Energy-Accuracy Tradeoff for Efficient Noise Monitoring and Prediction in Working Environments

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ABSTRACT

We explore the tradeoff between energy consumption and measurement accuracy for noise monitoring and prediction based on continuously collected data by wireless, energy-constrained IoT nodes. This tradeoff can be controlled by the sampling interval between measurements and is of interest for energy-efficient operation, but most often ignored in the literature. We study the influence of the sampling intervals on the accuracy of various noise indicators and metrics. To provide a context for the tradeoff, we consider the use case of noise monitoring in working environments and present a learning algorithm to also predict sound indicators. The results indicate that a proper tradeoff between energy consumption and accuracy can save considerable energy, while only leading to acceptable or insignificant reductions in accuracy, depending on the specific use case. For instance, we show that a system for monitoring and prediction can perform well for users and only uses around 7% of the energy compared to full sampling.

CCS CONCEPTS

• **Computer systems organization** → **Sensor networks**; • **Computing methodologies** → *Machine learning algorithms.*

KEYWORDS

Internet of Things, noise monitoring, machine learning, wireless sensor networks

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1 INTRODUCTION

Noise has a negative impact on health, causing sleep disruption, annoyance, cognitive impairment, can increase stress and blood pressure and lead to hearing loss [**?**]. Recent evidence suggests that urban noise levels worldwide consistently exceed recommended noise limits [**?**], which substantiates the need for more comprehensive noise monitoring. Traditional approaches, however, require expensive equipment and manual operation, which allows only temporary measurements at selected locations, which is why measurements are usually only used to complement or calibrate simulation models based on maps. Unfortunately, results with such approaches are often not sufficient to reflect actual noise characteristics, as Mioduszewski et al. [**?**] conclude. IoT systems consisting of many sensors that can perform fine-grained and continuous measurements are therefore a relevant option. To make such systems feasible, their cost-effective operation is essential [**?**], which motivates our focus on the wireless, energy-efficient and autonomous operation of IoT nodes that replenish their energy by harvesting, for instance via solar panels. Apart from efficient electronics and transmission, the sampling interval, i.e., the time between measurements, has a major impact on a node's power consumption. Longer sampling intervals allow longer sleep modes and require to process and transmit fewer data.

Most works on IoT noise measurement, however, don't discuss sampling intervals thoroughly, and simply choose static sampling intervals at design-time. This has the benefit of simplicity, but does not lead to efficient applications, especially when we consider that many applications don't need to meet constant accuracy levels. Instead, if a system adapts sampling intervals to its context, it can save energy and hence use cheaper energy supplies. This can increase the relevance of the data collected overall, since lower energy consumption enables lower system costs and easier deployment, and allows to cover phenomena like noise over a larger area with fine-grained coverage and permanently. Further, if a system uses energy-harvesting, it can bypass temporary energy shortages by providing less accuracy, instead of no data at all. This calls for approaches in which IoT nodes adapt their sampling intervals and by that influence with which accuracy and energy consumption they collect data. This adaptation requires some form of planning. In [?], for instance, we describe how to use reinforcement learning to train a policy for IoT nodes to optimize their energy consumption which can provide such adaptive planning.

In this paper, we focus on the use cases for noise monitoring and prediction of a working environment to explore the tradeoff between the accuracy of the measurements and the energy consumption of the nodes, caused by the selection of different sampling intervals. Our results show that selecting longer sampling intervals can lead to acceptable reductions in the accuracy, but significant energy savings. For instance, sampling with only 30 values instead of 450 in a 15-minute interval, the drop in accuracy will most likely not affect users but reduce the energy consumption of the system an order of magnitude down to 7% of the original consumption.

Our work is organized as follows: After an overview of related work on large-scale, continuous noise measurement and adaptive sampling in general, we describe our system setup in Sect. 3 and discuss noise indicators and derived labels. Sect. 4 studies the sensitivity of these metrics to increased sampling intervals. In Sect. 5 we study the use of machine learning to improve results by compensating systematic bias, and Sect. 6 studies the significance of accuracy when acquiring noise measurements as training data for predictions. We then discuss the overall implication for the energy-accuracy tradeoff in Sect. 7 and conclude.

