protection against injuries, the act calls for a fully satisfactory soundscape. The meaning of *fully satisfactory* has to be judged based on subjective perceptions from those it may concern.

Furthermore, The Workplace Regulation demands that workplaces are designed so that work stations are protected from noise, and so that the alertness of employees are not reduced by noise. With regards to the Regulations Concerning Action and Limit Values, we can categorise people performing focused work, such as in a working environment, into Group I. They have high demands for concentration, and require few disturbances in order to perform their work sufficiently.

4.6 Proposed User Requirements

Summed up, we want a good environment for focused work and learning. Furthermore, we want to follow the legal rules that exist for environmental noise in this context. This entails certain requirements for background noise, distribution of noise and noise events. The proposed user requirements are as follows:

- **UR1:** The noise should not be hazardous to the hearing of the user
- **UR2:** Users should be able to work without being disturbed by noise events
- **UR3:** The background noise should not be disturbing to the user during concentrated work
- **UR4:** The general noise level should enable cognitive performance

In the next chapter, these requirements will be translated into a proposal for technical requirements. That includes what indicators to use, and what level ranges they should have in order to obtain certain labels of quality.

Chapter 5

Technical Requirements for Noise Measurement

In this chapter we translate the user requirements from the previous chapter into technical requirements. This task is directly related to RQ2. We present and discuss several noise indicators, and propose a suite of metrics for working environments.

5.1 Noise Indicators

From the user requirements, we have to choose representing indicators in order to provide the correct information to the users. More specifically, we need indicators that can describe noise events, background noise, and the general noise level.

A survey conducted in an air-conditioned office building [138] assessed the correlation between a selection of noise indices and the subjective sensation of loudness and annoyance. 11 indicators were considered, including the indicators L_{Aeq} , L_{A10} , L_{A90} , and the Zwicker loudness levels [37]. Due to equipment constraints in the current thesis, the Zwicker method cannot be taken into consideration. The study found that the indicator L_{A90} had the strongest correlation with perceived loudness and annoyance, followed by the indicator L_{Aeq} . L_{A10} also showed some correlation. In a later study [147], the authors used a new approach to assess the same correlation for 16 indicators. With the new method, they reported L_{Aeq} as the best correlated indicator for subjective auditory sensation of noise annoyance, loudness and dissatisfaction. Combined with the fact that the indicator is easy to measure, they recommend the A-weighted equivalent sound pressure as a reference index in noise measurements. The second best rated indicator was the L_{A5} , suggesting that people tend to be especially influenced by peaks of noise.

Similarly, [120] conducted a study on the selection of indicators to characterise the noise in a variety of areas, evaluating 11 different indicators. They concluded that the indicators necessary for characterising different homogeneous periods during a day were L_{Aeq} , L_{A10} and L_{A90} . These results suggest that the indicators L_{Aeq} , L_{A10} and L_{A90} can represent the subjective perception of noise sufficiently.

A study on the characterisation of quiet rural areas [148] classified the indicator L_{A50} as important for measuring the quality of soundscapes. This view is supported by [149], which states that the L_{A50} indicator correlates best with the overall perceived loudness in their study on urban areas. The authors create a new indicator based on L_{A50} and $L_{A10} - L_{A90}$ to describe the sound quality; more specifically the sound pleasantness. The indicator is defined as $SQ_{indicators} = 19.08 - 0.19 \cdot L_{A50} - 0.06 \cdot (L_{A10} - L_{A90})$. Thus, it takes both the general noise level and noise variability into account.

A similar, interesting indicator is the Noise Pollution Level (NPL), utilised by [150]. The authors define the indicator as $NPL = L_{Aeq} + (L_{A10} - L_{A90})$, which is commonly known as L_{NPL} . It is a variant of L_{Aeq} that takes the short-term variability of noise into account. There exists a second definition of the noise pollution level in [151], defined as $NPL = L_{A50} + (L_{A10} - L_{A90}) + \frac{(L_{A10} - L_{A90})^2}{60}$. Here, they describe the indicator as widely used for representing the perceived noise level from transient noise sources, taking the irritation from impulse noise into account. Both these definitions are expressed in dBA, and take the noise variability into the equation. Thus, they are relevant for working environments where this kind of noise can be highly disturbing.

$SQ_{indicators}$, NPL and L_{NPL} all describe a similar phenomena, thus we only choose one of them for this thesis. Since the $SQ_{indicators}$ has a numerical scale, it is more difficult to translate the accuracy requirements for the indicator. Both the NPL and L_{NPL} uses the dB scale, but since the NPL is more widely used, we choose it for our suite of metrics.

Another study looked into how different noise indicators performed in an office environment dominated by noise from speech [152]. From studying six landscaped offices and 9 indicators they found that the indicators *preferred noise criterion* (PNC) curve [153], L_{Aeq} and the noise climate ($L_{A10} - L_{A90}$) correlated best with the auditory sensation of the employees. Due to equipment restrictions, the PNC curve will not be included in this thesis.

As presented in Section 2.1.5, L_{A10} is a measure of the peaks of noise, and L_{A90} is a measure of the background noise. Thus, these two indicators are good choices for describing noise events and the general background noise. The choice is supported by the related work presented above. There are other options for similar measures, such as L_{A5} and L_{A95} , but they are not frequently used in related work. Likewise, the extremities L_{Amax} and L_{Amin} are not very interesting in this context. The more important aspects of the soundscape is already covered by the other indicators. We care more about the general noise level than specific values, which is why they are omitted.

To describe the general noise level, there are several options. The most used and researched indicator is L_{Aeq} , and is therefore a natural choice. The L_{A50} is the median of the noise, thus describing a type of average noise level, without accounting for the extremities. We choose to include this indicator because it adds interesting information about the soundscape. The variability of noise can be described by $L_{A10} - L_{A90}$, but it is not a widely used indicator. Nevertheless, it provides interesting information not accounted for by the other chosen indicators, and is therefore included. For focused work, a highly varying noise level can be severely disturbing. As stated by [154], there are not many other indicators that can give the same information as this indicator.

In summary, the chosen noise indicators for this thesis are L_{Aeq} , L_{A10} , L_{A50} , L_{A90} and $L_{A10} - L_{A90}$. In addition, we will look at the NPL, presented in [151]. These indicators cover the general noise level, background level and noise events.

5.2 Time Intervals

When selecting time intervals to study, the choices are numerous. As presented in Section 2.2.4, the commonly utilised time intervals in related work are 1 hour, 15 minutes and 10 minutes. In this section, we justify the choice of time intervals used in this thesis.

First, we consider the shorter time intervals. Using the narrow intervals $T = 1$ minute or $T = 5$ minutes would make it difficult to analyse the results over time. In addition, the likeliness of people working in the same place for more than 5 minutes is high. Thus, it is reasonable to assume that the differences between the intervals would be small.

On the other hand, choosing broad intervals such as $T = 12$ hours or $T = 24$ hours involves the risk of overgeneralising the noise distribution. We would lose a lot of information, and the evening and night time is not necessarily interesting in a working environment perspective.

The academic cycle divides an hour into two segments; work and break. Lectures and exercise classes start 15 minutes past every whole hour, and lasts until the next full hour, for a duration of 45 minutes. It is then followed by a 15 minute break until the next lecture starts. Due to this, it is natural to use an interval of $T = 15$ minutes when studying noise in a workplace like Koopen. This choice is supported by the conventions of state-of-the-art research in the field, as presented in Section 2.2.4.

In addition, it is interesting to look at a time interval of $T = 1$ hour. Since Koopen is largely used for individual work, it is not certain that the academic cycle

will apply to all time periods. For this reason, categorising a whole hour is potentially beneficial. Moreover, it could uncover additional patterns for working periods.

Another interesting choice could be the time intervals $T = 30$ minutes or $T = 20$ minutes. However, these intervals probably do not add any new information than the already chosen intervals $T = 15$ minutes and $T = 1$ hour. Therefore they are not chosen for this context.

A full work day can generally be represented through an interval of 8 hours. This time interval would apply strongly to the workplaces of employees, since they are very likely to work in the same place for 8 hours. The users of Koopen do not necessarily stay at the same work station for the whole day, due to lectures and other interrupting activities. Yet, it is still relevant to investigate a full work day, if any users should choose to sit in Koopen for a whole day. We choose to investigate the 8 hour time period between 08:00 and 16:00.

In summary, the time intervals $T = 15$ minutes, $T = 1$ hour and $T = 8$ hours are chosen for the case study on the working environment Koopen.

5.3 Quality Labels

In this section we propose two different sets of quality labels for working environments. The assigned labels represent information that stakeholders can use to make decisions about noise. In order to decide the quality of a measured time interval, each interval will be assigned labels depending on varying criteria. The criteria include noise limits for different indicators.

In addition, Axelsson [155] discusses how to measure the quality of a soundscape. He argues that it is advantageous to include the appropriateness of a soundscape, rather than just rating it as good or bad. The recommendation of Axelsson is to rate the quality of a soundscape based on *pleasantness* and *eventfulness*, and to include the appropriateness in the review. The labels in this section are thus given based on appropriateness for a working environment, and the indicators that are chosen describe both the pleasantness and the eventfulness of a soundscape.

The first set of labels consists of three labels, shown in Table 5.1. The three labels describe the most essential information; is the area a good, fair or poor working environment? It does not say how good or how poor it is, thus providing a rather simple classification.

The second set of labels consists of five labels, shown in Table 5.2. This adds further depth to the labelling, showing more clearly the extremes of the noise. As a result, time periods that are ideal or damaging to hearing can be uncovered.

Particularly, the hazardous label can be helpful in identifying working environments that violates the laws regarding noise limits. It covers UR1, which the first set of labels does not. Additionally, this set describes better the appropriateness of the working environment.

Table 5.1: First set of labels for focused work. Description of three quality labels.

Quality	Description
Good	A fit working environment. Little disturbing noise, low background noise.
Fair	An acceptable working environment. Tolerable disturbing noise, moderate background noise.
Poor	An unacceptable working environment. Loud disturbing noise, high background noise.

Table 5.2: Second set of labels for focused work. Description of five quality labels.

Quality	Description
Excellent	The ideal working environment. Very little disturbing noise, very low background noise.
Good	A fit working environment. Little disturbing noise, low background noise.
Fair	An acceptable working environment. Tolerable disturbing noise, moderate background noise.
Poor	An unacceptable working environment. Loud disturbing noise, high background noise.
Hazardous	A working environment damaging/harmful to hearing. Very loud disturbing noise, very high background noise. Should be avoided at all cost.

5.4 Indicator Ranges

When deciding on the label ranges for the different indicators, it is important to understand which corresponding values that are good or poor. The related work presented below helps with this comprehension.

[12] report that when the equivalent sound level in offices is above 55 dBA $L_{Aeq,8h}$, office workers tend to be considerably annoyed by the noise. The annoyance increases significantly for noise levels from 55 to 60 dBA. For noise sources that are constant, the tolerance is higher than a $L_{Aeq,8h}$ of 55 dBA. They also reported that school children experience cognitive impairment from noise levels above 70 dBA $L_{Aeq,schoolhours}$.

[21] investigates the relationship between sound characteristics and acoustic satisfaction in open-plan offices. Their results showed that workers reported decreased acoustic satisfaction when noise levels exceeded 45 dBA. Conclusively, they argue that

acceptable acoustical conditions should have average noise levels, L_{Aeq} , of around 45 to 50 dBA.

Background noise is also a disturbing factor for focused work if it is too loud. [19] presents several studies suggesting that the background noise in schools and teaching areas should be kept between 55 dBA and 65A dB at a maximum, but levels below 55 dBA are preferable. We assume that this apply to the indicator L_{A90} . The same paper presents an overview of recommended noise limits for ambient noise in open plan classrooms in Denmark, Sweden, England and Wales, which lies around 30 to 40 dBA. For children in primary and secondary school, a suggested recommended upper noise limit for background noise is 35 dBA $L_{Aeq,30min}$ for unoccupied classrooms [140].

In [138], they reported that workers found the noise loud for levels above $L_{Aeq} = 49$ dBA, $L_{A10} = 51$ dBA and $L_{A90} = 45$ dBA. Moreover, workers found the noise annoying for levels above $L_{Aeq} = 55$ dBA, $L_{A90} = 48$ dBA. In a later study [147] with a new method, the authors reported that workers now experienced the noise as annoying for levels above $L_{Aeq} = 54$ dBA and $L_{A5} = 58$ dBA. Regarding the loudness, a level of $L_{Aeq} = 52$ dBA was found moderately loud. Additionally, this study introduced the factor of dissatisfaction; a moderate dissatisfaction was reported for levels above $L_{Aeq} = 55$ dBA and $L_{A5} = 59$ dBA.

From Directive 2003/10/EC [45] we can assume that a level above 80 dBA over time generally involves a risk of hearing damage. Therefore, during a full work day a worker should not be exposed to noise levels equivalent of $L_{Aeq,8h} = 80$ dBA. This limit can be converted to shorter time periods using a 3 dB exchange rate, as explained in Section 2.1.1. However, precautions should be made to avoid harm in such working environments. We are therefore encouraged to keep noise limits even lower than the stated levels in the directive.

The noise variability, $L_{A10} - L_{A90}$, can be evaluated based on the information presented in Section 2.1.1. A change of +10 dBA will, as stated, be experienced as a doubling of the loudness of sound. A change of ± 3 dBA is barely noticeable, but represents the doubling of the sound intensity. A ± 5 dBA change is clearly noticeable. Finally, a change of ± 6 dBA equals a doubling of the SPL. Thus, a variability of ± 3 dBA should be acceptable, while a variability of ± 10 dBA is likely to be perceived as highly disturbing. If we were to combine the results of L_{A10} and L_{A90} from [138], and calculate the level of which the variability would be perceived as loud, we would get a value of $51 - 45 = 6$ dBA.

With these results in mind, we create a suite of metrics for the chosen indicators. In the next section we define the technical requirements to be used in the analysis.

5.5 Suite of Metrics

Based on the user requirements and the preceding sections, we propose a suite of metrics below. The suite can be used as a tool when measuring noise to categorise good and poor intervals for working environments. More specifically, this suite of metrics is designed for student working environments like Koopen. Consequently, separate ranges may apply to different types of working environments; this suite must be applied with caution for other contexts.

In addition to the standard indicators, we include the NPL as defined in [151]. Based on the ranges of $L_{A50,15min}$ and $L_{A10} - L_{A90,15min}$, the quality range for the NPL over a 15 minute interval is calculated and presented below. The two proposed suite of metrics are shown in Tables 5.3 and 5.4. The ranges are expressed in dBA, and indicate the quality of the working environment within an interval.

Table 5.3: Suite of metrics 1. Indicators and their corresponding range in dBA for all 3 quality labels.

Indicator	Good	Fair	Poor
$L_{A10,15min}$	< 50	[50, 60]	> 60
$L_{A50,15min}$	< 45	[45, 55]	> 55
$L_{A90,15min}$	< 42	[42, 52]	> 52
$L_{Aeq,15min}$	< 47	[47, 57]	> 57
$L_{Aeq,1h}$	< 45	[45, 55]	> 55
$L_{Aeq,8h}$	< 43	[43, 53]	> 53
NPL_{15min}	< 48	[48, 61]	> 61
$L_{A10} - L_{A90,15min}$	< 3	[3, 5]	> 5

Table 5.4: Suite of metrics 2. Indicators and their corresponding range in dBA for all 5 quality labels.

Indicator	Excellent	Good	Fair	Poor	Hazard
$L_{A10,15min}$	< 40	[40, 50]	[50, 61]	[61, 85]	> 85
$L_{A50,15min}$	< 35	[35, 45]	[45, 56]	[56, 82]	> 82
$L_{A90,15min}$	< 32	[32, 42]	[42, 53]	[53, 79]	> 79
$L_{Aeq,15min}$	< 37	[37, 47]	[47, 58]	[58, 85]	> 85
$L_{Aeq,1h}$	< 35	[35, 45]	[45, 56]	[56, 79]	> 79
$L_{Aeq,8h}$	< 33	[33, 43]	[43, 54]	[54, 70]	> 70
NPL_{15min}	< 37	[37, 48]	[48, 61]	[61, 93]	> 93
$L_{A10} - L_{A90,15min}$	< 2	[2, 3]	[3, 5]	[5, 10]	> 10

Moreover, we compose a new indicator that combines the quality of three indi-

cators; L_{Aeq} , L_{A10} and L_{A90} . It describes the quality of the working environment for focused work, and is included in the suite of metrics. This composite indicator, hereafter called the Composite Quality Indicator (CQI), is defined in Table 5.5 and Table 5.6, corresponding to each suite. For the three-labelled suite, if the working environment is to be categorised as *good*, at least two indicators must be within the stated range. If any of them is rated as *poor*, the CQI will be rated as such; this rule overrides all other rules. Otherwise, the indicator will be rated as *fair*. For the five-labelled suite the same applies, but the label *hazardous* has the highest priority. The *excellent* label requires two of the indicators to be rated as *excellent*. Additionally, if one indicator is rated as *good* and one as *excellent*, the CQI is rated as *good*.

Table 5.5: Three quality labels of the Composite Quality Indicator (CQI_{15min}), based on three 15-minute interval indicators. The requirement in parenthesis state the number of indicators that must fulfil a category for the CQI to be rated in that category. The category *poor* overrides all other rules.

Good (at least two)	Fair	Poor (at least one)
$L_{A10} < 50$	$L_{A10} \in [50, 60]$	$L_{A10} > 60$
$L_{A90} < 42$	$L_{A90} \in [42, 52]$	$L_{A90} > 52$
$L_{Aeq} < 47$	$L_{Aeq} \in [47, 57]$	$L_{Aeq} > 57$

Table 5.6: Five quality labels of the Composite Quality Indicator (CQI_{15min}), based on three 15-minute interval indicators. The requirement in parenthesis state the number of indicators that must fulfil a category for the CQI to be rated in that category. The category *hazardous* overrides all other rules, followed by *poor*. The category *good* is also valid if one label is *excellent* and one is *good*.

Excellent (at least two)	Good (at least two)	Fair	Poor (at least one)	Hazardous (at least one)
$L_{A10} < 40$	$L_{A10} \in [40, 50)$	$L_{A10} \in [50, 61)$	$L_{A10} \in [61, 85]$	$L_{A10} > 85$
$L_{A90} < 32$	$L_{A90} \in [32, 42)$	$L_{A90} \in [42, 53)$	$L_{A90} \in [53, 79]$	$L_{A90} > 79$
$L_{Aeq} < 37$	$L_{Aeq} \in [37, 47)$	$L_{Aeq} \in [47, 58)$	$L_{Aeq} \in [58, 85]$	$L_{Aeq} > 85$

5.6 Accuracy Requirements

As presented in Section 2.1.1, the smallest change in noise a human can sense is generally defined as ± 3 dB. A change of ± 5 dB is generally clearly noticeable, while a change of $+10$ dB is perceived approximately as a doubling of the loudness. Thus, any errors under ± 3 dB can be categorised as acceptable, seeing that it is approximately unnoticeable for humans.

Accuracy requirements can be of varying precision. Table 5.7 shows an overview of different accuracy levels, based on conventions from state-of-the-art research in the field. These requirements act as a part of the suite of metrics in the analysis. Depending on the stakeholders' desired accuracy, the results will be different.

Table 5.7: Three accuracy levels.

Accuracy	Absolute error
Acceptable	< 3 dB
High	< 2 dB
Very high	< 1 dB
Particularly high	< 0.5 dB

In this chapter we defined a set of technical requirements based on user requirements. These will be studied in the trade-off analysis in Chapter 7, but first we present the method of data collection. The analysis will be based on noise data from the chosen working environment, and in the next chapter we describe the simple IoT system we designed and implemented for this purpose.

Chapter 6

Design of a Simple Noise Measurement IoT System

To collect noise data for the analysis in the SCME, we designed a system using the available equipment in the IoT lab at the Department of Information Security and Communication Technology (IIK) at NTNU. The system consists of equipment from Libelium, as described in section 2.3.1, an InfluxDB instance as described in section 2.3.2, and a router. The design and implementation of the system is described in detail below, along with ethics concerning the data collection.

6.1 Hardware

We had five Libelium devices available for this thesis. Each device consists of two components; a Libelium Waspnote Plug & Sense! Smart Cities Pro and a Libelium Noise Level Sensor. They are connected as shown in Figure 2.3 in Section 2.3.1. Both components are connected to power via USB ports, although the Smart Cities Pro has a limited battery integrated. The Wi-Fi module drains quite a bit of battery from the device, both when idle and when sending data. For convenience, we use a continuous power supply to avoid the device running out of battery. Further on in this work, we refer to the device consisting of the two components as a *Waspnote*. Additionally, we installed a Cisco router in Koopen to connect the Waspnotes to Wi-Fi. The router forwards data from the Waspnotes to the database.

A limitation of the noise sensor is the poor sensitivity to lower noise levels. As stated in Section 2.3.1, the calibrated range of the sensor is 50 to 100 dBA. Although the sensor can read lower levels, the uncertainty of the readings is higher. Due to the scope of this thesis it is not a major issue; we do not care specifically about the accuracy of each reading, but rather about the quality of the soundscape. Nevertheless, since we do not obtain very low noise readings in the data collection, it will affect the number of time intervals categorised with the quality label *excellent* as defined in Chapter 5. For further work on working environment noise we recommend using a noise sensor with a broader decibel range; especially for lower noise levels.

6.2 Software

We program each Wasmote to read the noise level every other second, and send the reading over Wi-Fi using User Datagram Protocol (UDP) to a central database. Due to practical reasons we chose UDP as the communication protocol, but it also involves an increased risk of data loss. Each reading has a tag with a time stamp and an identifier to indicate which sensor it came from. To reduce the number of transmissions, we sent the readings in bulks of four. Due to memory constraints in the Wasmotes, it was not possible to send larger bulks of data. In addition, the Wasmote micro-controller does not support multitasking, thus it cannot send and measure noise data simultaneously. Consequently, we will in practice lose some data points because of the data transmission.

Another limitation of the Wasmote is the lack of informative error messages. When the Wasmote occasionally fails, finding the cause is a challenge. Thus, we have to accept some failures during the data collection period. By experience, the problems are generally solved by a hard restart. Since all five nodes were installed, the resilience to handle errors if a Wasmote fails is higher.

All five Wasmotes send the data directly into the UDP API of the database, using the line protocol format. The database is an InfluxDB instance, run on a virtual server at NTNU. We chose Chronograf to visualise the data due to its seamless integration with InfluxDB, as shown in Figure 2.5 in Section 2.3.2. The visualisation was mainly used to check the data along the way during the collection period.

6.3 Physical Setup

An overview of the setup in Koopen is illustrated in Figure 6.1. It shows the placement of the components in the physical area. We spread the Wasmotes out to cover a broad area of Koopen, while being restricted to the available installation spots. Each Wasmote has a physical label with a number corresponding to the number in the overview.

Figure 6.2 shows the actual setup in Koopen for one of the Wasmotes. We installed the Wasmotes approximately 2.5 meters high above the ground, mainly to be out of the way from the whiteboards installed on the wall. The height of the sensors affect the read noise value, and they should preferably have been closer to the noise source. Due to restrictions in the physical area it was not possible in this project.

We attached an information note by each sensor, to inform the users of Koopen about the project and privacy concerns. The note is attached in Appendix B. This note may have affected the behaviour of the users, by giving them a feeling of being

“watched”. It may have affected the data we collected, if users produced higher or lower noise levels than usual. We assume in this thesis that it is not the case, since the monitoring period was nine weeks. Users are likely to forget about the equipment during this time. Besides, it is not significant for our experiment, since we define the collected data as the true value. Additionally, there is other monitoring equipment in the area from previous experiments, thus we assume that the users are used to these kind of studies.

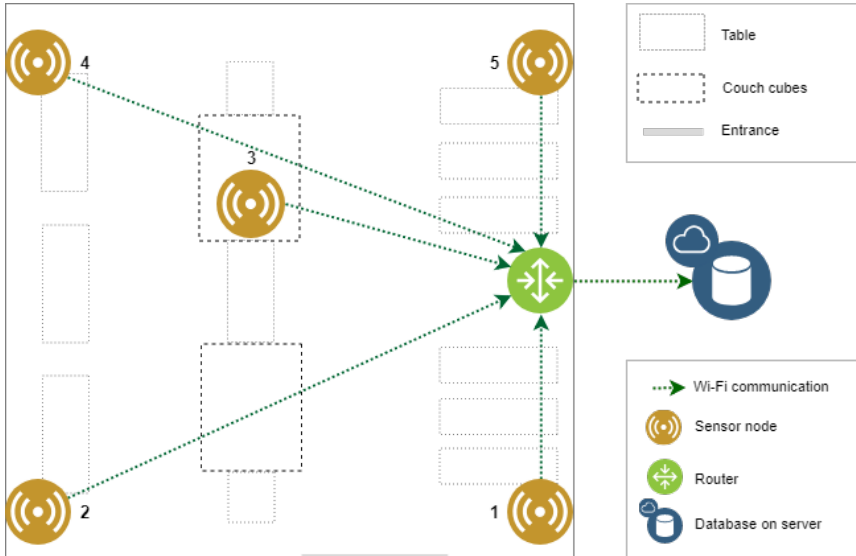


Figure 6.1: Setup in Koopen. Five sensors, one router and a central database is connected through Wi-Fi over the organisational network Eduroam.

6.4 Ethics

We recorded no personal information during this project; only numerical noise level values were collected. This was confirmed by the Norwegian Centre for Research Data (NSD) and the Norwegian Data Protection Authority (Datatilsynet). E-mail correspondence with the Norwegian Data Protection Authority on the issue is attached in Appendix C. NSD offers a chat service on their website, and through this service they confirmed that we do not process any personal information in this thesis.

The users of the working environment were informed about the privacy concerns through the information note. They were provided with a way to contact us if they had any questions or complaints about the project.