2 RELATED WORK

Most projects on large-scale and real-time noise measurement are focused on urban noise, as for instance SONYC [?], SENSEable [?], DYNAMAP [? ?] and CENSE [?]. In urban areas, traffic is a major concern and many approaches therefore perform noise measurements with the aim to calibrate or confirm sound propagation models based on maps. Some of the approaches also try to identify the origins of noise or perform noise event detection. Sevillano et al. [?] emphasize the significance of providing cost-effective solutions to cities, which have to adhere to legislation [?] and need to produce noise maps regularly. Advances in hardware engineering and electronics, like for example MEMS microphones, enable approaches based on cheaper sensor devices. Manvell [?] compares the cost and accuracy of several sound sensor technologies, with a focus on usability and suitability in different purposes. Manvell [?] and Bartalucci et al. [?] highlight the benefits of cheaper sensor hardware, but also emphasize the significance of the operating costs for periodic maintenance and calibration of the sensors. Regarding energy supplies, most of the low-cost approaches still rely on power provided by cables, and only some explore wireless options, which reduces deployment and operating costs. Ardouin et al. [?], for instance, present the design of a solar-powered device in the context of the CENSE project, and SONYC plans the use of solar-powered devices.

To our surprise, there is only little focus on the accuracy that stems from the number of samples taken and hence its influence on energy consumption. Zambon et al. address cost in [?] with an approach that tries to estimate daily average sound levels caused by different road types based on fewer hour-long measurements. However, this addresses sampling on a macro-time scale but is not intended for real-time monitoring. We want to address here use cases for continuous and real-time monitoring and prediction. Amongst those, some approaches don't even mention their sampling policy, and most others do not further justify their choice of sampling rates. Especially, we have not found noise monitoring approaches that vary their sampling rate or adjust their behavior according to the energy situation of the node.

Adapting sampling intervals actively to the needs of the application is applied in other domains. Event-sensitive sampling [?], for instance, alternates high and low frequency intervals, and uses higher frequencies for extended periods if an event was detected. This technique has been used for structural health monitoring and fire event monitoring applications. Similarly, Liu et al. [?] introduced an adaptive sampling strategy for online process monitoring and process change detection, which selects some data streams and ignores others depending on the resource status of the system. Another example of an error-accuracy tradeoff is Trihinas et al. [?], who proposed an adaptive monitoring framework for sampling and filtering for data streaming. They are capable of reducing energy consumption by 71% while keeping the system accuracy at least 89%. For human activity recognition, Cheng et al. [?] propose a learning algorithm that not only learns the parameters for activity classifier, but also the most energy-efficient frequency for the sampling, depending on the observations made.

3 SYSTEM SETUP

In our conceptual system, noise is measured by energy-constrained IoT nodes that transmit their measurements wirelessly. To ensure perpetual operation, a node's energy buffer can be charged by a solar panel. Calculation of the noise indicators can happen on-board of the IoT node or as part of the server backend. We study two different use cases:

- The system *monitors* noise and computes a number of noise indicators.
- The system *predicts* noise labels, for instance to indicate to students where they find a quiet place for focused work, as part of a campus information system.