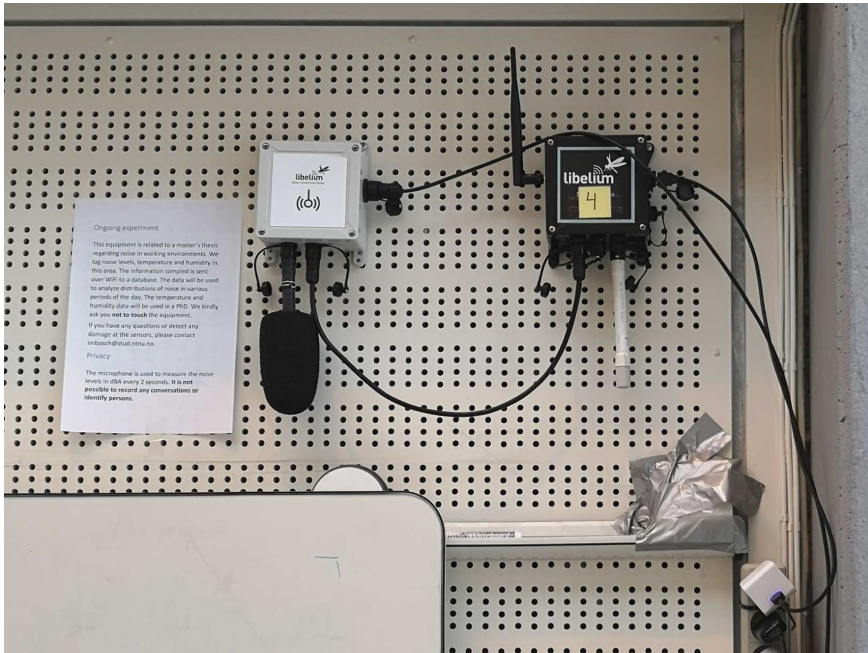


Figure 6.2: Setup in Koopen for node 4. An info note and the Wasp mote is attached to the wall. It is connected to power through a power socket.

In this chapter we explained how we collected the noise data from the chosen working environment. Next, we use this data to perform a trade-off analysis through a SCME, based on the requirements defined in the previous chapter. After the analysis, we will discuss the results in Chapter 8.

Chapter 7

Trade-Off Analysis

In this chapter we present the results from the trade-off analysis from the single-case mechanism experiment. The results will then be discussed in Chapter 8. The data is from sensor 3, which was the most stable Waspnote. The data basis is noise data from nine weeks, through February, March and April 2019. We removed the weekends and nighttime from the data set, since they are not considered relevant for working environments. We are only interested in the time period where the users are working, which we define as the time period 06:00 - 21:00. Students tend to have a variation in working hours, which is why we define such a broad period.

The time in Norway was moved one hour forward for daylight saving time during the data collection. We did not adjust for this in our data, because it does not have a significant impact on our results. We could have adjusted the time frame for analysis accordingly, but we chose not to. We define the truth of our data, and thus should any possible influence be small. This effect can be seen in the last week (week 14) in the visualisation of the true data, in Figure 7.1, Figure 7.2, Figure 7.6 and Figure 7.7.

After removing incomplete data intervals, we compared accuracy and cost using simple statistical analysis to make inferences from the data. The cost is represented in terms of sampling rate, and we assume that a twice as high sampling frequency equals twice the energy consumption, excluding other factors than the sampling. This means that a sampling rate of 4 seconds costs half of what a sampling rate of 2 seconds costs. We define the full data set as the *true* value of the noise. The accuracy is then compared by calculating the difference between the true value and the simulated down-sampling, in terms of error.

In the following sections we explain how we conducted the down-sampling, and we present the results from the simple statistical trade-off analysis. This includes the calculation of root mean squared error and variance for each indicator, the distribution of assigned labels, and the error in the label assignment.

7.1 Reducing the Sampling Frequency

The full data set was collected by sampling the noise level every other second, as described in Chapter 6. To simulate the reduction of sampling rate, we use a Python script that selects every X th sample from the full data set and creates new, reduced data sets. Ideally, this selection process should be random, to get a representative sample when the data basis becomes smaller. For this thesis we argue that the selection process is sufficient, due to the large amount of data combined with random data loss from the system.

Data was reduced by the rate shown in Table 7.1, which form the basis for further analysis. The reduced sets are compared to the full data set, as estimated values compared to a true value. Further on in the thesis, we denote the sets by their sampling rate. In example, using every 30th sample in the data set corresponds to a sampling rate of 1 minute. Then, the data basis for analysis on a 15 minute interval is in theory 15 samples. Due to the limitations mentioned in Chapter 6, the basis will in some cases be smaller. Intervals with a too thin data basis was removed from the set, since they likely would produce errors.

Table 7.1: Reduction of data set. The drawn samples, the corresponding simulated sampling rate, and the data basis for a 15 minute, 1 hour and 8 hour interval (number of samples/interval).

Sample drawn	Sampling rate	/15 min	/1 hour	/8 hours
All	2 sec	450	1,800	14,400
Every 2nd	4 sec	225	900	7,200
Every 5th	10 sec	90	360	2,880
Every 10th	20 sec	45	180	1,440
Every 15th	30 sec	30	120	960
Every 30th	1 min	15	60	480
Every 60th	2 min	7.5	30	240
Every 90th	3 min	5	20	160
Every 150th	5 min	3	12	96
Every 225th	7.5 min	2	8	64
Every 450th	15 min	1	4	32

7.2 Accuracy of Indicators

Based on the full data set we calculated the Root Mean Squared Error (RMSE) of the reduced data sets, to investigate the indicator accuracy when the sampling rate was reduced. First, we present a visualisation of the true data for all the indicators. Then, the RMSE is visualised in a table and several plots.

7.2.1 The True Data

The numerical values for the complete data sets of all the 15-minute indicators are shown in Figure 7.1 and Figure 7.2. The plots illustrate the soundscape to give a better understanding of the actual noise. The white fields represent missing data.

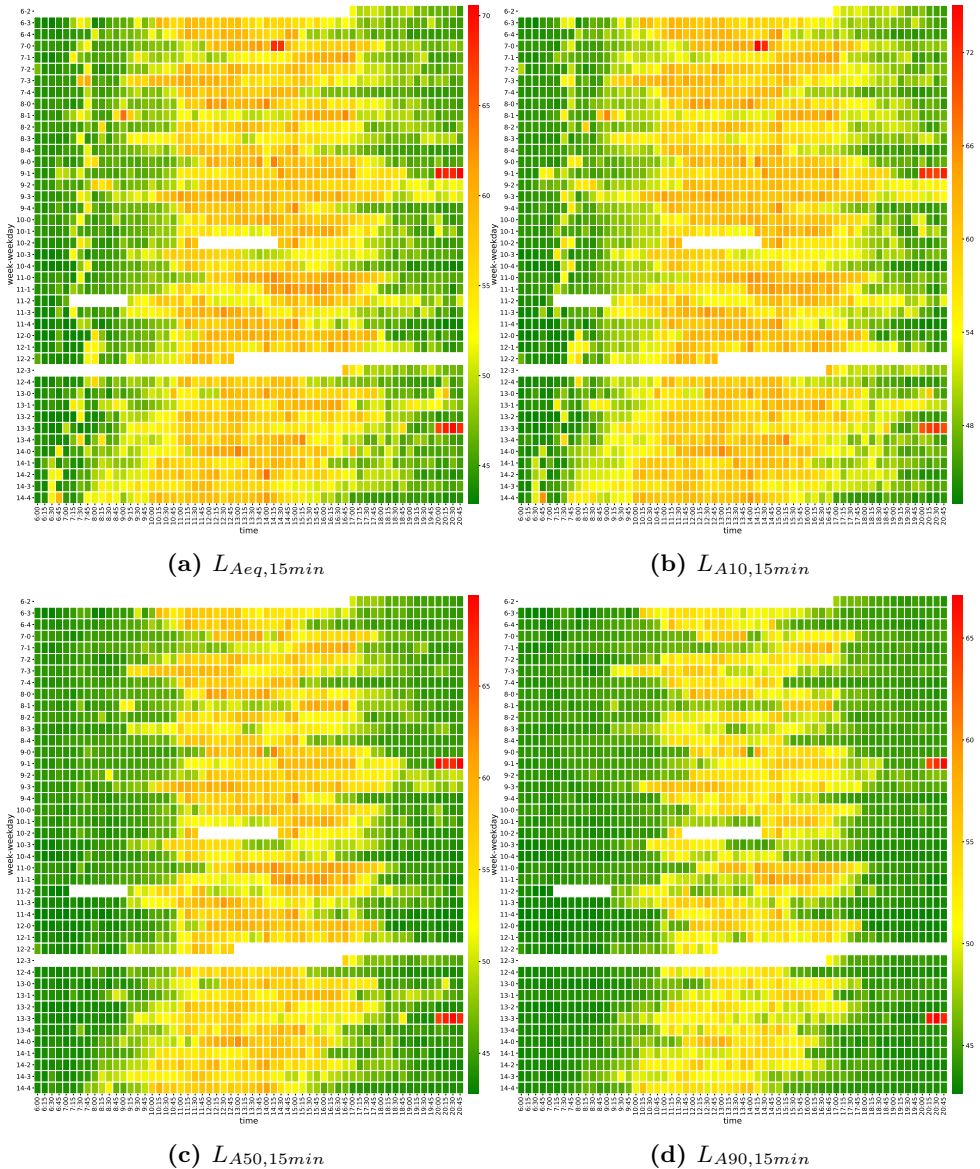


Figure 7.1: The numerical values for 15-minute intervals for the nine weeks of data, for four indicators. Each line is one day, labelled “week-weekday” (0 = Monday).

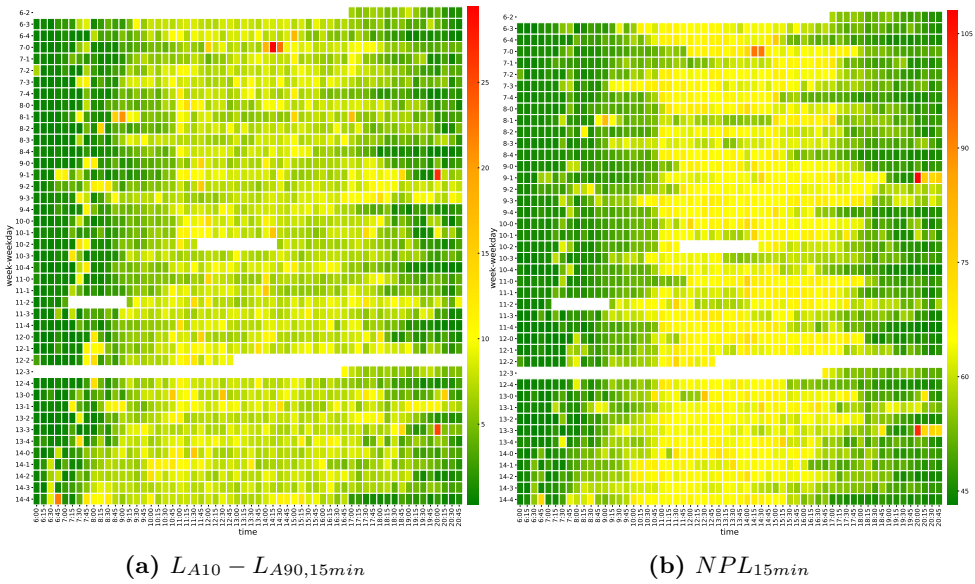


Figure 7.2: The numerical values for 15-minute intervals for the nine weeks of data, for two indicators. Each line is one day, labelled “week-weekday” (0 = Monday).

7.2.2 Root Mean Squared Error

The RMSE is the root of the Mean Squared Error (MSE), which indicates how different the estimated values of a calculated indicator are from the true value of an indicator. Thus, it is a measure of the quality of the estimator of an indicator, where values closer to zero are better. The MSE is calculated by formula 7.1:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \tilde{y}_i)^2 \quad (7.1)$$

where n is the number of intervals, y is the true value for interval i , and \tilde{y} is the estimated value for interval i . Thus, the RMSE is defined as follows, expressed in dB:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum_{i=1}^n (y_i - \tilde{y}_i)^2}{n}} \text{ dB} \quad (7.2)$$

Table 7.2 on page 75 shows the calculated RMSE values and standard deviation for the indicators, with three significant figures. The standard deviation shows the spread of the error. The higher the standard deviation, the more outliers in the data set. The four accuracy requirements are visualised by colours, based on the RMSE:

< 0.5 dB is green; < 1 dB is blue; < 2 dB is orange; < 3 dB is light red; > 3 dB is dark red. All colours except the dark red represent acceptable accuracy.

Table 7.2: RMSE \pm standard deviation of eight indicators, for 10 reduced sampling rates. RMSE is rounded to the closest 3 significant figures. The colour indicates which accuracy requirement that is met, based on the RMSE: green < 0.5; blue < 1; orange < 2; light red < 3; dark red > 3.

Rate	$L_{Aeq,15min}$	$L_{A10,15min}$	$L_{A50,15min}$	$L_{A90,15min}$
4 sec	0.398 \pm 0.324	0.318 \pm 0.240	0.133 \pm 0.101	0.138 \pm 0.112
10 sec	0.785 \pm 0.638	0.616 \pm 0.442	0.263 \pm 0.197	0.289 \pm 0.232
20 sec	1.03 \pm 0.822	0.898 \pm 0.635	0.412 \pm 0.308	0.419 \pm 0.333
30 sec	1.23 \pm 0.982	1.10 \pm 0.767	0.501 \pm 0.371	0.499 \pm 0.392
1 min	1.50 \pm 1.15	1.52 \pm 1.03	0.729 \pm 0.537	0.766 \pm 0.605
2 min	1.77 \pm 1.30	1.97 \pm 1.30	1.07 \pm 0.798	1.15 \pm 0.908
3 min	1.99 \pm 1.43	2.35 \pm 1.53	1.31 \pm 0.969	1.41 \pm 1.10
5 min	2.28 \pm 1.61	2.90 \pm 1.89	1.67 \pm 1.26	1.88 \pm 1.45
7.5 min	2.55 \pm 1.75	3.39 \pm 2.10	1.99 \pm 1.49	2.69 \pm 2.05
15 min	3.36 \pm 2.30	4.64 \pm 2.89	2.99 \pm 2.31	4.43 \pm 3.30

Rate	$L_{Aeq,1h}$	$L_{Aeq,8h}$	NPL_{15min}	$L_{A10} - L_{A90,15min}$
4 sec	0.295 \pm 0.238	0.0958 \pm 0.0742	0.472 \pm 0.353	0.346 \pm 0.254
10 sec	0.670 \pm 0.559	0.136 \pm 0.0821	0.923 \pm 0.655	0.687 \pm 0.483
20 sec	0.828 \pm 0.680	0.198 \pm 0.130	1.34 \pm 0.940	0.994 \pm 0.684
30 sec	1.06 \pm 0.877	0.188 \pm 0.116	1.66 \pm 1.17	1.22 \pm 0.842
1 min	1.31 \pm 1.07	0.232 \pm 0.124	2.35 \pm 1.59	1.74 \pm 1.15
2 min	1.43 \pm 1.11	0.323 \pm 0.193	3.22 \pm 2.15	2.38 \pm 1.52
3 min	1.59 \pm 1.21	0.469 \pm 0.302	3.87 \pm 2.54	2.91 \pm 1.83
5 min	1.87 \pm 1.38	0.581 \pm 0.341	4.82 \pm 3.10	3.73 \pm 2.26
7.5 min	1.87 \pm 1.29	0.796 \pm 0.492	5.80 \pm 3.58	4.71 \pm 2.65
15 min	2.49 \pm 1.69	1.28 \pm 0.911	7.89 \pm 4.56	6.83 \pm 3.27

The colours show the robustness of the indicators when they are reduced. A higher robustness allows for more down-sampling. From Table 7.2, the robustness of the indicators in order is as follows:

1. $L_{Aeq,8h}$
2. $L_{A50,15min}$
3. $L_{A90,15min}$
4. $L_{Aeq,1h}$
5. $L_{Aeq,15min}$
6. $L_{A10,15min}$
7. $L_{A10} - L_{A90,15min}$
8. NPL_{15min}

Since the $L_{A10} - L_{A90,15min}$ is based on two indicators, it is expected to be more sensitive to down-sampling; it will account for the error from both of the two other indicators. Similarly, the NPL_{15min} is based on both the $L_{A50,15min}$ and $L_{A10} - L_{A90,15min}$ and is affected by their errors. It is therefore expected to be the most sensitive indicator.

Both the $L_{A50,15min}$ and $L_{A90,15min}$ exclude the peaks of noise in their calculations, and is therefore more robust to down-sampling. It does not make a large difference to these two indicators if some peaks of noise are not detected by the noise measurement. On the other hand, if several peaks are sampled instead of general noise, it will make the indicator more inaccurate.

The indicators $L_{Aeq,8h}$ and $L_{Aeq,1h}$ equalise the noise over longer time periods, and is thus more robust to changes. It will not affect the results much if some extreme points are omitted or included; it will most likely equalise over time. The longer the time period, the more robust the indicator. Thus, the $L_{Aeq,15min}$ is fairly robust, but less than the other two equalising indicators.

The $L_{A10,15min}$ is a bit sensitive to down-sampling, because of its dependence on noise events. If too many events are left out or included, it will make the indicator less accurate.

Figure 7.3 on page 78 shows the RMSE for all indicators, with the four different accuracy requirements illustrated by dotted lines. The comparison of robustness is

visually clear, and supports the ordering presented above. All of the indicators stay under an RMSE of: 0.5 dB when the sampling rate is 4 seconds; 1 dB when the sampling rate is 10 seconds; 2 dB when the sampling rate is 30 seconds; 3 dB when the sampling rate is 1 minute.

The RMSE with variance for each indicator is shown in Figure 7.4 and Figure 7.5. The variance is represented by the light blue colour. As expected, it generally increases when the sampling rate is reduced. The sensitivity of the indicators is evident, and we can see that an RMSE below an accuracy requirement don't necessarily mean that the indicator will perform well with that sampling rate. If the variance is high, the number of outliers will be many.

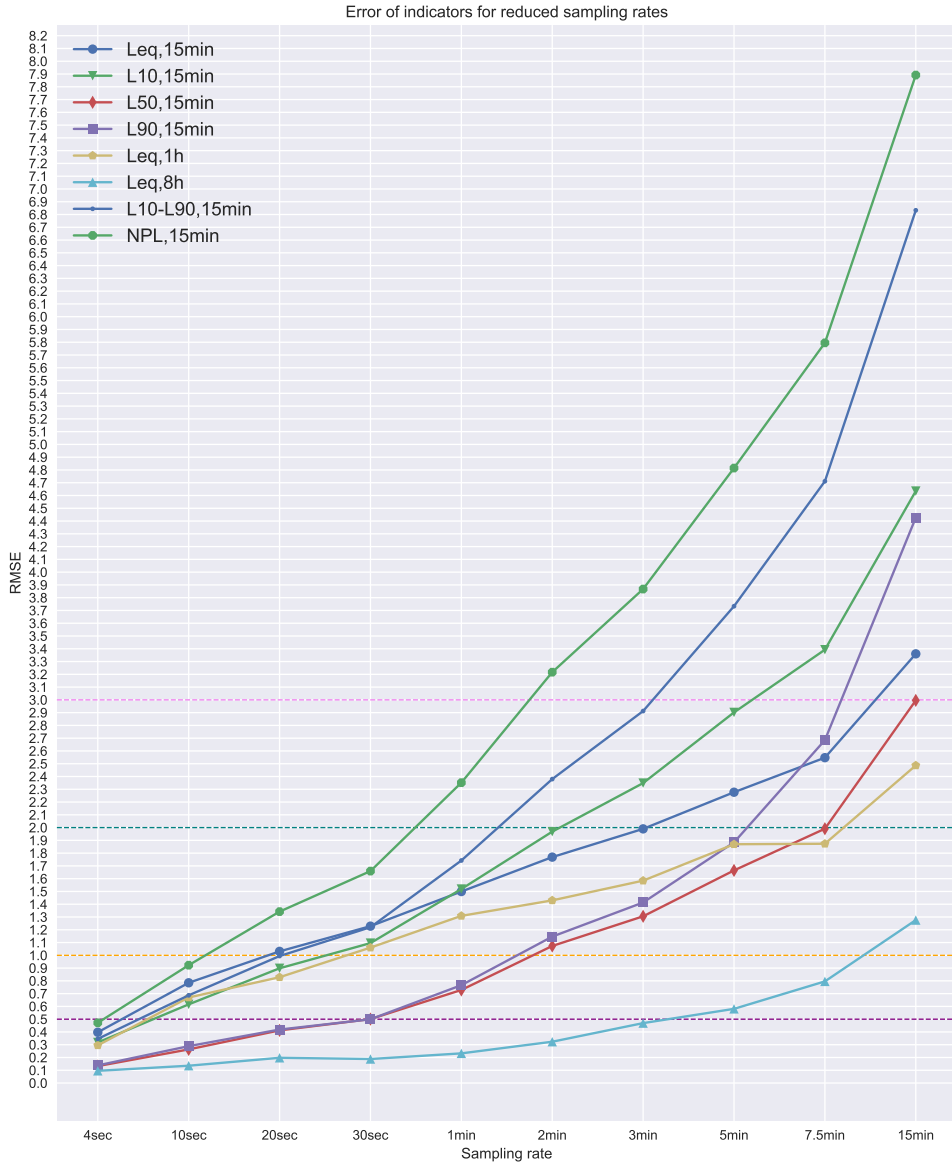


Figure 7.3: Plotted RMSE of 10 reduced data sets, for eight indicators. The horizontal lines marks the accuracy levels of 0.5 dB, 1 dB, 2 dB and 3 dB.

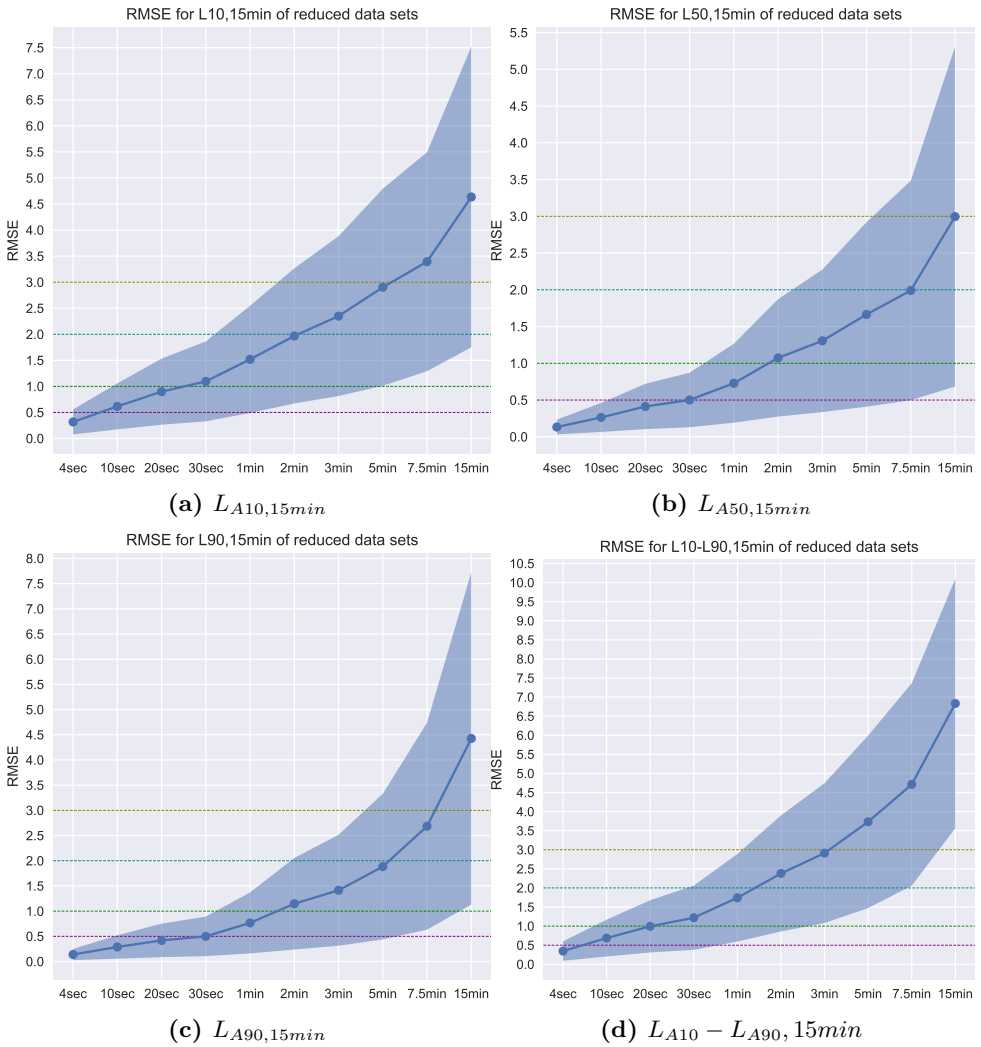


Figure 7.4: Plotted RMSE and the corresponding \pm standard deviation of 10 reduced data sets, for four 15-minute indicators. The horizontal lines mark the accuracy levels of 0.5 dB, 1 dB, 2 dB and 3 dB.

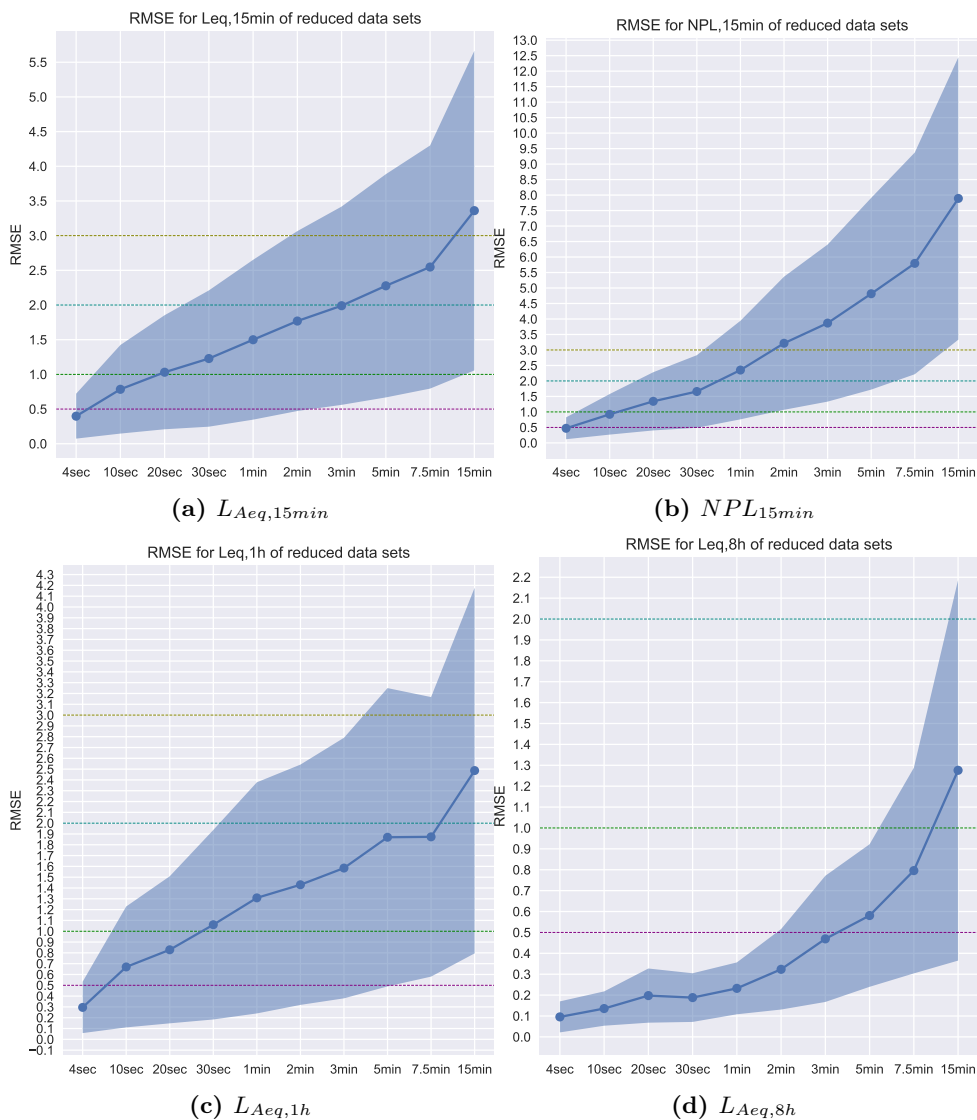


Figure 7.5: Plotted RMSE and the corresponding \pm standard deviation of 10 reduced data sets, for four indicators. The horizontal lines mark the accuracy levels of 0.5 dB, 1 dB, 2 dB and 3 dB.

7.3 Accuracy in Deciding Labels

To compare the label accuracy of different sampling rates, we use histograms and confusion matrices. The histogram compares the distributions of the assigned labels as the data set is being reduced. Thus, we can see what label is assigned more often as the accuracy of the data set changes. The confusion matrix shows the actual label that is assigned from the full data set, plotted against the assigned label for the reduced data set. This allows us to see how the labels are wrongly assigned, and any occurring bias.

7.3.1 The True Data

The assigned labels for the complete data sets of all the 15-minute indicators are shown in Figure 7.6 and Figure 7.7. These plots illustrate the soundscape, to give a better understanding of the noise in the working environment and the original distribution of labels. The white fields represent missing data, caused by errors in the data collection.

7.3.2 Distributions of Labels

The histograms presented in Figure 7.8 show which of the five quality labels that are assigned to the time intervals in the different data sets. The histograms are normalised, showing the percentage of labels assigned. The general trend of these label distributions is that when the sampling rate is reduced, an increasing amount of labels are wrongly assigned toward the good end of the scale. This indicates a positive estimator bias for these indicators.

For example, Figure 7.8e shows the distribution of labels for the indicator $L_{Aeq,15min}$. We can see that the label *good* is assigned more frequently as the data set is further reduced. Similarly, the same effect can be seen in Figure 7.8a, Figure 7.8d and Figure 7.8f, for $L_{A10,15min}$, $L_{A10}-L_{A90,15min}$ and NPL_{15min} . Moreover, $L_{Aeq,1h}$ has similar results, as shown in Figure 7.8g.

The most affected indicators are the $L_{A10}-L_{A90,15min}$, NPL_{15min} and $L_{A10,15min}$. When the sampling rate is reduced, we see an almost exponential increase in faulty label assignment. This is in line with the results from the indicator accuracy, which exposed these indicators as the most sensitive to down-sampling.

In contrast, the indicator $L_{A90,15min}$ shows an opposite result, as presented in Figure 7.8c. The label *poor* is assigned more frequently when the data set is reduced. Since this indicator measures the background noise, it will impact the indicator more if a noise event is included in the data set when the sampling rate is low. Figure 7.8b shows that the indicator $L_{A50,15min}$ is somewhat stable when reduced. A similar

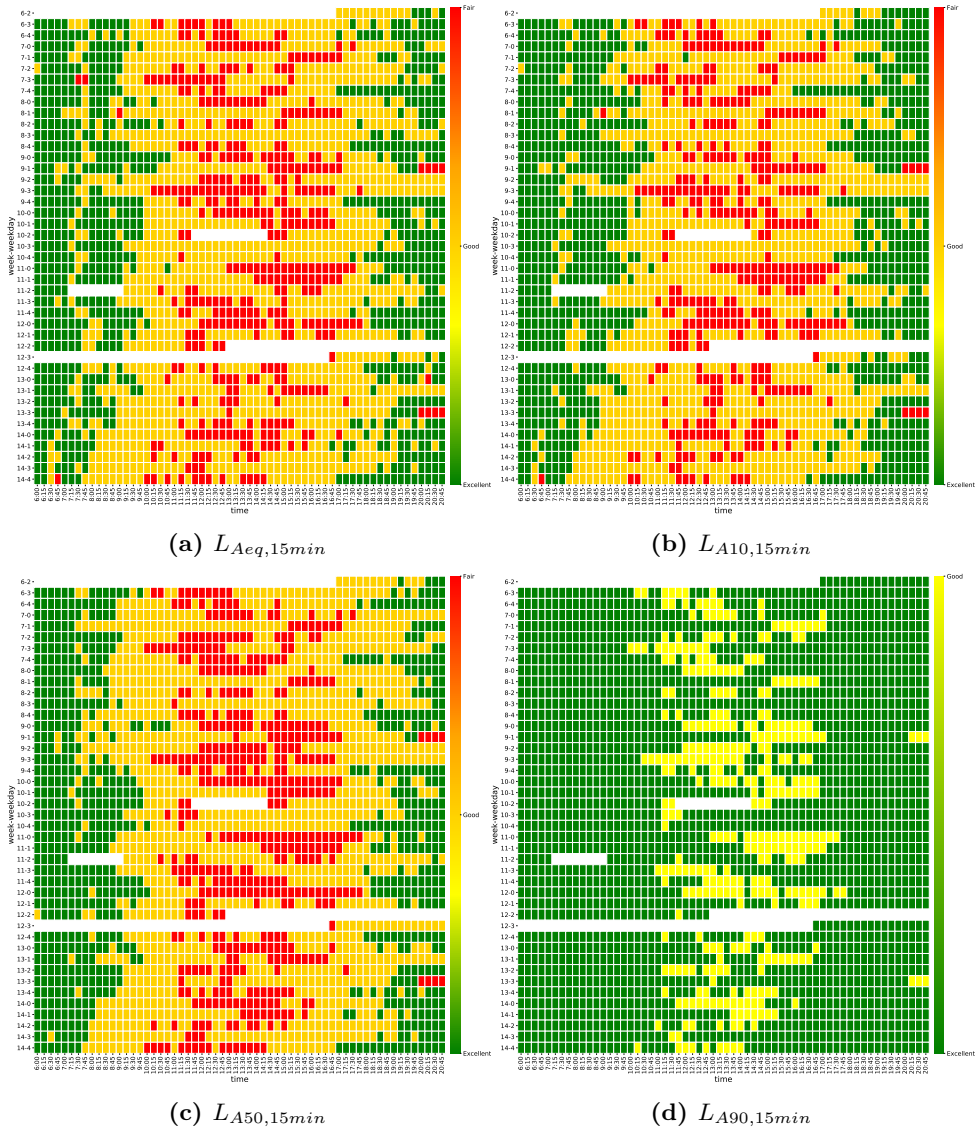


Figure 7.6: The distributed labels for 15-minute intervals for the nine weeks of data, for four indicators. Each line is one day, labelled “week-weekday” (0 = Monday).

result is shown in Figure 7.8h for $L_{Aeq,8h}$. This corresponds with the results presented on indicator accuracy, which showed that these two indicators were most robust.

Figure 7.9 shows the label distribution for the composite indicator CQI we created in Section 5.5. It is dependent on the labels of the indicators $L_{Aeq,15min}$, $L_{A10,15min}$

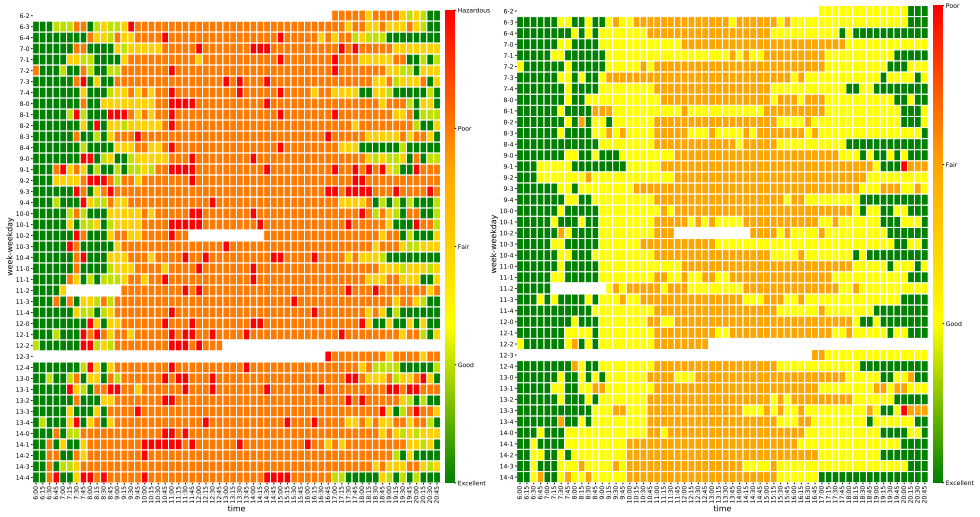
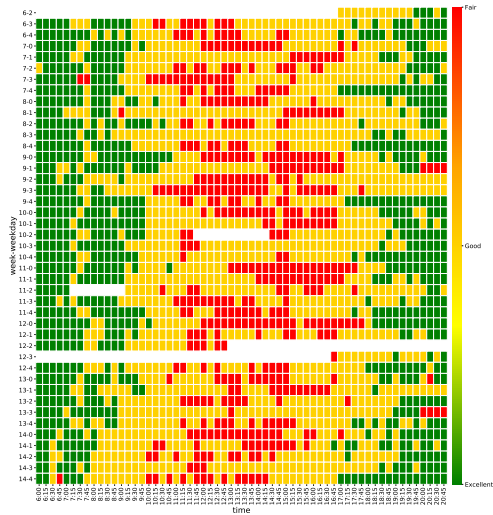
(a) $L_{A10} - L_{A90,15min}$ (b) NPL_{15min} (c) CQI_{15min}

Figure 7.7: The distributed labels for 15-minute intervals for the nine weeks of data, for three indicators. Each line is one day, labelled “week-weekday” (0 = Monday).

and $L_{A90,15min}$. Therefore, we see that both the label *good* and *poor* are assigned more frequently when the sampling rate is reduced; it is a mixture of the results from the three indicators. The label *poor* overrides all the other labels, thus it inherits all these wrongly assigned labels, especially impacted by $L_{A90,15min}$.

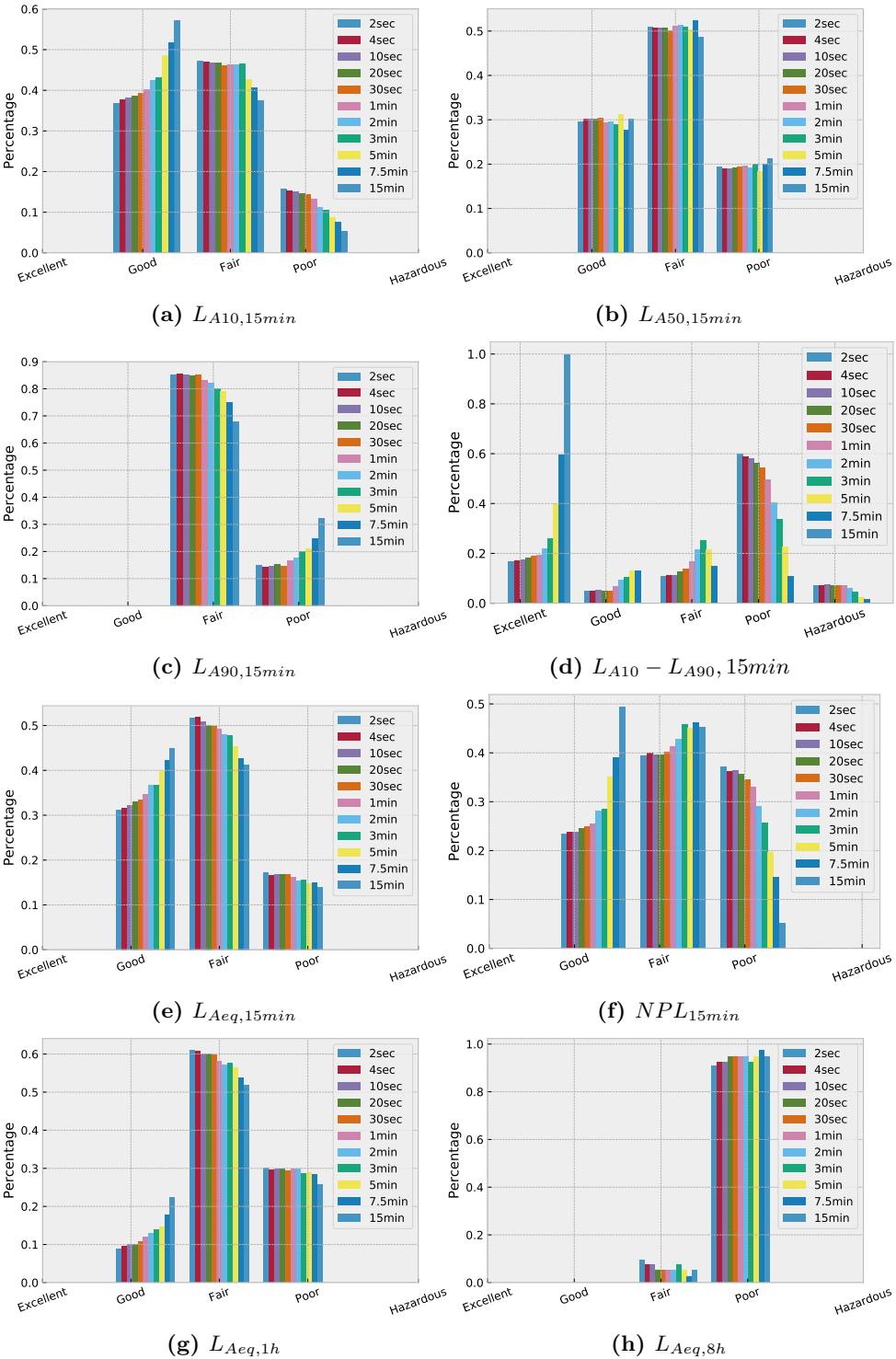


Figure 7.8: Histograms of assigned labels to eight indicators for 10 simulated sampling rates. The distribution is normalised.

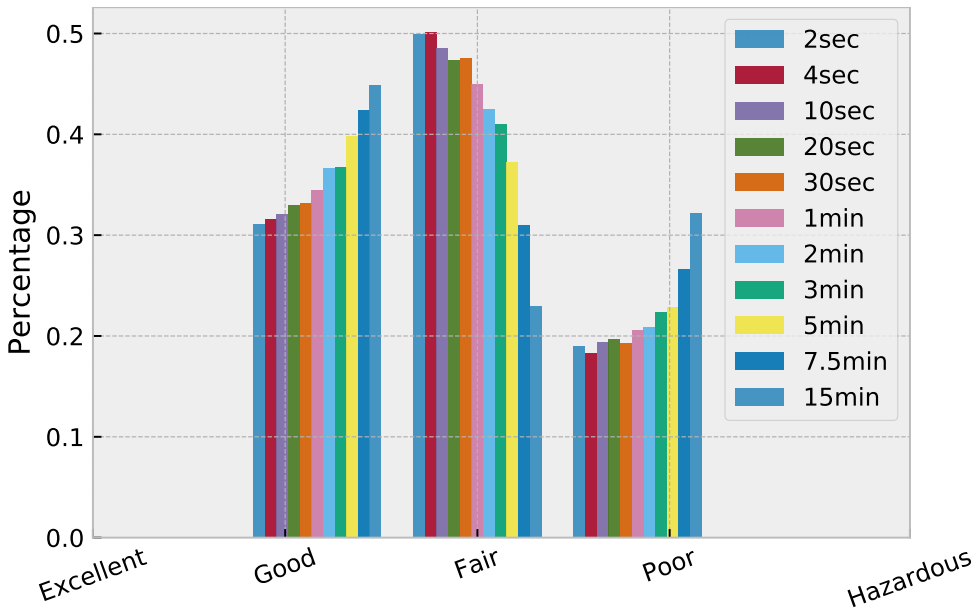


Figure 7.9: Histogram of assigned labels to the Composite Quality Indicator (CQI) for 10 simulated sampling rates. The distribution is normalised.

7.3.3 Confusion Matrices

In this section we present a selection of confusion matrices. One matrix is left out from each indicator because of lack of relevance, combined with space restrictions of the page. The full set of confusion matrices is attached in Appendix D.

The matrices are normalised to show the percentage of labels that are assigned to each interval. Along the diagonal of the matrix the result is the same for both data sets, but all labels occurring outside the diagonal is erroneously assigned. The further away from the diagonal, the worse the error.

The caption for each sub-figure indicates the sampling rate used in each data set. Unless otherwise stated, the following numerical values represent the different labels: Excellent = 0; Good = 1; Fair = 2; Poor = 3; Hazardous = 4.

Figure 7.10 shows a selection of confusion matrices for the indicator $L_{Aeq,15min}$. The indicator performs well down to a sampling rate of 30 seconds; less than 10 % of the labels are misassigned to the different categories. From this point, an increasing amount of the label *poor* are misassigned as *fair*. The same effect is seen for the label *fair*, which is frequently misassigned as *good* from a sampling rate of 2 minutes. These results correspond to the effect shown in the histogram in Figure 7.8e.

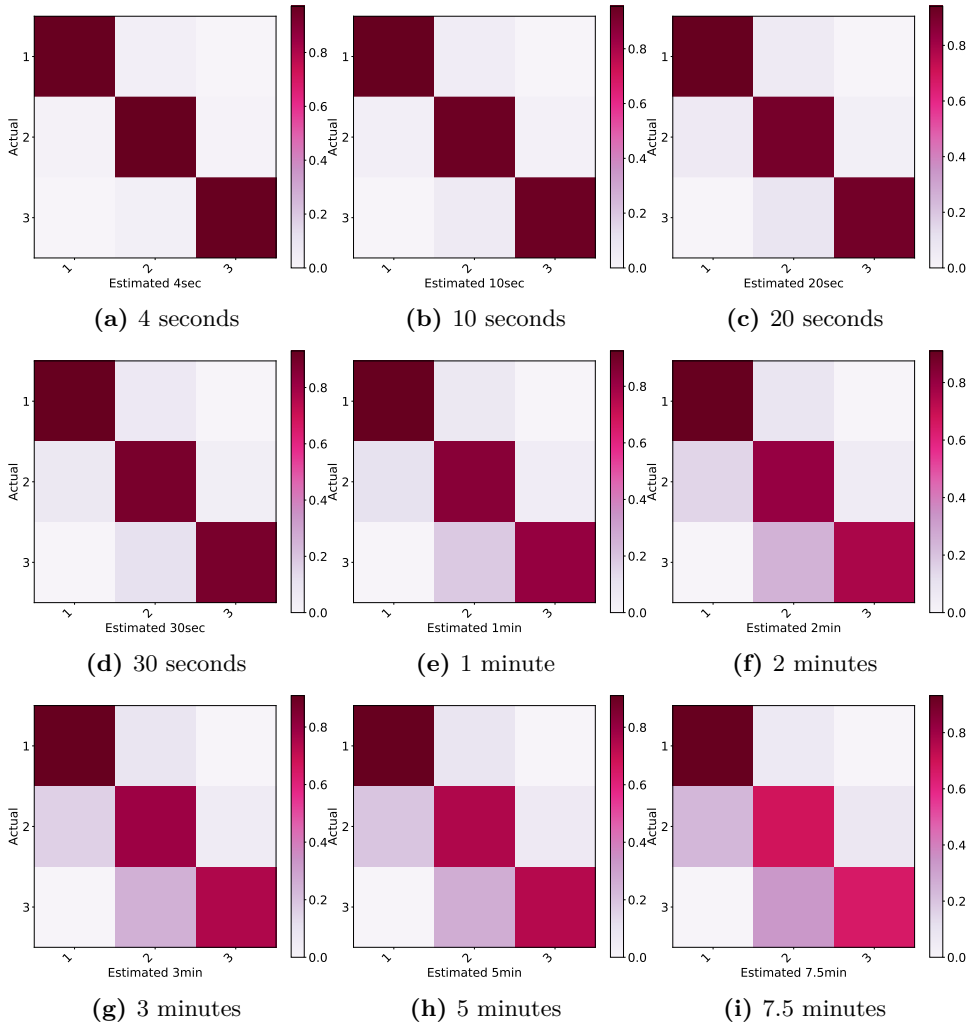


Figure 7.10: Confusion matrices of indicator $L_{Aeq,15min}$ for six sampling rates. Labels are displayed as follows, from the top left corner: Good = 1, Fair = 2, Poor = 3. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

Figure 7.11 shows a selection of confusion matrices for the indicator $L_{A10,15min}$. The indicator performs well down to a sampling rate of 10 seconds; around 10 % of the labels are misassigned as *fair* when they are *poor*. The positive bias from Figure 7.8a is evident as the sampling rate is further reduced. The most frequent error allocation is a *poor* interval categorised as *fair*, but *fair* intervals are also increasingly assigned the *good* label.

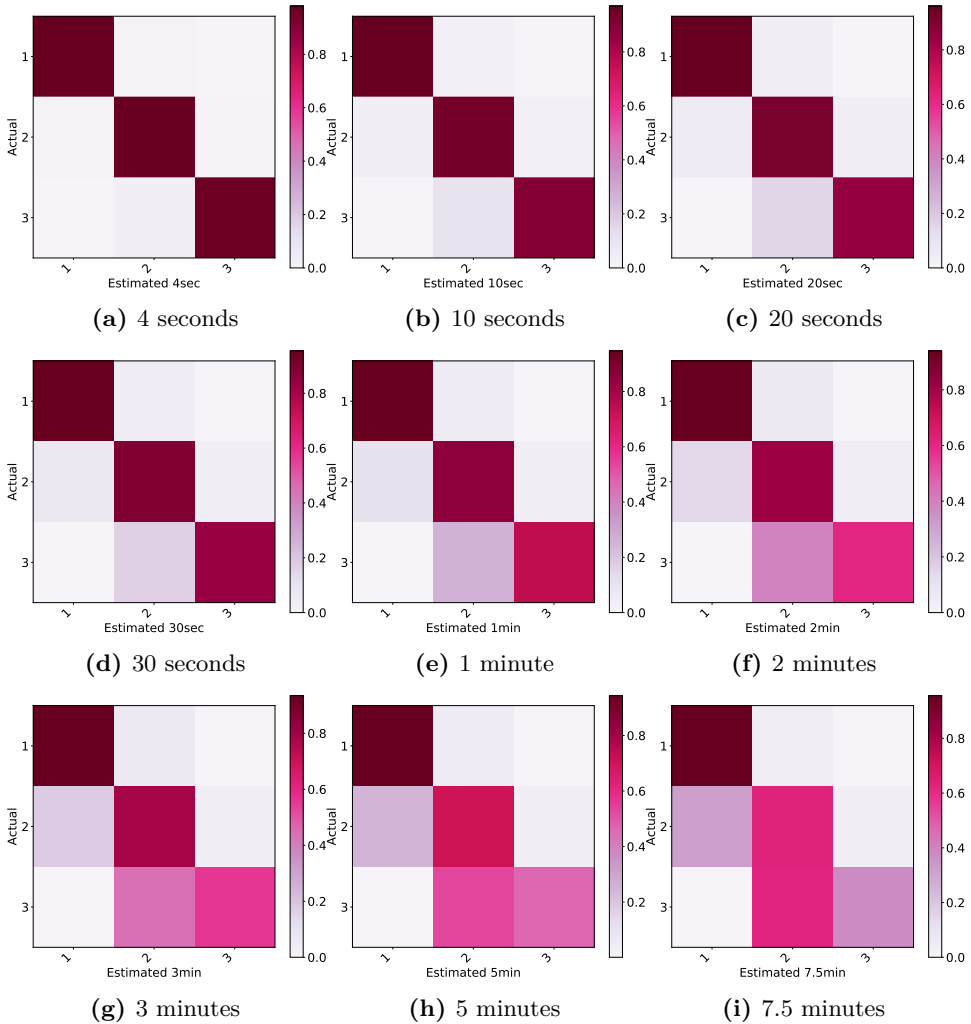


Figure 7.11: Confusion matrices of indicator $L_{A10,15min}$ for six sampling rates. Labels are displayed as follows, from the top left corner: Good = 1, Fair = 2, Poor = 3. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

Figure 7.12 shows a selection of confusion matrices for the indicator $L_{A50,15min}$. The indicator is quite stable, as shown in 7.8b. As the sampling rate reduces, both a negative and a positive bias appears. Some *good* labels are misassigned as *fair*, and some *poor* labels are misassigned as *fair*. The indicator performs quite well down to a sampling rate of 5 minutes.