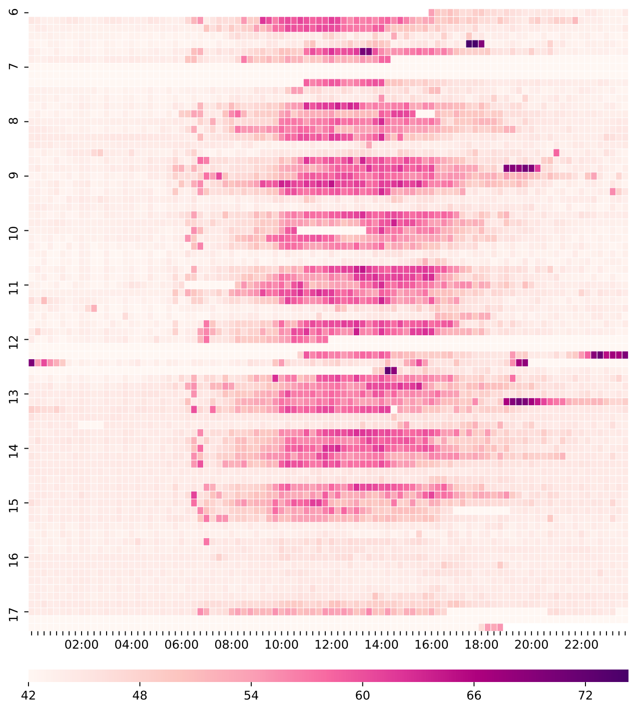

Figure 1: $L^{p,450}_{Aeq,\,15min}$ in dB for the observation period.

The basis of our experiment is noise data that we collected in a collaborative learning space for students that blends faculty-guided instructions with self-organized work.[1] We deployed Libelium Waspmotes with noise sensors [**?**]. They measure the A-weighted, equivalent continuous sound pressure level $L_{Aeq,T}$, which is a standard indicator used for noise measurement [**?**]. For the experiment, we collected samples with the SLOW setting of $T = 1\ s$. The sensors have an accuracy of ±0.5 dBA, corresponding to the Class 2 devices in IEC 61672 [**?**] and cover a frequency range from 20 Hz to 20 kHz, similar to the human hearing. For our use cases, we monitor and predict the soundscape of the working environment in periods of 15 minutes. We collected data with the highest sampling rate possible for the device, which means a new value for L_{Aeq} every 2 seconds, hence $n_{max} = 450$ samples per 15-minute period. In the following, each 15-minute period is numbered by index p. We also introduce sampling function $\mathbb{S}^p[n]$ that returns n selected samples of period p (for now, all 450 of the original samples).

To characterize a 15-minute period p with a single number, we calculate the equivalent continuous sound level $L^{p,n}_{Aeq,\,15min}$ from the individual samples as follows:

$$L^{p,n}_{Aeq,\,15min} = 10log(\frac{1}{n}\sum_{l\in\mathbb{S}^p[n]} 10^{\frac{l}{10}}) \qquad (1)$$

The superscript n represents how many samples are used for its calculation. Figure **??** shows the $L^{p,450}_{Aeq,\,15min}$ values of the observed period. Each row shows the 15-minute periods of a day. We see that noise is higher during working hours and the lowest during the night. Holidays (around week 16) and weekends are quieter than working days, and afternoons on Fridays tend to be quieter than those of other workdays. Some noise is also created by cleaning staff and social events.

Other noise indicators are N-percentage exceedance levels $L_{AN,T}$ of the collected sound pressure levels over a time interval T [**?**]. They can be determined using percentiles:

$$L^{p,n}_{AN,T} = percentile(100-N,\ \mathbb{S}^p[n]) \qquad (2)$$

We select $N \in \{10, 90\}$ and $T = 15\ min$. $L_{A90,\,15min}$ is the level of noise that is exceeded 90% of the time, hence an indicator for background noise, while $L_{A10,\,15min}$ is the level exceeded 10% of the time, capturing shorter noise events.

Since numeric values can be difficult for users to interpret, we also want to label each 15-minute period with one of five ordered categories to classify the soundscape:

$$SC^{p,n}_{15min} \in (excellent, good, fair, poor, hazardous) \qquad (3)$$

For working environments, we found a composite label based on $L_{Aeq,\,15min}$, $L_{A10,\,15min}$, $L_{A90,\,15min}$ most suitable [**?**]. The definition of the label is shown in Table **??**. For a working environment to score *excellent*, for example, the classifier requires two of the three indicators to have very low values, as described by the first rows. On the other side, to receive a *poor* rating, it's enough that any of them is above certain levels.

In the following, since we always use A-weighting and 15-minute periods, we simplify the notation to $L^{p,n}_{eq}$, $L^{p,n}_{10}$, $L^{p,n}_{90}$ and $SC^{p,n}$, with p identifying the period and n denoting the number of samples that went into their calculation.