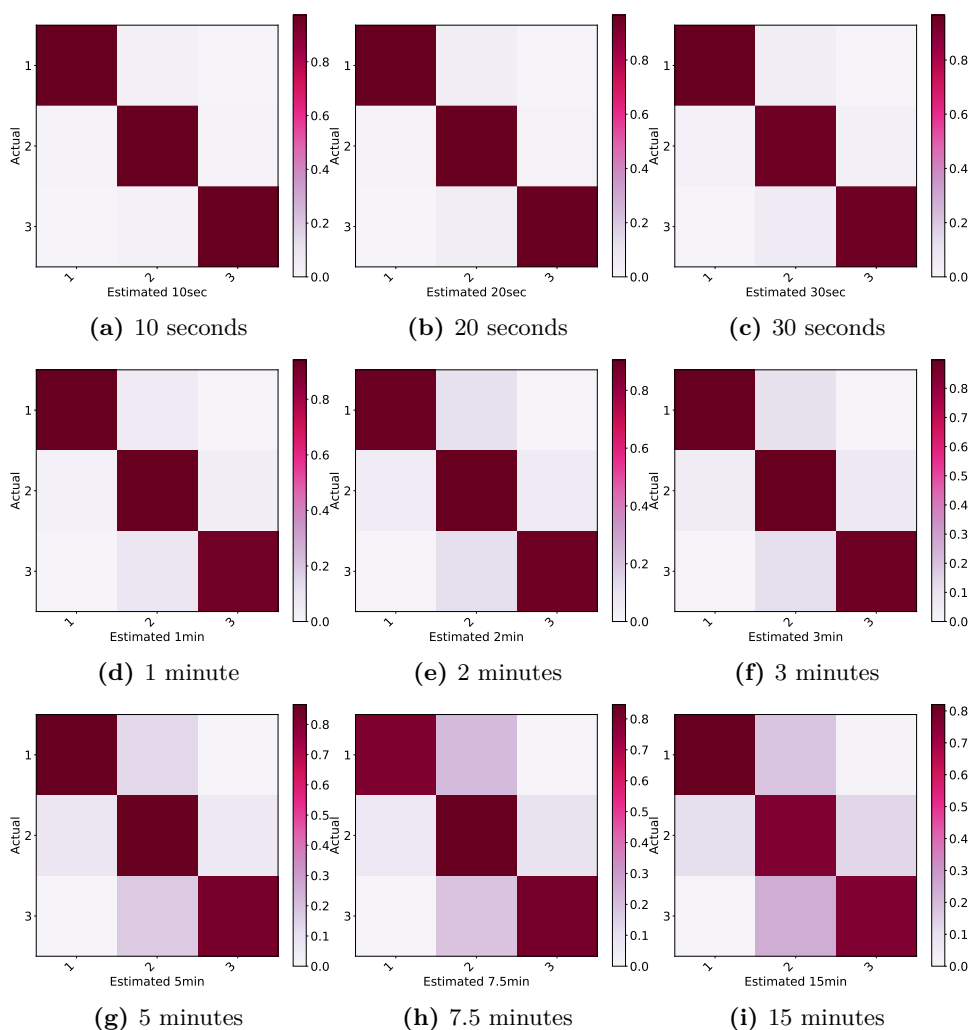


Figure 7.12: Confusion matrices of indicator $L_{A50,15min}$ for six sampling rates. Labels are displayed as follows, from the top left corner: Good = 1, Fair = 2, Poor = 3. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

Figure 7.13 shows a selection of confusion matrices for the indicator $L_{A90,15min}$. The value “True” represents the *fair* label, and the “False” represents the *poor* label. The indicator is relatively robust, down to a sampling rate of 7.5 minutes. For the 15 minute sampling rate, the negative bias shown in Figure 7.8c is very clear. Several *fair* labels are misassigned as *poor*.

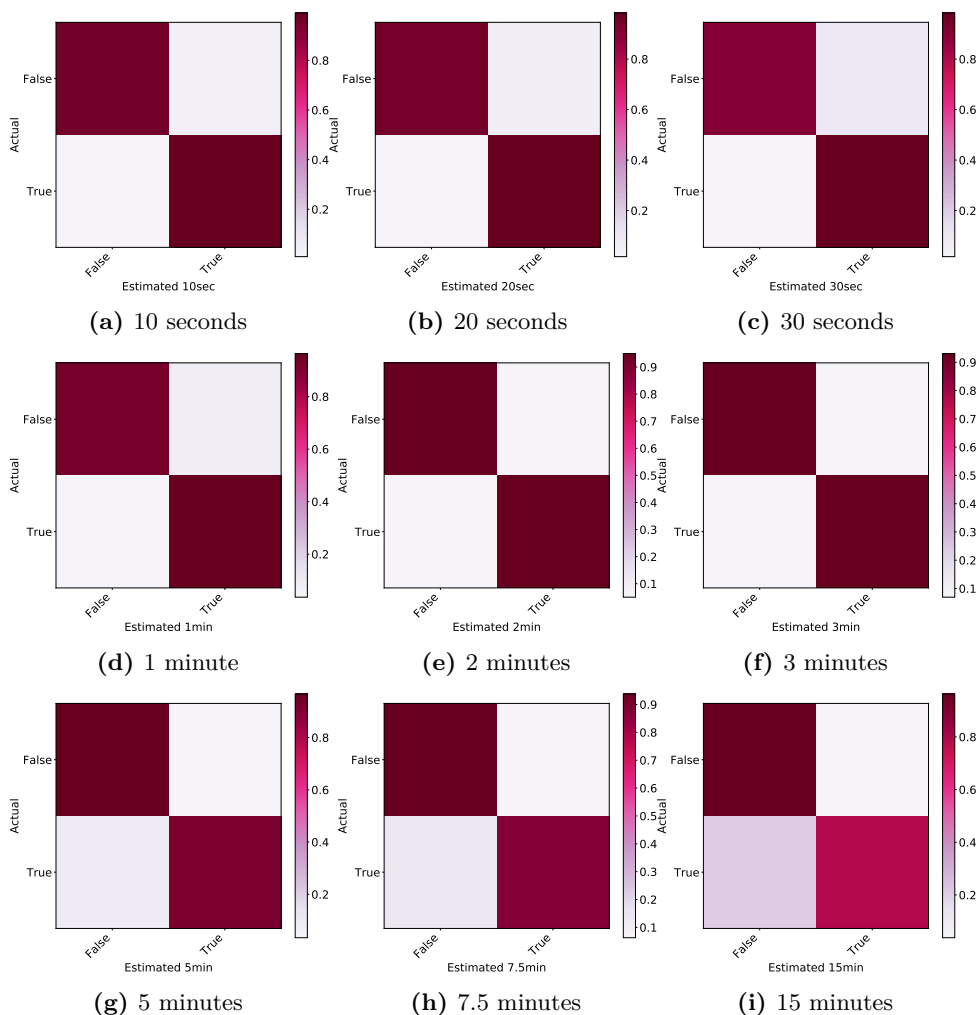


Figure 7.13: Confusion matrices of indicator $L_{A90,15min}$ for six sampling rates. Labels are displayed as follows, from the top left corner: Poor = False, Fair = True. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

Figure 7.14 shows a selection of confusion matrices for the indicator $L_{A10} - L_{A90,15min}$. This is the only indicator that is assigned all five labels, due to the variability of the values. As we can see, the indicator is very sensitive to down-sampling since it inherits the errors from both the $L_{A10,15min}$ and the $L_{A90,15min}$ indicator. Because of the low performance from a 2 minute sampling rate, we omit the rest of the confusion matrices. They are found in Appendix D.

The bias is acceptable for the 4 second sampling rate, but further on it quickly increases. There is both a positive and a negative bias; the positive bias is the strongest. Intervals labelled *hazardous* are wrongly categorised as *poor*, which is a critical error. Many *good* labels are also misassigned as *excellent*.

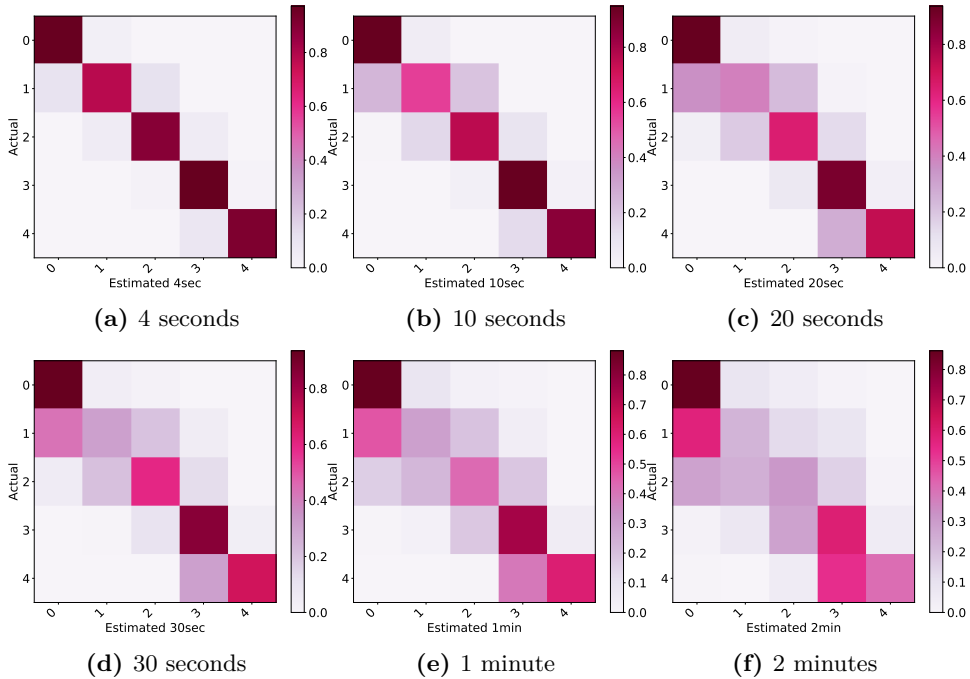


Figure 7.14: Confusion matrices of indicator $L_{A10} - L_{A90,15min}$ for six sampling rates. Labels are displayed as follows, from the top left corner: Excellent = 0, Good = 1, Fair = 2, Poor = 3, Hazardous = 4. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

Figure 7.15 shows a selection of confusion matrices for the indicator NPL_{15min} . This indicator is derived from the indicators $L_{A50,15min}$ and $L_{A10} - L_{A90,15min}$, making it one of the more sensitive indicators. The positive bias shown in Figure 7.8f is evident from a sampling rate of 2 minutes; all *hazardous* intervals are mislabelled as *poor*. Additionally, some of the *poor* labels are wrongly assigned as *fair*. This bias is also relatively noticeable for the 1 minute sampling rate.

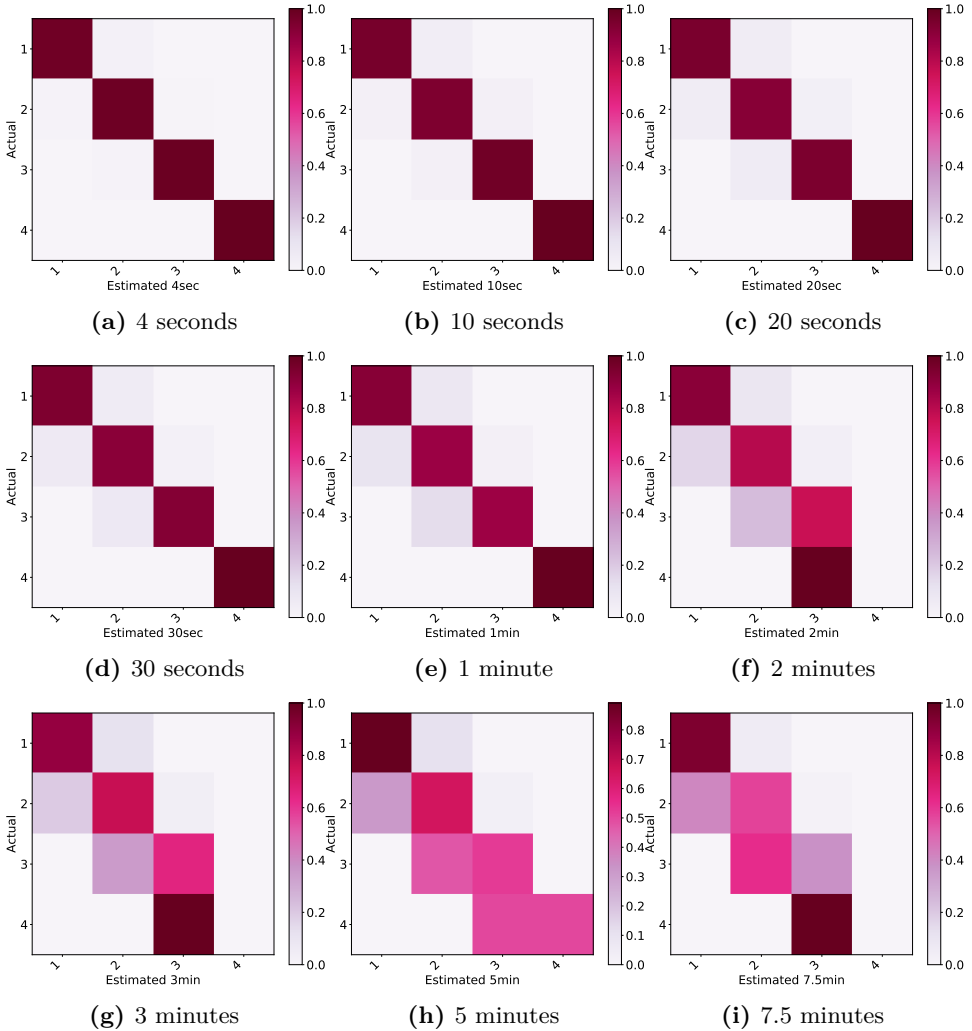


Figure 7.15: Confusion matrices of indicator NPL_{15min} for six sampling rates. Labels are displayed as follows, from the top left corner: Good = 1, Fair = 2, Poor = 3, Hazardous = 4. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

Figure 7.16 shows a selection of confusion matrices for the indicator CQI_{15min} . It performs well down to a sampling rate of 30 seconds. As we can see in Figure 7.9, a positive and negative bias is present from a sampling rate of 1 minute. Further on, it increases remarkably, as we see for the 7.5 minute sampling rate. The negative bias is mainly inherited from the indicator $L_{A90,15min}$, since the CQI places the greatest emphasis on *poor* and *hazardous* labels. The positive bias is inherited from the two other indicators, $L_{A10,15min}$ and $L_{Aeq,15min}$.

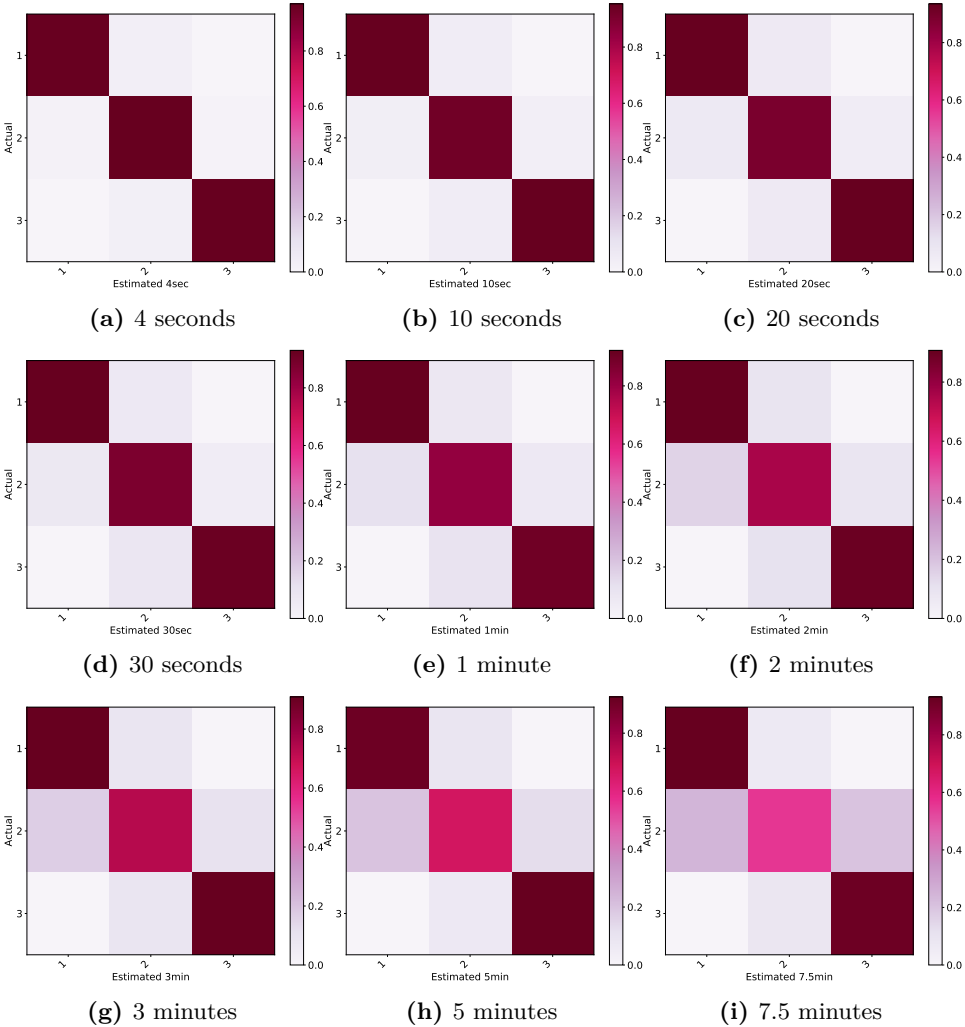


Figure 7.16: Confusion matrices of indicator CQI_{15min} for six sampling rates. Labels are displayed as follows, from the top left corner: Good = 1, Fair = 2, Poor = 3. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

Figure 7.17 shows a selection of confusion matrices for the indicator $L_{Aeq,1h}$. Because of the larger time interval, it is more robust than the $L_{Aeq,15min}$. It performs well in the down-sampling, although a small positive bias can be seen for lower sampling rates. Especially, some *fair* labels are misassigned as *good*. A few *poor* labels are wrongly assigned as *fair*.

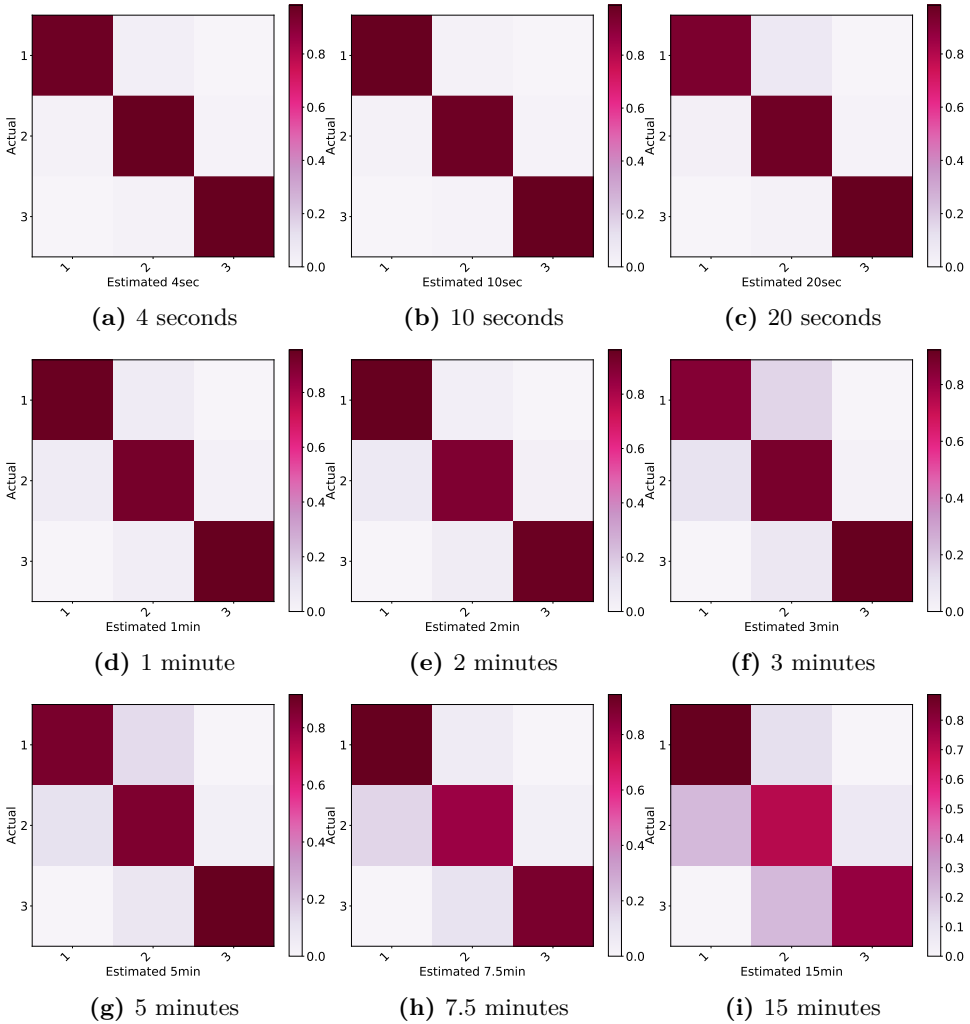


Figure 7.17: Confusion matrices of indicator $L_{Aeq,1h}$ for a selection of reduced data sets. Labels are displayed as follows, from the top left corner: Good = 1, Fair = 2, Poor = 3. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

Figure 7.18 shows a selection of confusion matrices for the indicator $L_{Aeq,8h}$. The value “True” represents the *fair* label, and the “False” represents the *poor* label. The matrices for this indicator are close to unchanged as the sampling rate is reduced, down to a 5 minute sampling rate. As shown in Figure 7.8h, very few labels are assigned as *fair*; almost all labels are *poor*. Thus, when the allocation of a *fair* label changes, the impact is large. For the sampling rates 7.5 and 15 minutes, the matrices are remarkably changed when this happens.

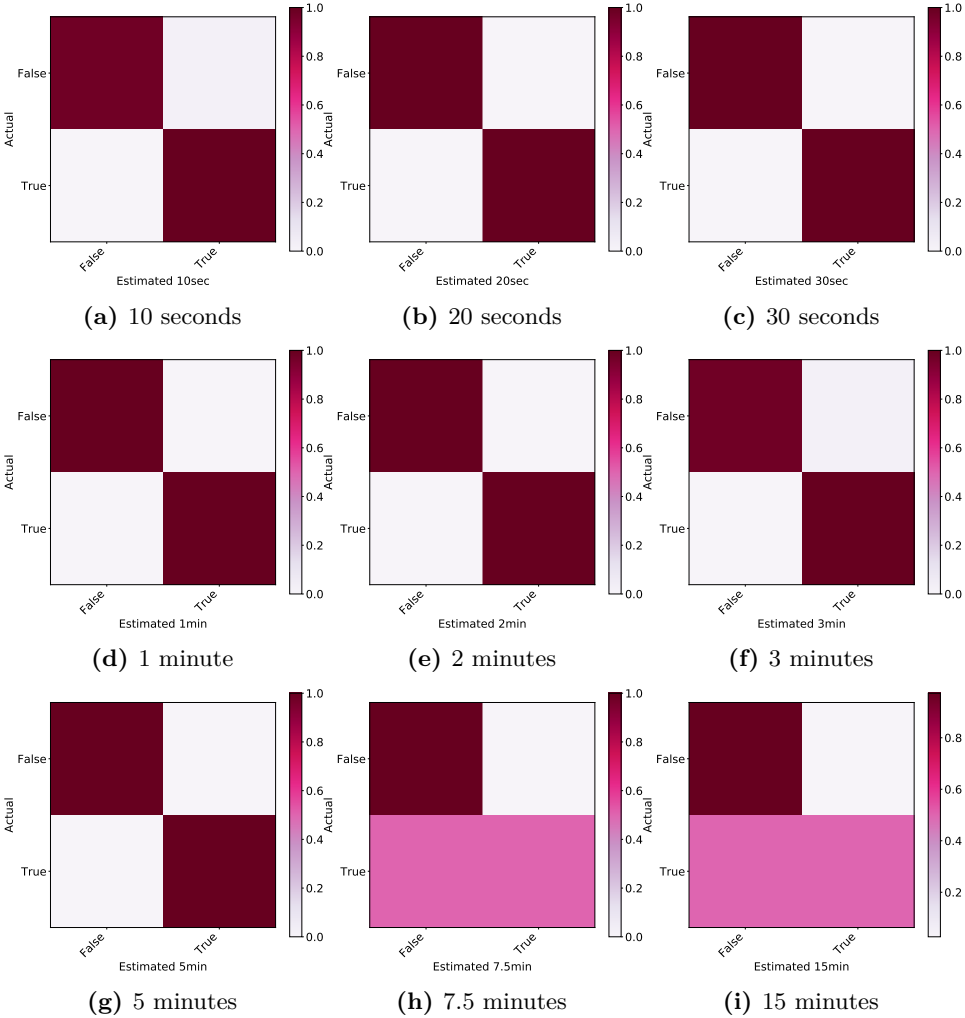


Figure 7.18: Confusion matrices of indicator $L_{Aeq,8h}$ for a selection of reduced data sets. Labels are displayed as follows, from the top left corner: Poor = False, Fair = True. The x-axis shows the predicted labels, and the y-axis shows the actual labels.

In this chapter we presented the results from the statistical trade-off analysis. In the following chapter we will discuss these results, along with the results from the two previous chapters, in terms of the research questions. These results enable us to answer the knowledge questions, in order to further answer the research questions.

Chapter 8

Discussion and Further Work

The main research goal of this thesis was to find out if noise measurement in working environments could be made more efficient, if we know what kind of information we want to base our decision-making on. So far, we have presented the background for achieving this goal. This includes previous work on noise measurement, the theoretical basis in the field of study, user requirements and technical requirements for noise measurement, and the trade-off analysis provided in the previous chapter.

In this chapter, we discuss the answers to our research questions, which supports us in designing our artifact. We then propose the designed artifact: a system for noise measurement with requirements and properties. We discuss the opportunities and limitations of the system, and suggestions for further work.

8.1 User Requirements for Noise Measurement

In order to design the system, we first needed to define user requirements that described what we were interested in knowing through the noise measurement. This represents the first research question, which was addressed in Chapter 4. It was defined as follows, decomposed into knowledge questions:

RQ1: What are the user requirements with respect to noise for working environments for focused work?

- What do people find disturbing while they work?
- What actions are people required to perform while working?

A literature review showed that people found several phenomena disturbing while working: speech; traffic noise; high variability in noise; high and varied background noise; occasional noise events; high general noise levels. The tasks users are required to perform were mainly defined as cognitive and arithmetic tasks. Based on related

work, we defined a set of user requirements for the selected working environment. These were created as a basis for the next research question.

- **UR1:** The noise should not be hazardous to the hearing of the user
- **UR2:** Users should be able to work without being disturbed by noise events
- **UR3:** The background noise should not be disturbing to the user during concentrated work
- **UR4:** The general noise level should enable cognitive performance

We can not validate these user requirements, neither is it part of the scope for this thesis. We could have conducted a survey for the stakeholders of the working environment to map the actual needs of the users. It would have been interesting to see the subjective opinions of the people in the chosen working environment. In this thesis, we assume that our definition is correct.

Those who want to apply this work to other contexts are responsible for defining suitable user requirements for their case. User requirements vary greatly based on the aim for noise monitoring, and what decisions that stakeholders need to make. These requirements are important, because they lay the foundation for the properties of the noise measurement system.

8.2 Technical Requirements for Noise Measurement

Next, we translated the user requirements into technical requirements, as defined in the second research question:

RQ2: How can these user requirements be translated into technical requirements for noise measurement?

- What metrics represent the phenomena that people find disturbing while they work?
- What metric values represent the level of which people are able to work?
- What suite of metrics represent the soundscape in which people can perform the required work tasks?
- What are the accuracy requirements for the metrics?

Chapter 5 showed that the disturbing phenomena could be translated into the following metrics: noise event are represented by L_{A10} ; background noise is represented

by L_{A90} ; the general noise level is represented by L_{Aeq} and L_{A50} ; the variability of noise is represented by $L_{A10} - L_{A90}$. The CQI represents the general noise level, including the variability of noise. For each of these indicators, we defined ranges of levels with different labels. Together, this formed a suite of metrics that was used as a basis for analysis in the next research question.

There were several indicators to choose from, and the choice of them affects the comparative analysis. Different indicators have different sensitivities in terms of accuracy, and choosing a less sensitive indicator causes an increased ability to down-sample. We chose L_{A10} over L_{A5} and L_{A2} , which would have been even more sensitive indicators. Similarly, we chose L_{A90} over L_{A95} , which is also a less sensitive indicator. The foundation for our choice was primarily the usage of the indicators in related work; more general indicators tend to be used more frequently. Thus, our results are affected by these design choices. If similar experiments are conducted in other contexts, the choice of indicators have to be tailored to the properties of that context.

A new, composite indicator was defined to represent the requirements for a good working environment; the CQI. It consists of the individual requirements of the 15-minute based indicators L_{A10} , L_{A90} and L_{Aeq} . We are not validating this indicator by testing it in different working environments; it is out of scope of this thesis and not the designed artifact. It is a proposed property of the artifact, but it must be validated by further experiments before we can rely on the results from this indicator alone.

In this thesis, we as designers did the translation of user requirements into technical requirements. Thus, we were also responsible for defining the accuracy requirements in the working environment. Stakeholders rarely know exactly what accuracy requirements they need; they are not fit to make such technical decisions. Depending on the user needs, system designers should choose which accuracy that is sufficient for a context.

We defined the accuracy requirements based on how humans perceive sound. We argue that if a person can not sense a change in the noise level, the change is insignificant. Thus, we defined an absolute error of < 3 dB as acceptable accuracy; a change of < 2 dB as high accuracy; a change of < 1 dB as very high accuracy; and a change of < 0.5 dB as particularly high accuracy. This definition is supported by related work, and conventions in the field.

8.3 Sampling Rate and Accuracy Trade-Off

The last research question concerns the ability to down-sample in a working environment and still meet requirements of accuracy and efficiency. In this section, we discuss the related questions for each noise indicator:

RQ3: How do the requirements affect the sampling- and transmission-rate in working environments for focused work, in terms of efficiency and accuracy?

- How much can we down-sample, and still meet the accuracy requirements?
- Which metrics are more suitable for down-sampling?
- How efficient is the down-sampling of the metrics?

The accuracy- and efficiency requirements will depend on what stakeholders want to know. If a stakeholder is interested in the quality of a working environment, the critical issue is the assigned label. The accuracy of the indicator itself is not that important, as long as the assigned quality label is correct. If a stakeholder needs to know the actual value of the noise, we might not be able to down-sample at all. Then, the indicator accuracy is most important. Ultimately, we aim to avoid changing the decisions of stakeholders made from the full data. Their decisions are based on the given information from the system, and we need to provide information with *good enough* accuracy.

We defined four accuracy requirements in Section 5.6. The weakest requirement is an absolute error of less than 3 dB, which is an acceptable accuracy. However, if the error changes the value of a label, it would be critical for label accuracy. As presented in Section 7.2.2, the RMSE describes the average error of the down-sampling. It is also important to take the variance of the error into consideration, to get a comprehension of the number of outliers and how it can affect the label accuracy.

Below we will discuss the impact of different sampling rates on the chosen indicators. In this thesis, the sampling rate also represents the transmission rate, because it affects the amount of data to send. The transmission rate could also be studied in terms of time intervals, if we define that only the value of the indicator, in example $L_{Aeq,15min}$, is sent. Here, we focus on the sampling rate as the main property.

Figure 8.1 shows a simplified version of the plotted RMSE for the different indicators, giving an overview of the results. In the sections below, we will take all the results from the analysis into consideration: the RMSE and standard deviation, plots of RMSE with marked accuracy requirements, distribution of labels, and

confusion matrices. We will also discuss the cost of the sampling rates, which are shown in Table 8.1. The 2 second sampling rate is the full sampling rate represented by a full cost, and the other sampling rate costs are expressed in terms of this full cost. Lastly, we will propose a set of required accuracy requirements for different stakeholder needs based on this discussion.

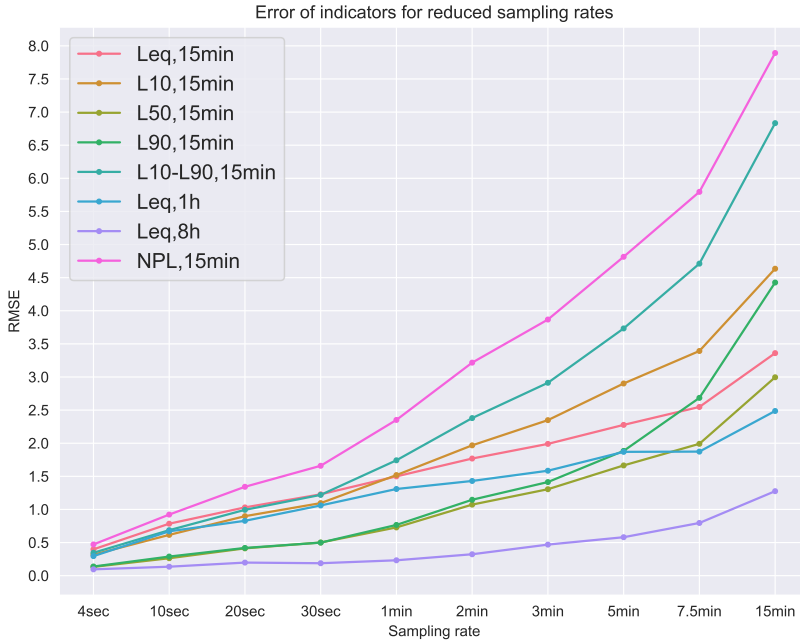


Figure 8.1: Plotted RMSE of ten reduced data sets, for eight indicators.

Table 8.1: The cost of different reduced sampling rates, compared to a full sampling rate defined with a cost = 1.

Rate	2sec	4sec	10sec	20sec	30sec	1min	2min	3min	5min	7.5min	15min
Cost	1	$\frac{1}{2}$	$\frac{1}{5}$	$\frac{1}{10}$	$\frac{1}{15}$	$\frac{1}{30}$	$\frac{1}{60}$	$\frac{1}{90}$	$\frac{1}{150}$	$\frac{1}{225}$	$\frac{1}{450}$

8.3.1 $L_{Aeq,15min}$

In terms of RMSE, the indicator performs well. As shown in Figure 7.5a, we are able to down-sample significantly and still remain under the 3 dB accuracy limit; we could use a simulated sampling rate of 7.5 minutes. The energy cost would then be 225 times better than sampling continuously every other second. This is a considerable improvement, and a good option if cost is the most important issue. Although, the variance is quite high. Looking at the confusion matrix for this sampling rate in Figure 7.10i, we see that a great deal of *fair* labels are incorrectly assigned as *good*. Some *poor* intervals are incorrectly assigned as *fair*. This is a result of the high variance, and the trend can also be seen in the histogram in Figure 7.8e. This positive bias should be adjusted for if we choose to apply this sampling rate.

If we require a better accuracy, we could consider the 2 dB limit. With a simulated sampling rate of 3 minutes, we get an RMSE right under the limit. The variance is still high; a part of the labels are wrongly assigned as *good* instead of *fair*, as shown in the confusion matrix in Figure 7.10g. Nevertheless, it could be a good trade-off if the cost of sampling is important. This strategy would make the sampling 90 times more efficient than sampling continuously every other second.

A sampling rate of 1 minute could be an alternative trade-off. The RMSE is below 2 dB, and adding the standard deviation still gives an error below 3 dB. This sampling rate uses 30 times less energy than the full sampling rate. There are a few labels that are misassigned; if that is an issue we rather recommend a sampling rate of 30 seconds. As seen in the confusion matrix in Figure 7.10d, very few labels are then wrongly assigned, and the RMSE plus standard deviation is just above 2 dB.

If we require that all of the estimated values have an error less than 2 dB, we can not reduce further than to a sampling rate of 20 seconds. With this simulated sampling rate, the RMSE is 1.03 dB, and the standard deviation is 0.822, which represents a high accuracy. For a even higher accuracy, we could sample every 10 seconds, with an RMSE of 0.785. As shown in Figure 7.10b, only a few labels are wrongly assigned for either of these two options.

Considering the most strict accuracy requirement of 0.5 dB, we can at most down-sample to a sampling rate of 4 seconds. It is still relatively efficient; we use half the energy of the full sampling. This option would be the preferred choice if the accuracy is more important than the cost.

8.3.2 $L_{A10,15min}$

This indicator is more sensitive than the $L_{Aeq,15min}$, as we can see from the RMSE in Figure 7.2. The RMSE of a sampling rate of both 3 minutes and 5 minutes is below

3 dB, which are respectively 90 and 150 times more efficient than a full sampling rate. A considerable amount of intervals are categorised as *good* when they actually are *fair*, and some as *fair* when they actually are *bad*. This is likely caused by noise events being excluded from the data set. If saving costs is the most important issue, these sampling rates could be used. However, the user should be aware of the reduced accuracy, and adjust the results accordingly. If noise events is an important factor for a stakeholder, we recommend that higher accuracy is prioritised.

Similarly, some labels are incorrectly assigned for sampling rates of 1 minute and 2 minutes. The cost of these two sampling rates are 30 and 60 times lower than a full sampling rate, respectively. Both of these sampling rates have an RMSE below 2 dB, but with a portion of variance. If we require that all samples have an error less than 2 dB, we must utilise a sampling rate of 30 seconds. It is still quite efficient; 15 times less costly than the full sampling rate. Based on the needs of users, these sampling rates can provide a sufficient trade-off between accuracy and efficiency.

For an accuracy requirement of 1 dB, almost all samples are covered for a sampling rate of 10 seconds. Only a handful of labels are wrongly assigned, and only a few samples will end up with a higher error. We save 5 times the energy of a full sampling rate. A sampling rate of 4 seconds would meet the 0.5 dB accuracy requirement, and still save half of the cost of sampling. These two options are good if accuracy of measurements is the most important, while we still want some improved efficiency.

The trend of positive bias is present for this indicator as well. We see in Figure 7.8a that a considerable amount of labels are increasingly assigned as *good* when the sampling rate is reduced. This should be taken into account if a lower sampling rate is chosen.

8.3.3 $L_{A50,15\text{min}}$

This indicator is quite robust. The RMSE is below 3 dB for all sampling rates, as shown by the RMSE in Table 7.2. For a sampling rate of 15 minutes the average accuracy is acceptable, but the standard deviation is very high. This leads to a great amount of wrongly assigned labels, as we can see in the confusion matrix in Figure 7.12i. The most frequent errors are *poor* intervals categorised as *fair*, and *good* intervals categorised as *fair*. Thus, the bias is both positive and negative; the positive is slightly stronger. If this sampling rate is chosen, the stakeholder should be aware of the bias and possibly adjust for it. If cost is the largest issue, this is a good choice; it consumes 450 times less energy than a full sampling rate.

The sampling rate of 7.5 minutes still has much of the same bias as the 15 minute sampling rate. Additionally, the variance is high even though the RMSE is just below 2 dB. Nevertheless, it is 225 times more efficient than using a full sampling

rate, making it a very cost-effective option. If we want to be nearer the 2 dB limit, a sampling rate of 5 minutes could be a better option. The RMSE plus the standard deviation is still below 3 dB. A few labels are misassigned as *fair* when they actually are *bad*, but this can be adjusted for. This is still a very efficient strategy, 150 times less costly than a full sampling rate.

To strictly keep the 2 dB limit, we can use a sampling rate of 2 minutes. Very few labels are misassigned, as we can see in Figure 7.12e. The RMSE plus the standard deviation is below 2 dB. This is 60 times more efficient than a full sampling rate, making it a good trade-off between accuracy and cost.

Concerning the 1 dB limit, there are two options. Depending on the softness of the accuracy limit and the importance of cost, the choice stands between the sampling rates 1 minute and 30 seconds. If we use a 1 minute sampling rate, some of the errors would exceed the 1 dB limit, but the mean error is below. This means that a bit more labels are wrongly assigned than with the 30 second sampling rate. For both options, very few labels are assigned erroneously. However, there is a small positive bias for either of them. The sampling rate of 30 seconds is the better option if the accuracy is more important than the cost; RMSE plus standard deviation is below 1 dB. It is still 15 times less costly than the full sampling rate. The 1 minute option is even more cost-effective, being 30 times less costly than the full sampling rate. It would be the choice if the cost is more important than the accuracy, while the accuracy still is important.

If we want to stay completely below the 0.5 dB limit, a sampling rate of 10 seconds is sufficient. It is still 10 times more efficient than the full sampling rate, but holds a particularly high accuracy. Very few labels are misassigned, as shown in Figure 7.12a. The sampling rate of 20 seconds can be chosen if we allow some larger errors; the total error is still below 1 dB.

8.3.4 $L_{A90,15min}$

This indicator is only assigned two different labels: *fair* and *poor*. Most of the assigned labels are *fair*, as seen in Figure 7.8c, which affects the label accuracy in a positive direction. Because of this, we can apparently down-sample a lot without the labels changing; the confusion matrix in Figure 7.13h seems almost unchanged. However, the indicator accuracy in Figure 7.4c shows that the RMSE and the variance is relatively high. Thus, the label accuracy may not be that robust for more varying background noise.

A sampling rate of 7.5 minutes has an RMSE below 3 dB, but due to the high variance a sampling rate of 5 minutes would be better for this accuracy requirement. Some samples will have an error above 3 dB, but it is an acceptable trade-off if the

cost is the most important. A sampling rate of 5 minutes is 150 times more efficient than a full sampling rate.

Two good trade-offs between cost and accuracy are the sampling rates of 1 and 2 minutes. The 2 minute sampling rate is more cost-effective, using 60 times less energy than a full sampling rate. The accuracy is still high, with an RMSE just above 1 dB and a variance just above 2 dB. A sampling rate of 1 minute is 30 times less costly than a full sampling rate, with an RMSE below 1 dB accuracy and a standard deviation of 0.605 dB. This alternative is a good choice if also very high accuracy is important. Although, if we require a more strict 1 dB accuracy limit, the variance for the 1 minute sampling rate is too high. The sampling rate of 30 seconds is the better choice; the variance is within the limits, and the RMSE is very low.

A sampling rate of 10 seconds provides the highest accuracy requirement of 0.5 dB. The RMSE is just below 0.3 dB, and if we add the standard deviation we get a value just above 0.5 dB. Very few samples will end up above this limit. While being particularly high in accuracy, this option is also 5 times less costly than the full sampling rate.

8.3.5 L_{A10} - $L_{A90,15min}$

Since this indicator is dependent on two other indicators and their errors, it is one of the most sensitive to down-sampling. Hence, it does not perform well in terms of label accuracy, as we can see in the confusion matrix in Figure 7.14. If the label accuracy of this indicator is very important to the stakeholders, we don't recommend down-sampling more than 4 seconds. It is still twice as efficient as the full sampling rate, but a few labels are still misassigned with a positive bias. This can be accounted for if this sampling rate is chosen.

If the indicator accuracy is the important factor, it is possible to down-sample more. A sampling rate of 2 minutes will provide an RMSE below 3 dB, but with a relatively high variance. Alternatively, a 1 minute sampling rate has a variance below 3 dB and an RMSE below 2 dB. This is considered an acceptable accuracy, but the users need to be aware of the positive bias that is present. Figure 7.14e shows that a considerable amount of labels are misassigned. The results needs to be adjusted accordingly if this sampling rate is to be used for decision-making based on labels.

For higher accuracy, a sampling rate of 30 seconds can be utilised. The RMSE is below 2 dB, and if we add the standard deviation we get a value just above 2 dB. Since a lot of labels still are wrongly assigned, as shown in Figure 7.14d, a better option could be the sampling rate of 20 seconds. It performs a bit better on label accuracy, and the variance is well below the 2 dB limit. Both options are good trade-offs between accuracy and cost.

The 1 dB limit can be met with a sampling rate of 10 seconds. The variance is somewhat high, but if the cost is important it can be an acceptable trade-off. It is still 5 times more efficient than the full sampling rate. To get a variance below 1 dB, the sampling rate can be reduced to 4 seconds. We save half the cost, but obtain a very high accuracy. If we require a particularly high accuracy, with an error below 0.5 dB, we have to sample at the full frequency. It will require the full cost; there is no other option that provides a good enough accuracy for such a sensitive indicator.

8.3.6 NPL_{15min}

The most sensitive indicator is the NPL. Since it depends on the $L_{A50,15min}$ and $L_{A10} - L_{A90,15min}$, it also inherits their errors. Although, there is still some potential for down-sampling this indicator.

The label accuracy performs acceptable down to a sampling rate of 30 seconds, as shown in the confusion matrix in Figure 7.15e. There is a small positive bias, but it can be adjusted for. With this sampling rate, we get an RMSE below 2 dB and a variance within the 3 dB limit. This is an acceptable indicator accuracy; for lower sampling rates the variance is too high for the indicator to perform sufficiently. The sampling rate of 30 seconds is 15 times more efficient than the full sampling rate, making it a cost-effective option.

There are two good trade-offs between cost and accuracy: sampling rates of 10 and 20 seconds. The variance of the 20 second sampling rate is a little above the 2 dB limit, but it is 10 times more efficient than the full sampling rate. If we require all errors to be below that limit, the 10 second sampling rate is a better option. The RMSE is below 1 dB, and if we add the standard deviation it stays well below the 2 dB limit. This choice is still 5 times more efficient than the full sampling rate.

To hold a 1 dB accuracy, the 4 second sampling rate is the best option. Both the RMSE and the added variance is below 1 dB, and at the same time this strategy is half as energy consuming as the full sampling rate. If we require the highest accuracy of 0.5 dB, we need to use the full sampling rate. The variance for a 4 second sampling rate is too high for it to perform well enough.

8.3.7 CQI_{15min}

The CQI is based on the label accuracies of $L_{A10,15min}$, $L_{A90,15min}$ and $L_{Aeq,15min}$. Thus, the result depends on the ability to down-sample those three indicators. Since the labels *hazardous* and *poor* override all the other labels, the CQI has a negative bias mainly from all the misassigned *poor* labels of the $L_{A90,15min}$. This can be seen in the histogram in Figure 7.9. Additionally, there is a positive bias inherited from the $L_{A10,15min}$ and $L_{Aeq,15min}$.

Both of these biases need to be adjusted for if we down-sample this indicator. Figure 7.16i clearly show the effect of this bias of the label accuracy. Limited mainly by the $L_{A10,15min}$, we recommend a down-sampling of maximum 1 minute. The confusion matrix for this option is shown in Figure 7.16e. This sampling rate does have a bit of wrongly assigned labels, but performs acceptable on the average.

A sampling rate of 30 seconds is a more accurate option, with even fewer erroneous assignments of labels. In fact, there is not much difference from this sampling rate and the 20 second sampling rate, as we can see in Figure 7.9. This is a good option with high accuracy and a 60 times more efficient sampling than a full sampling rate.

For even higher accuracies, the remaining options are sampling rates of 10 seconds and 4 seconds. These are respectively 5 times and 2 times more efficient than the full sampling rate. These approaches both save energy and hold very good accuracies. If the accuracy is the most important, a full sampling rate is required.

8.3.8 $L_{Aeq,1h}$

This indicator has a longer time interval, making it more robust to down-sampling. As we can see in the histogram in Figure 7.8g, there is a positive bias produced by the reduced sampling rate. It is lower than for the $L_{Aeq,15min}$, but it should be adjusted for if lower sampling rates are used. Looking at the confusion matrix in Figure 7.17f, a small negative bias also appears. Some *good* labels are wrongly assigned as *fair*.

The bias is not a major issue down to a sampling rate of 2 minutes. For this sampling rate, the RMSE is only 1.43 dB, and the variance is acceptable; combined it is well below 3 dB. It is a good trade-off between the 2 dB accuracy limit and cost. In Figure 7.5c we see that a sampling rate of 3 minutes also has a variance below the 3 dB limit. With this sampling rate there will be more misassigned labels, thus a higher bias adjustment is needed. A sampling rate of 30 seconds provides an RMSE and a variance below 2 dB. It is the best choice if we require all values to be below 2 dB.

If cost is the major factor to consider, we could even use a sampling rate of 7.5 minutes. The variance is just above 3 dB, which is acceptable if we tolerate some misassigned labels. It is a good choice for the 3 dB accuracy limit. The sampling rate of 15 minutes could be used, but the variance is very high, and a lot of labels are misassigned. It is therefore not recommended by us.

For the 1 dB accuracy limit, there are two options: the 10 second and 20 second sampling rate. Both have an RMSE below 1 dB, but the 20 second sampling rate has a higher variance. Based on the need of the user, either cost or accuracy can be

prioritised. The indicator accuracy is very high for both the options, and very few labels are wrongly assigned.

A sampling rate of 4 seconds meets the strictest requirement of 0.5 dB. The variance is a bit higher, but it should be sufficient for most cases. We still save half the energy of a full sampling rate. If accuracy is very important, we recommend a full sampling rate.

8.3.9 $L_{Aeq,8h}$

This indicator uses the largest time interval, and is therefore the most robust indicator; the noise is equalised over a longer period. As we see in the confusion matrix in Figure 7.18, the label accuracy is very stable down to a sampling rate of 5 minutes. A reason for this robustness may be that most of the labels are assigned as *poor*, and when there is a small negative bias, this trend increases. A likely explanation for the bias may be that higher noise levels are included while the data basis for analysis decreases, making a bigger impact on the result.

Due to this robustness, a sampling rate of 15 minutes is sufficient if we look at the indicator accuracy. It is a highly efficient solution; 450 times less costly than a full sampling rate. Both the RMSE and the variance are well below the 3 dB limit; with the variance we barely exceed the 2 dB limit. The variance is a bit high for this sampling rate, making the label accuracy lower. It should be adjusted for if this sampling rate is utilised. The stakeholders need to decide what is most important if this indicator is used. It covers a whole day, thus a wrongly assigned label has a potentially larger effect than for a 15 minute interval. We recommend a sampling rate of 5 minutes to avoid misallocated labels, and still get a very high accuracy. The RMSE is only 0.58 dB, and adding the variance we stay below 1 dB. If cost-effectiveness is more important, a sampling rate of 7.5 minutes provides a 225 times more efficient strategy than a full sampling rate. The indicator accuracy is still high, but some labels may be misassigned.

If the indicator accuracy is highly important, a sampling rate of 2 minutes can be used. The RMSE is below 0.5 dB, and with the variance it barely exceeds the 0.5 dB limit. It is still 60 times less costly than a full sampling rate.

Our results for this indicator are affected by the distribution of only two labels, and the sampling rates should be applied with caution. The results may be very different for other contexts, if the label distribution is more diverse.

8.4 A System for Noise Monitoring in Working Environments

Based on the trade-off analysis and the preceding discussion, we propose a system as a solution to the noise problem in working environments for focused work. This system is the designed artifact, which has been validated through the case study on a chosen working environment in this thesis. The implementation of this system is not part of the thesis.

Table 8.2 shows an overview of the results presented in Section 8.3. We see that there is a potential for down-sampling for all of the indicators. Based on the needs of the stakeholders, designers can compose a set of chosen indicators to fit the requirements of a context. Both accuracy requirements and what information that is needed will affect the noise measurement system. Considering the utilised technical details in the related work in Section 2.2.4, the use of our proposed system could improve the efficiency of sampling noticeably. The extent of the improvement will differ based on the needs for each context, but since most of the related work use continuous sampling rates, the potential is substantial.

In the case study in this thesis, the Koopen working environment, we propose the usage of the indicator CQI to decide the quality of the working environment. It takes the general noise, background noise and noise events into account. Students can decide if they want to work there during an interval based on the label. A sampling rate of 1 minute is 30 times more efficient than a full sampling rate, and provides a good enough accuracy for this context. As a supplement, the $L_{A10} - L_{A90}$ can be included to judge the variability of the noise, with the same sampling rate.

The results from this case study should be interpreted with caution, because they are likely not directly applicable to any other context. Contexts with different noise distributions will require different sampling rates, and other indicators may be required to get the desired information. System designers must validate the user requirements in each context, to make sure that the foundation for the system properties is correctly defined.

Additionally, it is important to bear in mind the possible bias of the results. The definition of the user requirements and the technical requirements could have led to bias for the results, causing the data basis for the analysis to be influenced. Further validation of the system is needed to obtain a higher external inference.

Table 8.2: Recommended sampling rate for each indicator based on four different accuracy requirements, and what kind of noise each indicator measures.

Indicator	Measures	<3 dB	<2 dB	<1 dB	<0.5 dB
$L_{Aeq,15min}$	General	5 min	1 min	10 sec	2 sec
$L_{A10,15min}$	Events	3 min	1 min	10 sec	4 sec
$L_{A50,15min}$	General	7.5 min	5 min	1 min	10 sec
$L_{A90,15min}$	Background	5 min	2 min	30 sec	10 sec
$L_{A10} - L_{A90,15min}$	Variability	1 min	20 sec	4 sec	2 sec
NPL	General & Variability	30 sec	10 sec	4 sec	2 sec
CQI	General & Events & Background	1 min	30 sec	10 sec	2 sec
$L_{Aeq,1h}$	General	7.5 min	2 min	20 sec	4 sec
$L_{Aeq,8h}$	General	15 min	7.5 min	5 min	2 min

8.5 Adaptiveness

The findings support the hypothesis that it is possible to down-sample noise data and still get accurate results for decision-making. In turn, this highlights the potential for adaptiveness in noise measurements. If a noise measurement system can adjust the sampling rate based on its remaining battery capacity and the distribution of noise in a context, it is reasonable to assume that it will become more efficient and accurate than with a static sampling approach.

If the system knows what kind of noise to expect, it does not have to measure noise that often. For example, if the system expects a time interval to be assigned the quality label *poor*, and the measured noise within the first minutes of that interval correspond to this label, it can assign the label *poor* and stop measuring until the next interval. However, if the measured noise differs from the expected range, the system can adjust the sampling rate to get a more accurate measurement. If the goal is to make correct decisions based on the given information, we need only sample with an accuracy that does not change the original decision that would have been made from the complete information.

In connection with this thesis, a PhD student created a machine-learning algorithm to predict the soundscape quality of a working environment. Based on the data collected from the IoT system we presented in Chapter 6, she trained the algorithm to predict the numerical indicator value and the quality label of a 15 minute interval. A

paper is currently being written on this project [156]. The preliminary results indicate that it is possible to achieve an acceptable trade-off between the energy consumption and the accuracy of the prediction through down-sampling. In other words, even though a higher sampling rate will give a prediction closer to the truth, we can still achieve a good prediction while saving energy, depending on our needs. This suggests that there is a potential for an adaptive sampling rate based on predictions in working environments. Further work is required on adaptive sampling to investigate the capabilities of such a system.

8.6 Concluding Remarks and Further Work

In this thesis we looked at the potential of efficient noise monitoring in working environments for focused work. Based on a case study on a student working environment, we proposed user requirements and technical requirements for sampling. For data collection, we designed an IoT system that sampled the noise level every other second for nine weeks. This data was the basis for a trade-off statistical analysis on energy cost and accuracy, when we simulated a sampling rate reduction. Finally, we proposed how noise can be measured efficiently and accurately in such a working environment.

Based on this case study, we proposed an abstract system for noise monitoring that can be adapted to different contexts. The results of this research suggest that the potential for sampling rate reduction is high, if we know what information we need to make certain decisions. Due to limitations in time and resources in this thesis, we recommend further validation of the system before it is applied to other contexts with different noise distributions.

Through this research, we highlighted the potential for adaptive noise monitoring. This research will serve as a base for future studies on adaptive sampling strategies, providing an important insight into the effect of when IoT sensors sample less data and therefore use less of their energy. Further work is needed on the topic to define the required properties of such an adaptive system. Our results in this thesis indicate that it is possible to save great amounts of energy by utilising an adaptive approach.

References

- [1] M. S. Hammer, T. K. Swinburn, and R. L. Neitzel, “Environmental noise pollution in the united states: developing an effective public health response,” *Environmental health perspectives*, vol. 122, no. 2, pp. 115–119, 2013.
- [2] Teach Engineering, “Lesson: Ultrasonic devices at the speed of sound!” <https://www.teachengineering.org/lessons/view/mis-2227-ultrasonics-uses-arduino-ultrasound-technology>. Accessed: 2019-03-12.
- [3] NTi Audio, “Fast, slow, impulse time weighting - what do they mean?.” <https://www.nti-audio.com/en/support/know-how/fast-slow-impulse-time-weighting-what-do-they-mean>. Accessed: 2019-04-03.
- [4] Libelium, “New sound level sensor to control noise pollution.” <http://www.libelium.com/new-sound-level-sensor-to-control-noise-pollution>, 2019. Accessed: 2019-02-26.
- [5] InfluxData, “Open source time series platform.” <https://www.influxdata.com/time-series-platform/>, 2019. Accessed: 2019-02-26.
- [6] R. J. Wieringa, *Design science methodology for information systems and software engineering*. Springer, 2014.
- [7] NTNU, “Koopen - elektrobygget.” <https://www.ntnu.no/laeringsarealer/koop>, 2019. Accessed: 2019-02-26.
- [8] K. Furberg, “Dette kan bli en modell for NTNUs nye campusløsning.” <https://www.universitetsavisa.no/campus/2016/03/01/Dette-kan-bli-en-modell-for-NTNUs-nye-campusl%C3%B8sning-18367752.ece>, 2016. Accessed: 2019-02-26.
- [9] Lovdata, “Forskrift om tiltaksverdier og grenseverdier for fysiske og kjemiske faktorer i arbeidsmiljøet samt smitterisikogrupper for biologiske faktorer (forskrift om tiltaks- og grenseverdier), kapittel 1. innledende bestemmelser og 2. støy.” <https://lovdata.no/dokument/SF/forskrift/2011-12-06-1358>, 2011. Accessed: 2019-04-02.

- [10] N. Garg, T. Saxena, and S. Maji, “Long-term versus short-term noise monitoring: Strategies and implications in india,” *Noise Control Engineering Journal*, vol. 63, no. 1, pp. 26–35, 2015.
- [11] W. H. Organization *et al.*, “Burden of disease from environmental noise: Quantification of healthy life years lost in europe,” in *Burden of disease from environmental noise: Quantification of healthy life years lost in Europe*, pp. 126–126, 2011.
- [12] W. Passchier-Vermeer and W. F. Passchier, “Noise exposure and public health.,” *Environmental health perspectives*, vol. 108, no. suppl 1, pp. 123–131, 2000.
- [13] K. Fuks, S. Moebus, S. Hertel, A. Viehmann, M. Nonnemacher, N. Dragano, S. Möhlenkamp, H. Jakobs, C. Kessler, R. Erbel, *et al.*, “Long-term urban particulate air pollution, traffic noise, and arterial blood pressure,” *Environmental health perspectives*, vol. 119, no. 12, pp. 1706–1711, 2011.
- [14] M. Sørensen, Z. J. Andersen, R. B. Nordsborg, T. Becker, A. Tjønneland, K. Overvad, and O. Raaschou-Nielsen, “Long-term exposure to road traffic noise and incident diabetes: a cohort study,” *Environmental health perspectives*, vol. 121, no. 2, pp. 217–222, 2012.
- [15] J. Selander, M. E. Nilsson, G. Bluhm, M. Rosenlund, M. Lindqvist, G. Nise, and G. Pershagen, “Long-term exposure to road traffic noise and myocardial infarction,” *Epidemiology*, pp. 272–279, 2009.
- [16] W. Q. Gan, H. W. Davies, M. Koehoorn, and M. Brauer, “Association of long-term exposure to community noise and traffic-related air pollution with coronary heart disease mortality,” *American journal of epidemiology*, vol. 175, no. 9, pp. 898–906, 2012.
- [17] J. L. Mayes, “Urban noise levels are high enough to damage auditory sensorineural health,” *Cities & Health*, pp. 1–7, 2019.
- [18] N. S. Reed, A. Altan, J. A. Deal, C. Yeh, A. D. Kravetz, M. Wallhagen, and F. R. Lin, “Trends in health care costs and utilization associated with untreated hearing loss over 10 years,” *JAMA Otolaryngology–Head & Neck Surgery*, vol. 145, no. 1, pp. 27–34, 2019.
- [19] B. Shield, E. Greenland, J. Dockrell, *et al.*, “Noise in open plan classrooms in primary schools: A review,” *Noise and Health*, vol. 12, no. 49, p. 225, 2010.
- [20] S. Banbury and D. C. Berry, “Disruption of office-related tasks by speech and office noise,” *British journal of psychology*, vol. 89, no. 3, pp. 499–517, 1998.
- [21] M. Navai and J. Veitch, “Acoustic satisfaction in open-plan offices: Review and recommendations,” 01 2003.
- [22] H. Jahncke, *Cognitive performance and restoration in open-plan office noise*. PhD thesis, Luleå tekniska universitet, 2012.

- [23] A. Lie, M. Skogstad, H. A. Johannessen, T. Tynes, I. S. Mehlum, K.-C. Nordby, B. Engdahl, and K. Tambs, “Occupational noise exposure and hearing: a systematic review,” *International archives of occupational and environmental health*, vol. 89, no. 3, pp. 351–372, 2016.
- [24] L. Ruge, B. Altakrouri, and A. Schrader, “Soundofthecity - continuous noise monitoring for a healthy city,” in *2013 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*, pp. 670–675, IEEE, 2013.
- [25] E. Directive, “Directive 2002/49/ec of the european parliament and the council of 25 june 2002 relating to the assessment and management of environmental noise,” *Official Journal of the European Communities, L*, vol. 189, no. 18.07, p. 2002, 2002.
- [26] S. Abba and B. E. Patrick, “Smart framework for environmental pollution monitoring and control system using iot-based technology,” *Sensors & Transducers*, vol. 229, no. 1, pp. 84–93, 2019.
- [27] J. Segura-Garcia, J. Navarro-Ruiz, J. Perez-Solano, J. Montoya-Belmonte, S. Felici-Castell, M. Cobos, and A. Torres-Aranda, “Spatio-temporal analysis of urban acoustic environments with binaural psycho-acoustical considerations for iot-based applications,” *Sensors*, vol. 18, no. 3, p. 690, 2018.
- [28] P. Maijala, Z. Shuyang, T. Heittola, and T. Virtanen, “Environmental noise monitoring using source classification in sensors,” *Applied Acoustics*, vol. 129, pp. 258–267, 2018.
- [29] C. Mydlarz, J. Salamon, and J. P. Bello, “The implementation of low-cost urban acoustic monitoring devices,” *Applied Acoustics*, vol. 117, pp. 207–218, 2017.
- [30] J. E. Noriega-Linares, A. Rodriguez-Mayol, M. Cobos, J. Segura-García, S. Felici-Castell, and J. M. Navarro, “A wireless acoustic array system for binaural loudness evaluation in cities,” *IEEE Sensors Journal*, vol. 17, no. 21, pp. 7043–7052, 2017.
- [31] M. Quintana-Suárez, D. Sánchez-Rodríguez, I. Alonso-González, and J. Alonso-Hernández, “A low cost wireless acoustic sensor for ambient assisted living systems,” *Applied Sciences*, vol. 7, no. 9, p. 877, 2017.
- [32] J. P. Bello, C. Silva, O. Nov, R. L. DuBois, A. Arora, J. Salamon, C. Mydlarz, and H. Doraiswamy, “Sonyc: A system for the monitoring, analysis and mitigation of urban noise pollution,” *arXiv preprint arXiv:1805.00889*, 2018.
- [33] Y. Alsouda, S. Pillana, and A. Kurti, “A machine learning driven iot solution for noise classification in smart cities,” *arXiv preprint arXiv:1809.00238*, 2018.
- [34] J. Ye, T. Kobayashi, and M. Murakawa, “Urban sound event classification based on local and global features aggregation,” *Applied Acoustics*, vol. 117, pp. 246–256, 2017.

- [35] E. H. Berger, *The Noise Manual*. Aiha, 2003.
- [36] “NEK IEC 61672-1:2013: Electroacoustics – Sound level meters – Part 1: Specifications,” standard, International Electrotechnical Commission, Sept. 2013.
- [37] “ISO 532-1:2017: Acoustics – Methods for calculating loudness – Part 1: Zwicker method.,” standard, International Electrotechnical Commission, June 2017.
- [38] “ISO 1996-1:2016: Acoustics – Description, measurement and assessment of environmental noise – Part 1: Basic quantities and assessment procedures,” standard, International Organization for Standardization, Oct. 2017.
- [39] “ISO 11690-1:1996: Acoustics – Recommended practice for the design of low-noise workplaces containing machinery – Part 1: Noise control strategies,” standard, International Organization for Standardization, Nov. 1996.
- [40] “ISO 12913-1:2014: Acoustics – Soundscape – Part 1: Definition and conceptual framework.,” standard, International Electrotechnical Commission, Sept. 2014.
- [41] “ISO 37120:2018: Sustainable cities and communities – Indicators for city services and quality of life.,” standard, International Organization for Standardization, July 2018.
- [42] “IEC 60050-801:1994: International Electrotechnical Vocabulary (IEV) – Part 801: Acoustics and electroacoustics.,” standard, International Electrotechnical Commission, July 1994.
- [43] J. Beaumont and E. Petitjean, “Driving force, pressure and state indicators,” in *Technical Meeting on Noise Indicators, WHO Europe, Bruxelles*, Citeseer, 2003.
- [44] Trondheim Kommune, “Map of municipality of trondheim.” <https://kart5.nois.no/trondheim/Content/Main.asp?layout=trondheim&time=1539189528&vwr=asv>. Accessed: 2019-03-04. Choose filter "Støysoner 2017" and zoom 1:20,000.
- [45] E. Directive, “Directive 2003/10/ec on the minimum health and safety requirements regarding the exposure of workers to the risks arising from physical agents (noise),” *Official Journal of the European Union*, vol. 42, pp. 38–44, 2003.
- [46] Lovdata, “Forskrift om grenseverdier for støy.” <https://lovdata.no/dokument/LTI/forskrift/2002-10-04-1089>, 2002. Accessed: 2019-03-04.
- [47] Lovdata, “Forskrift om begrenning av forurensning (forurensningsforskriften), del 2. støy, kapittel 5. støy – kartlegging, handlingsplaner og tiltaksgrenser for eksisterende virksomhet.” https://lovdata.no/dokument/SF/forskrift/2004-06-01-931/KAPITTEL_2-1#KAPITTEL_2-1, 2004. Accessed: 2019-03-04.
- [48] Lovdata, “Lov om arbeidsmiljø, arbeidstid og stillingsvern mv. (arbeidsmiljøloven), kapittel 4. krav til arbeidsmiljøet.” <https://lovdata.no/dokument/NL/lov/2005-06-17-62>, 2005. Accessed: 2019-03-25.

- [49] Lovdata, “Forskrift om utforming og innretning av arbeidsplasser og arbeidslokaler (arbeidsplassforskriften), kapittel 2, paragraf 16. støy og vibrasjoner.” <https://lovdata.no/dokument/SF/forskrift/2011-12-06-1356?q=2003/10/EF>, 2011. Accessed: 2019-03-25.
- [50] Lovdata, “Forskrift om utførelse av arbeid, bruk av arbeidsutstyr og tilhørende tekniske krav (forskrift om utførelse av arbeid). tredje del: Krav til arbeid med fysiske risikofaktorer. kapittel 14. arbeid som kan medføre eksponering for støy eller mekaniske vibrasjoner. paragraf 14-6. særskilte tiltak mot støy ved overskridelse av tiltaksverdiene.” <https://lovdata.no/dokument/SF/forskrift/2011-12-06-1357>, 2011. Accessed: 2019-04-02.
- [51] Arbejdsmiljø i Danmark, “Støj.” <https://amid.dk/regler/at-vejledninger/stoej-d-6-1-5/>. Accessed: 2019-04-02.
- [52] Verein Deutscher Ingenieure, “Vdi-richtlinie: Vdi 2058 blatt 3. beurteilung von lärm am arbeitsplatz unter berücksichtigung unterschiedlicher tätigkeiten (assessment of noise in the working area with regard to specific operations).” https://www.vdi.de/uploads/tx_vdirili/pdf/2203575.pdf. Accessed: 2019-04-02.
- [53] B. B. H. und Metall, “Dguv information 209-023: Lärm am arbeitsplatz,” nov 2013.
- [54] Rechtsinformationssystem des Bundes, “Bundesrecht konsolidiert: Verordnung lärm und vibrationen § 5, tagesaktuelle fassung.” <https://www.ris.bka.gv.at/NormDokument.wxe?Abfrage=Bundesnormen&Gesetzesnummer=20004576&Paragraf=5>. Accessed: 2019-04-02.
- [55] G. Rey Gozalo and J. Barrigón Morillas, “Analysis of sampling methodologies for noise pollution assessment and the impact on the population,” *International journal of environmental research and public health*, vol. 13, no. 5, p. 490, 2016.
- [56] M. M. Morales, D. V. Aparicio, A. M. Garcia, A. Garcia, A. Merelles, and F. Ballester, “An acoustic map of a district in the city of valencia,” *International journal of environmental studies*, vol. 39, no. 1-2, pp. 65–77, 1991.
- [57] J. Wesler, “Community noise survey of medford, massachusetts,” *The Journal of the Acoustical Society of America*, vol. 54, no. 4, pp. 985–995, 1973.
- [58] A. Price, “Community noise survey of greater vancouver,” *The Journal of the Acoustical Society of America*, vol. 52, no. 2A, pp. 488–492, 1972.
- [59] A. Ramírez and E. Domínguez, “Modeling urban traffic noise with stochastic and deterministic traffic models,” *Applied Acoustics*, vol. 74, no. 4, pp. 614–621, 2013.
- [60] A. Calixto, F. B. Diniz, and P. H. Zannin, “The statistical modeling of road traffic noise in an urban setting,” *Cities*, vol. 20, no. 1, pp. 23–29, 2003.
- [61] M. Cai, J. Zou, J. Xie, and X. Ma, “Road traffic noise mapping in guangzhou using gis and gps,” *Applied Acoustics*, vol. 87, pp. 94–102, 2015.

- [62] J. C. Seong, T. H. Park, J. H. Ko, S. I. Chang, M. Kim, J. B. Holt, and M. R. Mehdi, "Modeling of road traffic noise and estimated human exposure in fulton county, georgia, usa," *Environment international*, vol. 37, no. 8, pp. 1336–1341, 2011.
- [63] A. González, M. G. Cardozo, E. P. Rocamora, A. Bracho, *et al.*, "Urban noise: Measurement duration and modelling of noise levels in three different cities," *Noise control engineering journal*, vol. 55, no. 3, pp. 367–372, 2007.
- [64] L. M. Han, Z. Haron, K. Yahya, S. A. Bakar, and M. N. Dimon, "A stochastic simulation framework for the prediction of strategic noise mapping and occupational noise exposure using the random walk approach," *PloS one*, vol. 10, no. 4, p. e0120667, 2015.
- [65] A. Garcia and L. Faus, "Statistical analysis of noise levels in urban areas," *Applied Acoustics*, vol. 34, no. 4, pp. 227–247, 1991.
- [66] C. Steele, "A critical review of some traffic noise prediction models," *Applied acoustics*, vol. 62, no. 3, pp. 271–287, 2001.
- [67] D. Geraghty and M. O'Mahony, "Investigating the temporal variability of noise in an urban environment," *International Journal of Sustainable Built Environment*, vol. 5, no. 1, pp. 34–45, 2016.
- [68] J. Romeu, M. Genescà, T. Pàmies, and S. Jiménez, "Street categorization for the estimation of day levels using short-term measurements," *Applied Acoustics*, vol. 72, no. 8, pp. 569–577, 2011.
- [69] C. Guarnaccia, D. Singh, J. Quartieri, S. Nigam, M. Kumar, and N. E. Mastorakis, "Honking noise contribution to road traffic noise prediction," in *AIP Conference Proceedings*, vol. 1982, p. 020042, AIP Publishing, 2018.
- [70] H. Hamdad, C. Pézerat, B. Gauvreau, C. Locqueteau, and Y. Denoual, "Sensitivity analysis and propagation of uncertainty for the simulation of vehicle pass-by noise," *Applied Acoustics*, vol. 149, pp. 85–98, 2019.
- [71] A. E. Engedy, J. Lechleitner, and A. Mahdavi, "Sound propagation in urban canyons: a case study of simulation reliability," *Journal of Building Performance Simulation*, pp. 1–15, 2018.
- [72] N. Garg and S. Maji, "A critical review of principal traffic noise models: Strategies and implications," *Environmental Impact Assessment Review*, vol. 46, pp. 68–81, 2014.
- [73] J. Quartieri, N. Mastorakis, G. Iannone, C. Guarnaccia, S. D'ambrosio, A. Troisi, and T. Lenza, "A review of traffic noise predictive models," in *Recent Advances in Applied and Theoretical Mechanics, 5th WSEAS International Conference on Applied and Theoretical Mechanics (MECHANICS'09) Puerto De La Cruz, Tenerife, Canary Islands, Spain December*, pp. 14–16, 2009.

- [74] N. Kwon, J. Lee, M. Park, I. Yoon, and Y. Ahn, “Performance evaluation of distance measurement methods for construction noise prediction using case-based reasoning,” *Sustainability*, vol. 11, no. 3, p. 871, 2019.
- [75] A. A. Ahmed and B. Pradhan, “Vehicular traffic noise prediction and propagation modelling using neural networks and geospatial information system,” *Environmental monitoring and assessment*, vol. 191, no. 3, p. 190, 2019.
- [76] IEEE Internet of Things (IoT) Initiative, “Towards a definition of the internet of things (iot). revision 1 - published 27 may 2015.” https://iot.ieee.org/images/files/pdf/IEEE_IoT_Towards_Definition_Internet_of_Things_Revision1_27MAY15.pdf. Accessed: 2019-04-07.
- [77] Urbiotica, “Urbiotica - noise monitoring.” <https://www.urbiotica.com/en/smart-solutions-2/noise-monitoring/>. Accessed: 2019-03-02.
- [78] SensorTeam, “The iot soundsensor©.” <https://www.iotsoundsensor.com/en/>. Accessed: 2019-03-02.
- [79] Yanzi Networks, “The yanzi solution.” <https://www.yanzi.se/solution/>. Accessed: 2019-03-02.
- [80] iComfort, “icomfort - smart iot for better workplaces..” <http://www.icomfort.it/>, 2019. Accessed: 2019-04-15.
- [81] S. Santini, B. Ostermaier, and R. Adelman, “On the use of sensor nodes and mobile phones for the assessment of noise pollution levels in urban environments,” in *2009 Sixth International Conference on Networked Sensing Systems (INSS)*, pp. 1–8, IEEE, 2009.
- [82] E. Kanjo, “Noisespy: A real-time mobile phone platform for urban noise monitoring and mapping,” *Mobile Networks and Applications*, vol. 15, no. 4, pp. 562–574, 2010.
- [83] R. Rana, C. T. Chou, N. Bulusu, S. Kanhere, and W. Hu, “Ear-phone: A context-aware noise mapping using smart phones,” *Pervasive and Mobile Computing*, vol. 17, pp. 1–22, 2015.
- [84] N. Panagiotou, N. Zygouras, I. Katakis, D. Gunopulos, N. Zacheilas, I. Boutsis, V. Kalogeraki, S. Lynch, and B. O’Brien, “Intelligent urban data monitoring for smart cities,” in *Joint European conference on machine learning and knowledge discovery in databases*, pp. 177–192, Springer, 2016.
- [85] M.-L. Marsal-Llacuna, J. Colomer-Llinàs, and J. Meléndez-Frigola, “Lessons in urban monitoring taken from sustainable and livable cities to better address the smart cities initiative,” *Technological Forecasting and Social Change*, vol. 90, pp. 611–622, 2015.

- [86] A. Solanas, C. Patsakis, M. Conti, I. S. Vlachos, V. Ramos, F. Falcone, O. Postolache, P. A. Pérez-Martínez, R. Di Pietro, D. N. Perrea, *et al.*, “Smart health: a context-aware health paradigm within smart cities,” *IEEE Communications Magazine*, vol. 52, no. 8, pp. 74–81, 2014.
- [87] J. Segura-Garcia, M. Garcia-Pineda, M. Tamarit-Tronch, R. Cibrian, and R. Salvador-Palmer, “Cost-effective ehealth system based on a multi-sensor system-on-chip platform and data fusion in cloud for sport activity monitoring,” *Electronics*, vol. 7, no. 9, p. 183, 2018.
- [88] Z. Ji, I. Ganchev, M. O’Droma, L. Zhao, and X. Zhang, “A cloud-based car parking middleware for iot-based smart cities: Design and implementation,” *Sensors*, vol. 14, no. 12, pp. 22372–22393, 2014.
- [89] C. Bartalucci, F. Borchi, M. Carfagni, R. Furferi, L. Governi, R. Silvaggio, S. Curcuruto, and L. Nencini, “Design of a prototype of a smart noise monitoring system,” in *Proceedings of the 24th International Congress on Sound and Vibration (ICSV24), London, UK*, pp. 23–27, 2017.
- [90] C. Wang, G. Chen, R. Dong, and H. Wang, “Traffic noise monitoring and simulation research in xiamen city based on the environmental internet of things,” *International Journal of Sustainable Development & World Ecology*, vol. 20, no. 3, pp. 248–253, 2013.
- [91] S. Santini and A. Vitaletti, “Wireless sensor networks for environmental noise monitoring,” *6. Fachgespräch Sensornetzwerke*, p. 98, 2007.
- [92] S. Santini, B. Ostermaier, and A. Vitaletti, “First experiences using wireless sensor networks for noise pollution monitoring,” in *Proceedings of the workshop on Real-world wireless sensor networks*, pp. 61–65, ACM, 2008.
- [93] E. Murphy and E. A. King, “Strategic environmental noise mapping: Methodological issues concerning the implementation of the eu environmental noise directive and their policy implications,” *Environment international*, vol. 36, no. 3, pp. 290–298, 2010.
- [94] P. Mioduszewski, J. A. Ejsmont, J. Grabowski, and D. Karpiński, “Noise map validation by continuous noise monitoring,” *Applied Acoustics*, vol. 72, no. 8, pp. 582–589, 2011.
- [95] L. Nencini, P. De Rosa, E. Ascari, B. Vinci, and N. Alexeeva, “Senseable pisa: A wireless sensor network for real-time noise mapping,” *Proceedings of the EU-RONOISE, Prague, Czech Republic*, pp. 10–13, 2012.
- [96] B. Vinci, A. Tonacci, C. Caudai, P. De Rosa, L. Nencini, and L. Pratali, “The senseable pisa project: Citizen-participation in monitoring acoustic climate of mediterranean city centers,” *CLEAN–Soil, Air, Water*, vol. 45, no. 7, p. 1600137, 2017.

- [97] Senseable Pisa, “Senseable pisa - sensing the city..” <https://senseable.it/>, 2019. Accessed: 2019-04-12.
- [98] J. Paulo, P. Fazenda, T. Oliveira, and J. Casaleiro, “Continuous sound analysis in urban environments supported by fiware platform,” *Proceedings of the EuroRegio2016/TecniAcústica*, vol. 16, pp. 1–10, 2016.
- [99] J. C. Farrés, “Barcelona noise monitoring network,” in *Proceedings of the EuroNoise*, pp. 218–220, 2015.
- [100] F. Mietlicki, C. Mietlicki, and M. Sineau, “An innovative approach for long-term environmental noise measurement: Rumeur network in paris region,” in *Proceedings of the EuroNoise*, 2015.
- [101] RUMEUR, “Rumeur - réseau de mesure de l’environnement sonore en Île-de-france..” <https://rumeur.bruitparif.fr/main>, 2019. Accessed: 2019-04-12.
- [102] J. Segura Garcia, J. Pérez Solano, M. Cobos Serrano, E. Navarro Camba, S. Felici Castell, A. Soriano Asensi, and F. Montes Suay, “Spatial statistical analysis of urban noise data from a wasn gathered by an iot system: Application to a small city,” *Applied Sciences*, vol. 6, no. 12, p. 380, 2016.
- [103] Cense, “Characterization of urban sound environments.” <http://cense.iftstar.fr/en/>, 2019. Accessed: 2019-04-07.
- [104] J. Picaut, A. Can, J. Ardouin, P. Crépeaux, T. Dhorne, D. Écotière, M. Lagrange, C. Lavandier, V. Mallet, C. Mietlicki, *et al.*, “Characterization of urban sound environments using a comprehensive approach combining open data, measurements, and modeling,” *The Journal of the Acoustical Society of America*, vol. 141, no. 5, pp. 3808–3808, 2017.
- [105] F. Alías, R. Alsina-Pagès, J. Carrié, and F. Orga, “Dynamap: A low-cost wasn for real-time road traffic noise mapping,” *Proceedings of the Techni Acustica, Cadiz, Spain*, pp. 24–26, 2018.
- [106] DYNAMAP, “Documents - deliverables, reports, publications, and presentations.” <http://www.life-dynamap.eu/documents/#official-reports>, 2019. Accessed: 2019-04-11.
- [107] X. Sevillano, J. C. Socoró, F. Alías, P. Bellucci, L. Peruzzi, S. Radaelli, P. Coppi, L. Nencini, A. Cerniglia, A. Bisceglie, *et al.*, “Dynamap—development of low cost sensors networks for real time noise mapping,” *Noise Mapping*, vol. 3, no. 1, 2016.
- [108] J. C. Socoró, R. M. Alsina-Pagès, F. Alías, and F. Orga, “Acoustic conditions analysis of a multi-sensor network for the adaptation of the anomalous noise event detector,” in *Multidisciplinary Digital Publishing Institute Proceedings*, vol. 4, p. 51, 2019.
- [109] G. Zambon, R. Benocci, and G. Brambilla, “Cluster categorization of urban roads to optimize their noise monitoring,” *Environmental monitoring and assessment*, vol. 188, no. 1, p. 26, 2016.

- [110] SONYC, “Sonyc - sounds of new york city..” <https://wp.nyu.edu/sonyc/>, 2019. Accessed: 2019-04-15.
- [111] I. Hakala, I. Kivela, J. Ihalainen, J. Luomala, and C. Gao, “Design of low-cost noise measurement sensor network: Sensor function design,” in *2010 First International Conference on Sensor Device Technologies and Applications*, pp. 172–179, IEEE, 2010.
- [112] I. Kivelä, C. Gao, J. Luomala, and I. Hakala, “Design of noise measurement sensor network: Networking and communication part,” in *Proceedings of the 5th International Conference on Sensor Technologies and Applications, Côte d’Azur, France*, pp. 21–27, 2011.
- [113] J. Polastre, R. Szewczyk, and D. Culler, “Telos: enabling ultra-low power wireless research,” in *Proceedings of the 4th international symposium on Information processing in sensor networks*, p. 48, IEEE Press, 2005.
- [114] D. Manvell, “Utilising the strengths of different sound sensor networks in smart city noise management,” in *Proceedings of the EuroNoise*, 2015.
- [115] T. Basten and P. Wessels, “An overview of sensor networks for environmental noise monitoring,” *21st International Congress on Sound and Vibration 2014, ICSV 2014*, vol. 5, pp. 3660–3667, 01 2014.
- [116] A. Bertrand, “Applications and trends in wireless acoustic sensor networks: A signal processing perspective,” in *2011 18th IEEE symposium on communications and vehicular technology in the Benelux (SCVT)*, pp. 1–6, IEEE, 2011.
- [117] Libelium, “Libelium website.” <http://www.libelium.com/>, 2019. Accessed: 2019-02-25.
- [118] J. Kang, F. Aletta, E. Margaritis, and M. Yang, “A model for implementing soundscape maps in smart cities,” *Noise Mapping*, vol. 5, no. 1, pp. 46–59, 2018.
- [119] D. Botteldooren, B. De Coensel, D. Oldoni, T. Van Renterghem, and S. Dauwe, “Sound monitoring networks new style,” in *Acoustics 2011: Breaking New Ground: Annual Conference of the Australian Acoustical Society*, pp. 1–5, Australian Acoustical Society, 2011.
- [120] L. Brocolini, C. Lavandier, M. Quoy, and C. Ribeiro, “Measurements of acoustic environments for urban soundscapes: Choice of homogeneous periods, optimization of durations, and selection of indicators,” *The Journal of the Acoustical Society of America*, vol. 134, no. 1, pp. 813–821, 2013.
- [121] Miljødirektoratet, “Veileder m-290 (2015). måling av støy fra industri. immisjonsmålemetode.” <http://www.miljodirektoratet.no/Documents/publikasjoner/M290/M290.pdf>. Accessed: 2019-03-04.
- [122] D. S. Cho, J. H. Kim, and D. Manvell, “Noise mapping using measured noise and gps data,” *Applied acoustics*, vol. 68, no. 9, pp. 1054–1061, 2007.

- [123] R. M. Alsina-Pagès, R. Garcia Almazán, M. Vilella, and M. Pons, “Noise events monitoring for urban and mobility planning in andorra la vella and escaldes-engordany,” *Environments*, vol. 6, no. 2, p. 24, 2019.
- [124] K. M. Paiva, M. R. A. Cardoso, and P. H. T. Zannin, “Exposure to road traffic noise: Annoyance, perception and associated factors among brazil’s adult population,” *Science of the Total Environment*, vol. 650, pp. 978–986, 2019.
- [125] Libelium, “Wasmote plug & sense! technical guide.” http://www.libelium.com/downloads/documentation/wasmote_plug_and_sense_technical_guide.pdf, 2019. Accessed: 2019-02-25.
- [126] Libelium, “Smart cities pro technical guide.” http://www.libelium.com/downloads/documentation/smart_cities_pro_sensor_board.pdf, 2019. Accessed: 2019-02-25.
- [127] Libelium, “Wasmote plug & sense! sensor guide.” http://www.libelium.com/downloads/documentation/wasmote_plug_and_sense_sensors_guide.pdf, 2019. Accessed: 2019-02-25.
- [128] Libelium, “Wasmote IDE user guide.” http://www.libelium.com/downloads/documentation/wasmote_ide_user_guide.pdf, 2019. Accessed: 2019-02-25.
- [129] Libelium, “Wasmote programming guide.” http://www.libelium.com/downloads/documentation/wasmote_programming_guide.pdf, 2019. Accessed: 2019-02-25.
- [130] InfluxData, “InfluxData website.” <https://www.influxdata.com/>, 2019. Accessed: 2019-02-26.
- [131] InfluxData, “Time series database (TSDB) explained.” <https://www.influxdata.com/time-series-database/>, 2019. Accessed: 2019-02-26.
- [132] InfluxData, “InfluxDB line protocol tutorial.” https://docs.influxdata.com/influxdb/v1.7/write_protocols/line_protocol_tutorial/, 2019. Accessed: 2019-02-26.
- [133] C. Robson and K. McCartan, *Real world research*. John Wiley & Sons, 2016.
- [134] P. Cronin, F. Ryan, and M. Coughlan, “Undertaking a literature review: a step-by-step approach,” *British journal of nursing*, vol. 17, no. 1, pp. 38–43, 2008.
- [135] B. Willis, “The advantages and limitations of single case study analysis,” *E-International Relations*, 2014.
- [136] L. K. Michaelsen and M. Sweet, “The essential elements of team-based learning,” *New directions for teaching and learning*, vol. 2008, no. 116, pp. 7–27, 2008.
- [137] B. Berglund, P. Hassmen, and R. S. Job, “Sources and effects of low-frequency noise,” *The Journal of the Acoustical Society of America*, vol. 99, no. 5, pp. 2985–3002, 1996.

- [138] U. Ayr, E. Cirillo, and F. Martellotta, “An experimental study on noise indices in air conditioned offices,” *Applied Acoustics*, vol. 62, no. 6, pp. 633–643, 2001.
- [139] B. M. Shield and J. E. Dockrell, “The effects of noise on children at school: A review,” *Building Acoustics*, vol. 10, no. 2, pp. 97–116, 2003.
- [140] J. E. Dockrell and B. M. Shield, “Acoustical barriers in classrooms: The impact of noise on performance in the classroom,” *British Educational Research Journal*, vol. 32, no. 3, pp. 509–525, 2006.
- [141] B. M. Shield and J. E. Dockrell, “The effects of environmental and classroom noise on the academic attainments of primary school children,” *The Journal of the Acoustical Society of America*, vol. 123, no. 1, pp. 133–144, 2008.
- [142] P. Lundquist, K. Holmberg, U. Landstrom, *et al.*, “Annoyance and effects on work from environmental noise at school,” *Noise and Health*, vol. 2, no. 8, p. 39, 2000.
- [143] J. C. Vischer, “The effects of the physical environment on job performance: towards a theoretical model of workspace stress,” *Stress and Health: Journal of the International Society for the Investigation of Stress*, vol. 23, no. 3, pp. 175–184, 2007.
- [144] J. C. Vischer, “Towards an environmental psychology of workspace: how people are affected by environments for work,” *Architectural science review*, vol. 51, no. 2, pp. 97–108, 2008.
- [145] K. Freihoefer, D. Guerin, C. Martin, H.-Y. Kim, and J. K. Brigham, “Occupants’ satisfaction with, and physical readings of, thermal, acoustic, and lighting conditions of sustainable office workspaces,” *Indoor and Built Environment*, vol. 24, no. 4, pp. 457–472, 2015.
- [146] A. Haapakangas, V. Hongisto, J. Hyönä, J. Kokko, and J. Keränen, “Effects of unattended speech on performance and subjective distraction: The role of acoustic design in open-plan offices,” *Applied Acoustics*, vol. 86, pp. 1–16, 2014.
- [147] U. Ayr, E. Cirillo, I. Fato, and F. Martellotta, “A new approach to assessing the performance of noise indices in buildings,” *Applied acoustics*, vol. 64, no. 2, pp. 129–145, 2003.
- [148] B. De Coensel and D. Botteldooren, “The quiet rural soundscape and how to characterize it,” *Acta Acustica united with Acustica*, vol. 92, no. 6, pp. 887–897, 2006.
- [149] P. Ricciardi, P. Delaitre, C. Lavandier, F. Torchia, and P. Aumond, “Sound quality indicators for urban places in paris cross-validated by milan data,” *The Journal of the Acoustical Society of America*, vol. 138, no. 4, pp. 2337–2348, 2015.

- [150] M. D. Giv, K. G. Sani, M. Alizadeh, A. Valinejadi, and H. A. Majdabadi, “Evaluation of noise pollution level in the operating rooms of hospitals: A study in iran,” *Interventional Medicine and Applied Science*, vol. 9, no. 2, pp. 61–66, 2017.
- [151] J. J. Peirce, R. Weiner, R. Matthews, and P. A. Vesilind, *Environmental engineering*. Butterworth-Heinemann, 2003.
- [152] S. Tang and C. Wong, “Performance of noise indices in office environment dominated by noise from human speech,” *Applied Acoustics*, vol. 55, no. 4, pp. 293–305, 1998.
- [153] L. L. Beranek, W. E. Blazier, and J. J. Figwer, “Preferred noise criterion (pnc) curves and their application to rooms,” *The Journal of the Acoustical Society of America*, vol. 50, no. 5A, pp. 1223–1228, 1971.
- [154] A. Can, S. Michel, B. De Coensel, C. Ribeiro, D. Botteldooren, and C. Lavandier, “Comparison of noise indicators in an urban context,” in *INTER-NOISE and NOISE-CON Congress and Conference Proceedings*, vol. 253, pp. 775–783, Institute of Noise Control Engineering, 2016.
- [155] Ö. Axelsson, “How to measure soundscape quality,” in *Proceedings of the Euronoise 2015 conference*, pp. 1477–1481, 2015.
- [156] F. Alawad, I. M. V. Bosch, and F. A. Kraemer, “Energy-accuracy trade-off for efficient noise monitoring and prediction in working environments,” 2019. To be submitted.

Appendix

Schedule for Koopen

Below is the schedule for the area called Koopen, for spring 2019. Different courses are shown in different colours.



Koopen

En arena for kooperativ læring

Koopen er et av NTNUs piloter i Campus-prosjektet. Her utprøves nye læringsformer i regi av Elsys-programmet. I vårsemesteret 2019 har Koopen timeplanfestet bruk som vist under:

	mandag	tirsdag	onsdag	torsdag	fredag
08:15			TTT4270	TTT4260	TTT4270
09:00					
09:15					
10:00					
10:15					
11:00					
11:15	TFE4172				
12:00					
12:15		TFE4172			
13:00					
13:15	TFE4260				
14:00					
14:15			TTT4146		
15:00					
15:15					
16:00					
16:15					
17:00					
17:15					
18:00					
18:15					
19:00					
19:15					
20:00					

Utenom timeplanfestede aktiviteter er arealet primært forbeholdt studenter ved Elsys-studieprogrammet.

Figure A.1: Schedule for Koopen, spring 2019.

Appendix **B** Information Note

Below is the information note for Koopen, attached by each sensor.

Ongoing experiment

This equipment is related to a master's thesis regarding noise in working environments. We log noise levels, temperature and humidity in this area. The information sampled is sent over WiFi to a database. The data will be used to analyze distributions of noise in various periods of the day. The temperature and humidity data will be used in a PhD. We kindly ask you **not to touch** the equipment.

If you have any questions or detect any damage at the sensors, please contact imbosch@stud.ntnu.no.

Privacy

The microphone is used to measure the noise levels in dBA every 2 seconds. **It is not possible to record any conversations or identify persons.**

Appendix

E-Mail Correspondence with the Norwegian Data Protection Authority

Below is the e-mail correspondence with the Norwegian Data Protection Authority (Datatilsynet). They confirm that this project does not handle personal information. To cite: “*You do not need to apply or notify the Norwegian Data Protection Authority about your project*”.



Ida Marie V. Bosch <[REDACTED]>

Støymåling ifm masteroppgave

Veiledning <veiledning@datatilsynet.no>

20. november 2018 kl. 10:34

Til: "[REDACTED]"

Hei, og takk for e-posten din.

Vår juridiske veiledningstjeneste gir deg kortfattet rådgivning. Det betyr at alle våre svar kun er veiledende.

Du stiller spørsmål om personopplysningsloven kommer til anvendelse og om det er søknadsplikt for ditt prosjekt.

Lovens virkeområde

Datatilsynet forvalter personvernregelverket i Norge. For at disse regelen skal komme til anvendelse er det et vilkår at man behandler personopplysninger.

Det du må vurdere i din sak er om dataene du samler inn er å regne som personopplysninger. Hvis de ikke er det kommer ikke loven til anvendelse.

Her skriver vi om personopplysninger: [Hva er en personopplysning?](#)

Basert på det du skriver om hvilke data du skal samle inn vil personopplysningsloven trolig ikke komme til anvendelse, men her må du foreta en grundig vurdering selv.

Søknadsplikt

Du trenger ikke å søke eller melde fra til Datatilsynet om prosjektet ditt.

Øvrig

De fleste utdanningsinstitusjoner for høyere utdanning har et personvernombud. Virksomhetens personvernombud fungerer som kontaktperson for spørsmål om behandling av personopplysninger og de rettigheter du har etter personopplysningsregelverket. For videre spørsmål om personvernregelverket anbefaler vi deg å først ta kontakt med personvernombudet.

Vi håper dette er til hjelp.

Vennlig hilsen

[REDACTED]
Juridisk konsulent, Datatilsynet



Telefon: (+47) [REDACTED]
Postadresse: Postboks 458 Sentrum, 0105 Oslo
Besøksadresse: Tollbugata 3, 0152 Oslo

datatilsynet.no
personvernbloggen.no
twitter.com/datatilsynet
nyhetsbrev

Fra: Ida Marie Vestgøte Bosch [REDACTED]
Sendt: tirsdag 13. november 2018 11.39
Til: Postkasse <postkasse@Datatilsynet.no>
Emne: Støymåling ifm masteroppgave

Hei,

Jeg skriver masteroppgave til våren, og skal i den anledning drive med støymåling. Jeg lurer derfor på om det er noen lover knyttet til personvern e.l. og om jeg evt må søke noen tillatelser eller melde inn prosjektet. Jeg kunne ikke finne noe om dette på deres hjemmesider.

Jeg skal plassere ut noen sensorer som kun tar opp støyverdi, dvs dBA-verdi i et periodisk intervall. Planen er å få plassert dem ut i det offentlige rom, feks ved en vei eller i et nabolag e.l. Sensorene vil sende data trådløst til et aksesspunkt, samt lagre data lokalt på SD-kort. Det blir ikke lagret noen opplysninger om mennesker, og lyd/bilde vil ikke bli tatt opp (sensoren støtter heller ikke dette). Planen er å ha dem utplassert 4 uker.

Ser fram til å høre fra dere.

--

Med vennlig hilsen,

Ida Marie V. Bosch

+47 [REDACTED]

Appendix **D**

Confusion Matrices

Confusion matrices sorted by indicator, for the 10 sampling rates. Labels are displayed as follows: Excellent = 0, Good = 1, Fair = 2, Poor = 3, Hazardous = 4 or Poor = False, Fair = True. The x-axis shows the predicted labels, and the y-axis shows the actual labels. The matrices are normalised.

- Figure D.1: $L_{Aeq,15min}$
- Figure D.2: $L_{A10,15min}$
- Figure D.3: $L_{A50,15min}$
- Figure D.4: $L_{A90,15min}$
- Figure D.5: $L_{A10}-L_{A90,15min}$
- Figure D.6: $L_{Aeq,1h}$
- Figure D.7: $L_{Aeq,8h}$
- Figure D.8: NPL_{15min}
- Figure D.9: CQI_{15min}

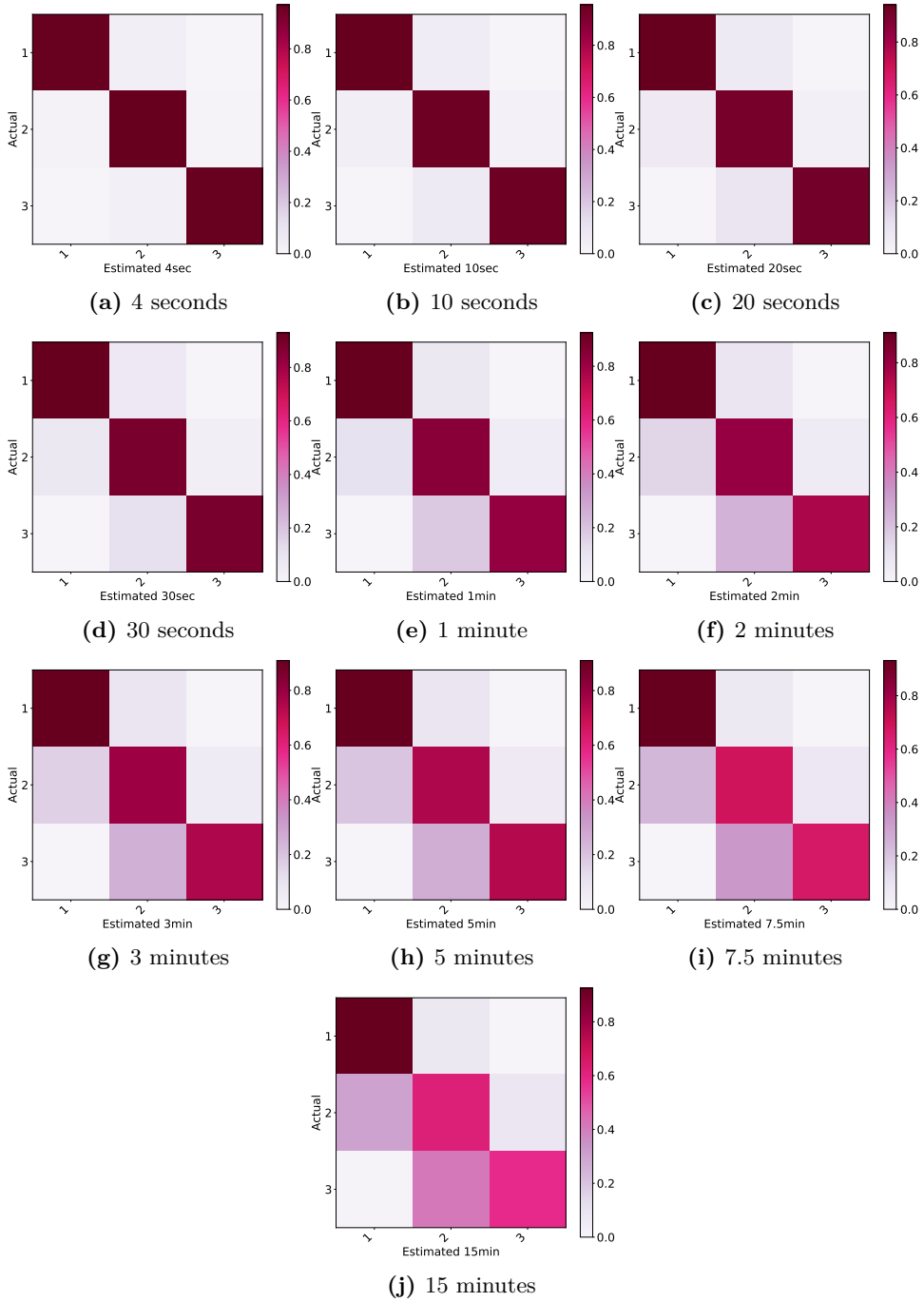
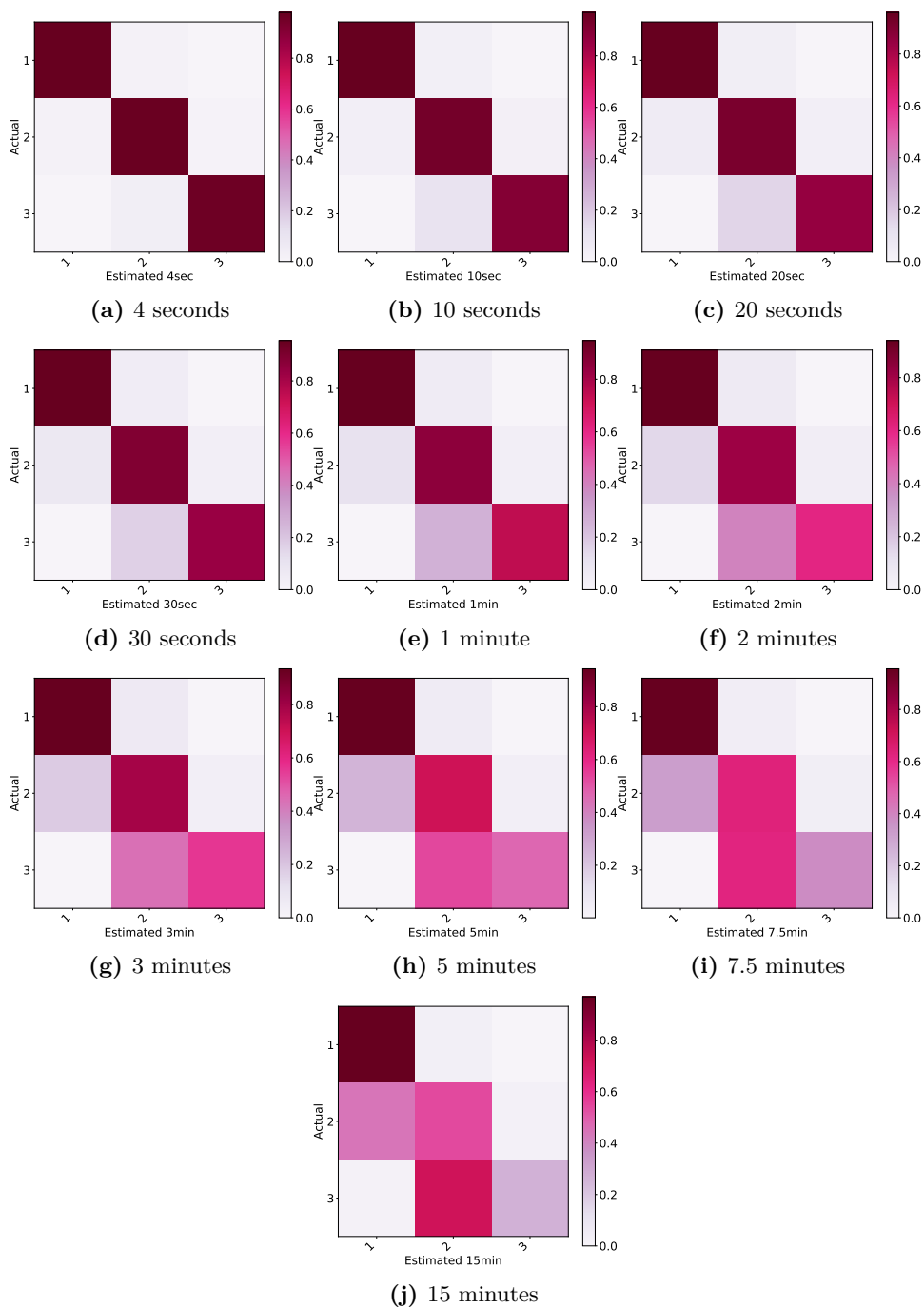


Figure D.1: $L_{Aeq,15min}$

Figure D.2: $L_{A10,15min}$

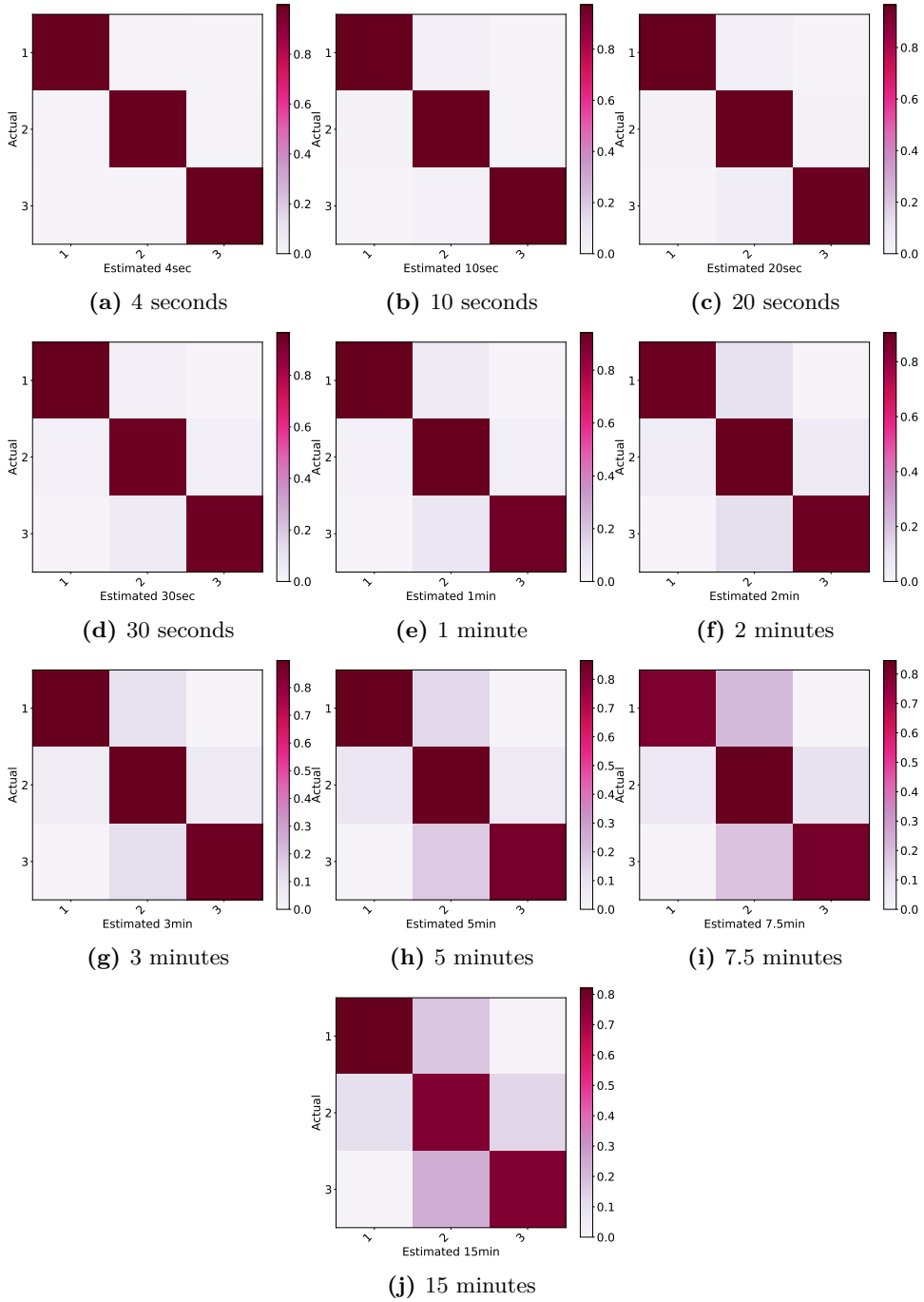


Figure D.3: $L_{A50,15min}$

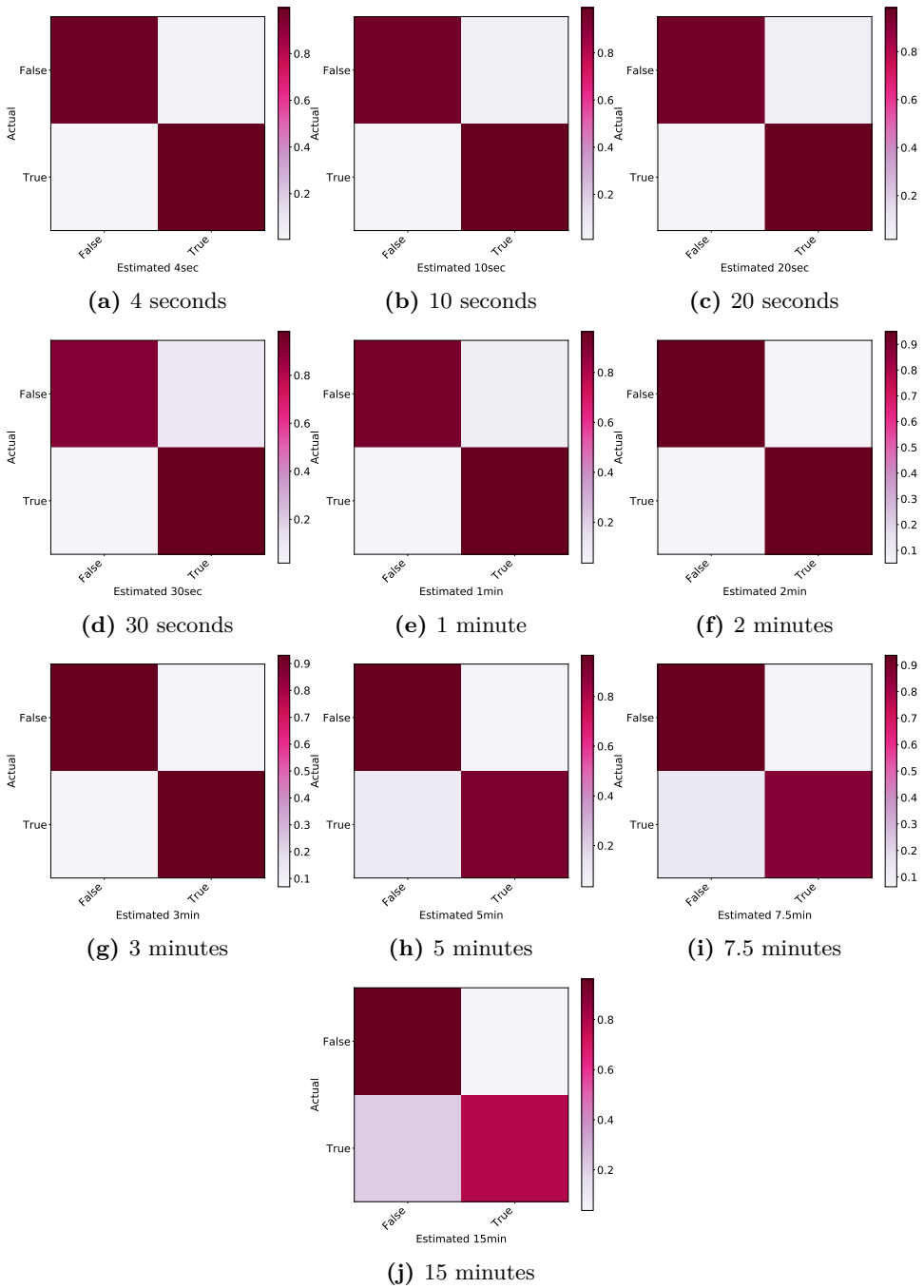


Figure D.4: $L_{A90,15\text{min}}$

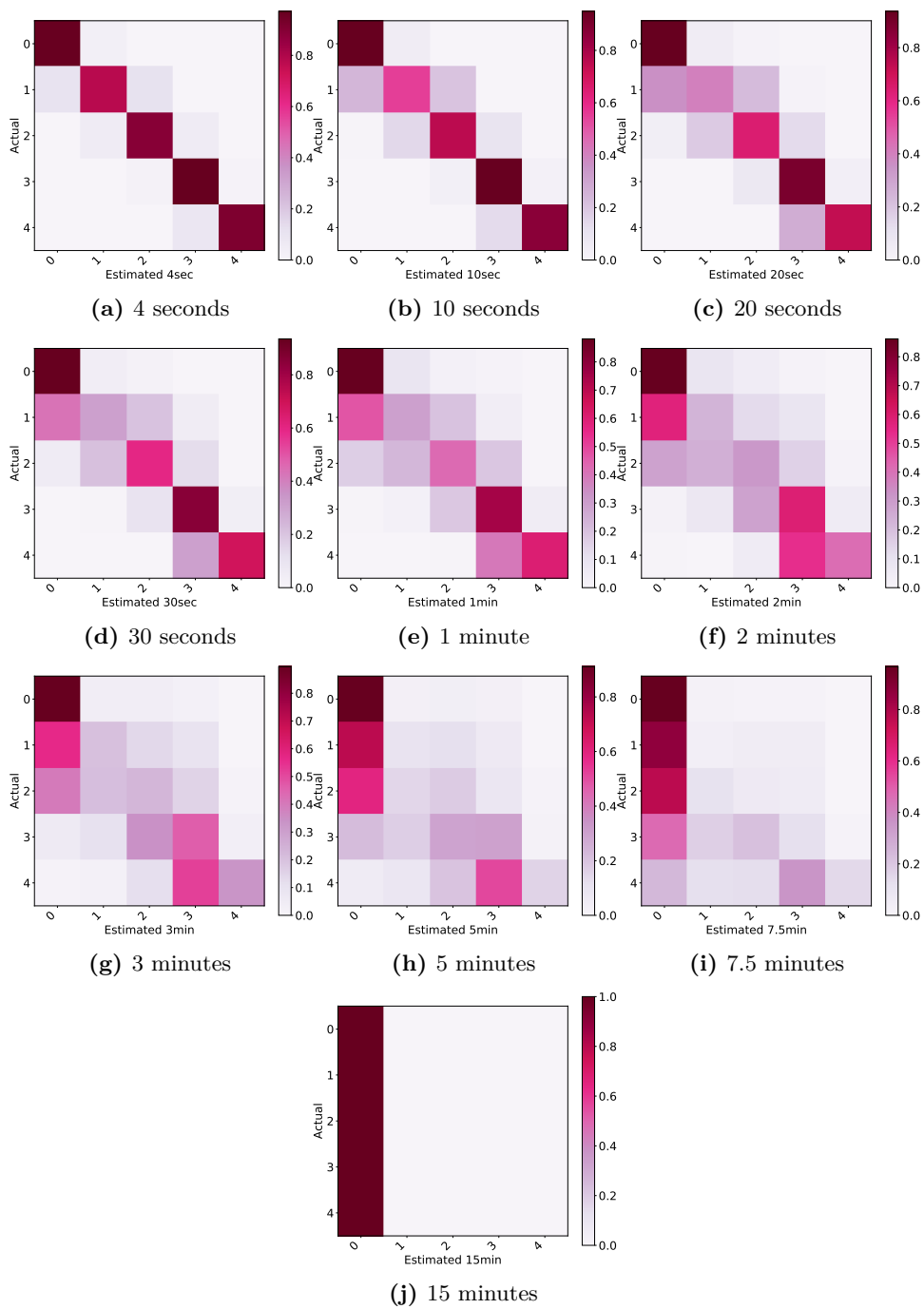


Figure D.5: $L_{A10-L_{A90,15min}}$

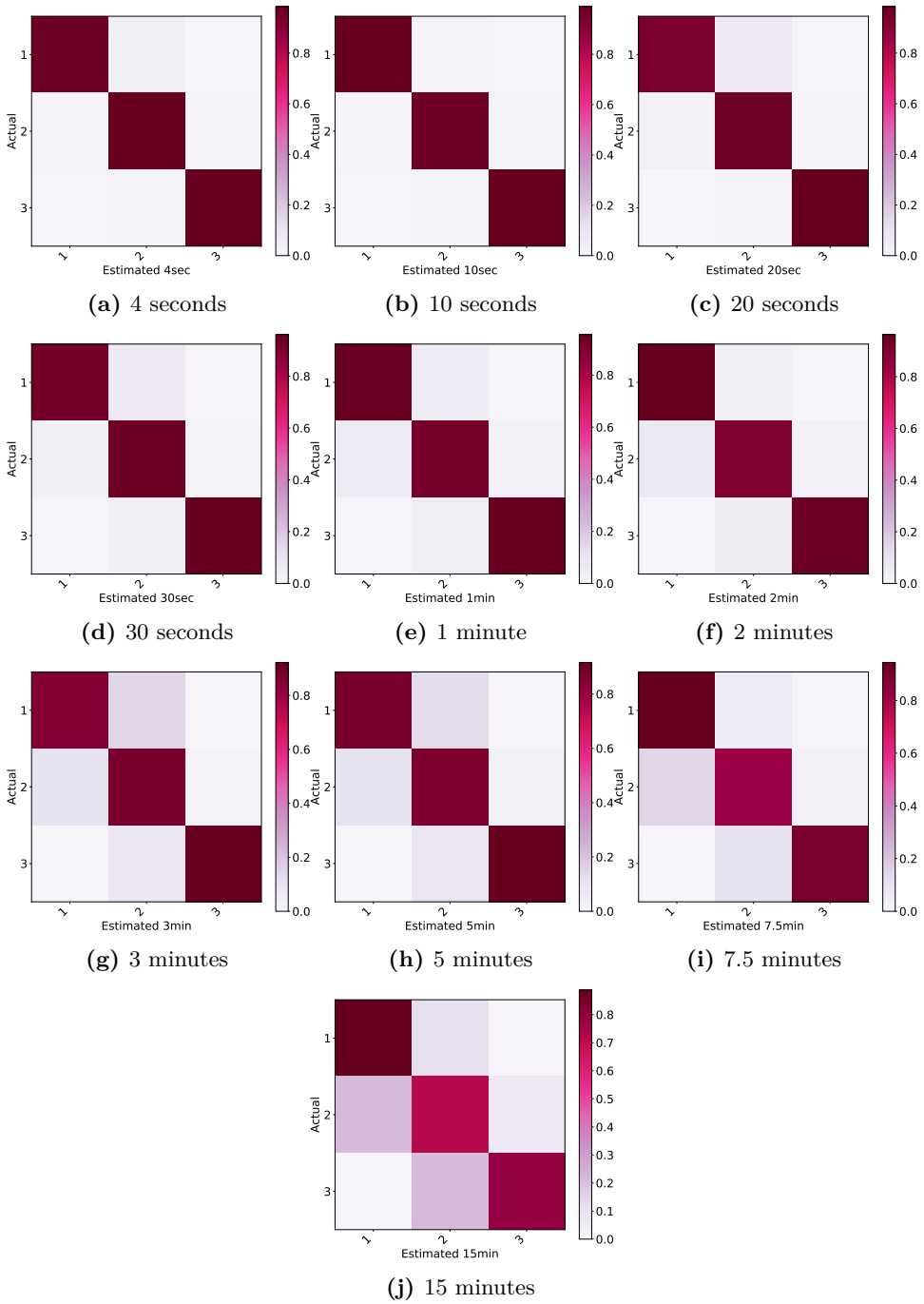


Figure D.6: $L_{Aeq,1h}$

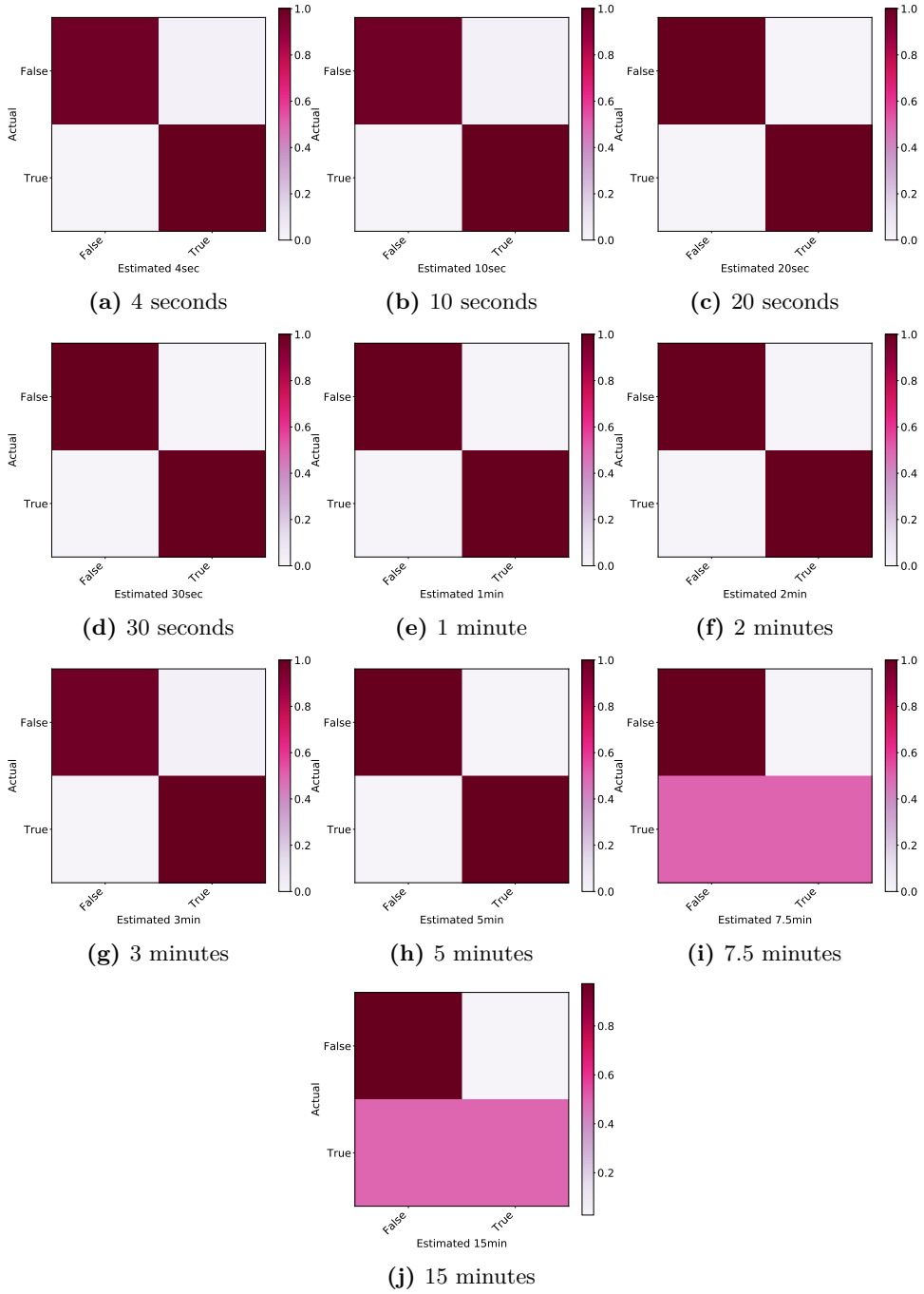
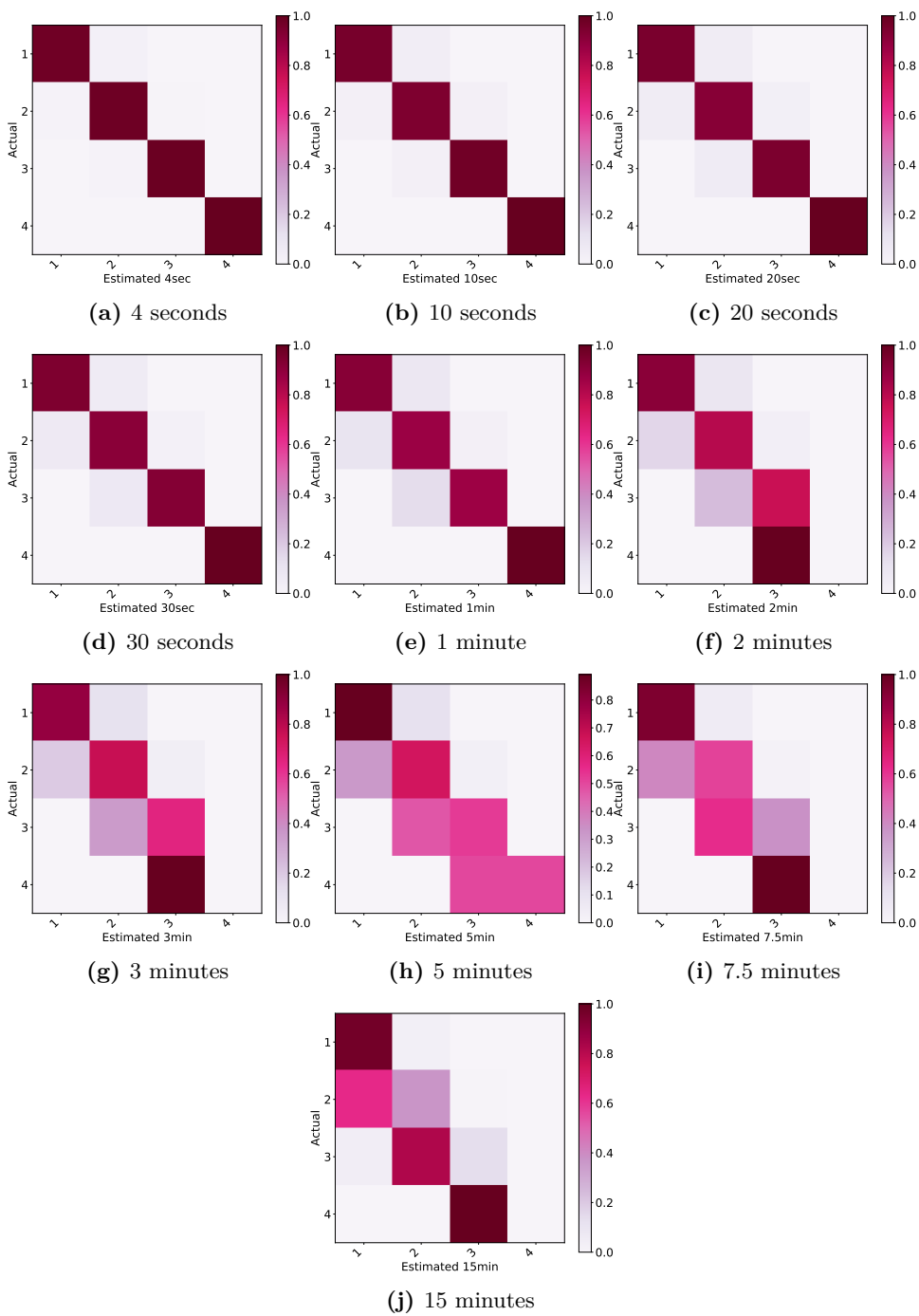


Figure D.7: $L_{Aeq,8h}$

Figure D.8: NPL_{15min}

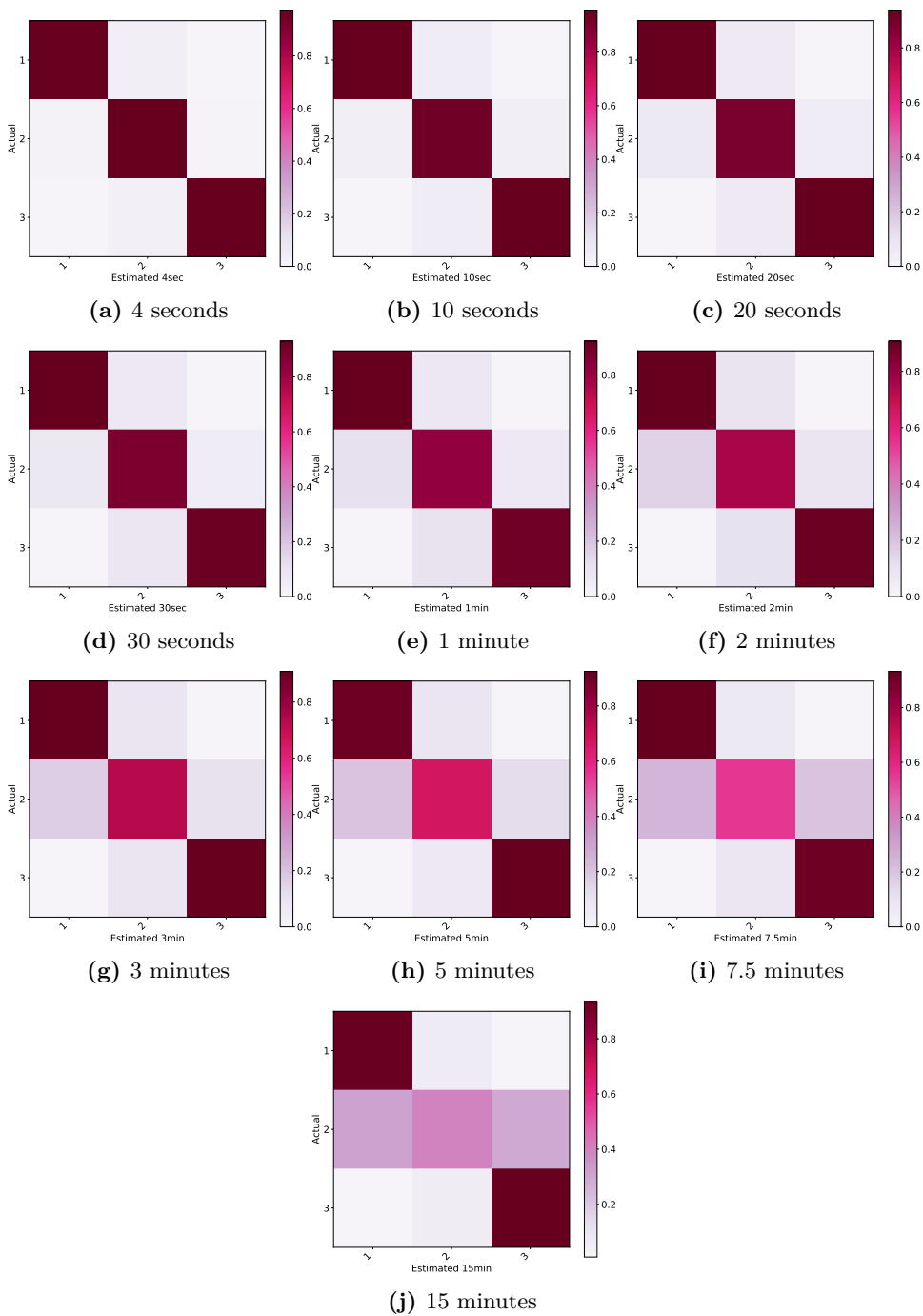


Figure D.9: CQI_{15min}