Excellent		$L_{A10} < 40$	$\wedge$	$L_{A90} < 32$		
	$\vee$	$L_{A10} < 40$	$\wedge$	$L_{Aeq} < 37$		
	$\vee$	$L_{Aeq} < 37$	$\wedge$	$L_{A90} < 32$		
Good		$40 \le L_{A10} < 50$	$\wedge$	$32 \le L_{A90} < 42$		
	$\vee$	$40 \le L_{A10} < 50$	$\wedge$	$37 \le L_{Aeq} < 47$		
	$\vee$	$37 \le L_{Aeq} < 47$	$\wedge$	$32 \le L_{A90} < 42$		
Fair		$50 \le L_{A10} < 61$	$\wedge$	$42 \le L_{A90} < 53$	$\wedge$	$47 \le L_{Aeq} < 58$
Poor		$61 \le L_{A10} < 85$	$\wedge$	$53 \le L_{A90} < 79$	$\wedge$	$58 \le L_{Aeq} < 85$
Hazardous		$L_{A10} > 85$	$\wedge$	$L_{A90} > 79$	$\wedge$	$L_{Aeq} > 85$

Table 1: Soundscape label *SC* based on noise indicators.

[1] The experiment data is available at https://github.com/Faiga91/Koopen

Interval	Samples n in 15 min	Energy Consumption
2 s	450	100 %
4 sec	225	50 %
10 sec	90	20 %
20 sec	45	10 %
30 sec	30	7 %
60 sec	15	3 %
120 sec	7.5	2 %
180 sec	5	1 %

Table 2: Different sampling modes of the sensor devices.

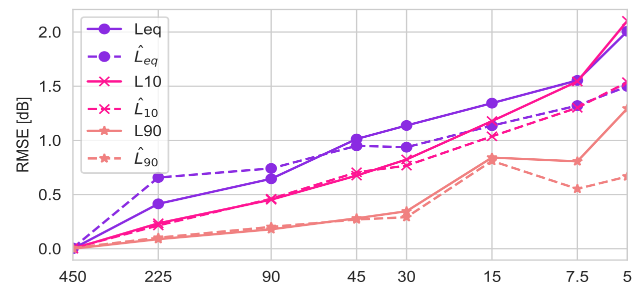

Figure 2: RMSE for noise indicators for different number of samples n. Dashed lines show errors after bias compensation.

4 EFFECT OF INCREASED SAMPLING INTERVALS

The main elements of the energy cost for a sensor node are related to transmission, computation and sensing, but their portion depends on the specific setting, see for instance [?]. We assume in the following a fixed cost per measurement, including any computation and transmission costs. The energy consumption will hence depend mainly on the sampling intervals between measurements, listed in Table ??, together with estimates for the resulting energy consumption.

Of course, depending on the phenomena observed, longer sampling intervals have influence on the accuracy of the collected data and hence the overall performance of the system. We simulate longer sampling intervals by selecting only a subset of the originally sampled measurements. Full sampling, with a power consumption of 100 %, results in $n = 450$ samples in a 15-minute period. When the device only samples $n = 90$ times during the same period, the power consumption is reduced to 20 %. Function $\mathbb{S}^p[n]$ again selects n samples out of the available 450, as equally spaced as possible, but now n also takes values < 450. This selection allows us to simulate a sensor that uses longer sampling intervals.

To study the error when sampling less frequent, we use the values for the indicators calculated with all samples ($n = 450$) as ground truth, and hence observe the error when using indicators calculated according to (??) for $L_{eq}^{p,n}$ and (??) for $L_{10}^{p,n}$ and $L_{90}^{p,n}$ with fewer samples, i.e., $n < 450$:

$$e^{p,450}(n) = L^{p,450} - L^{p,n} \tag{4}$$

Figure ?? shows boxplots of the errors for selected n in its upper row. They reveal that with decreasing samples n, indicators L_{eq} and L_{10} have a negative bias, i.e., they tend to underestimate the noise level, while L_{90} has a positive bias.

We also calculate the root mean squared error (RMSE) over *all* 15-minute intervals in the test set:

$$RMSE_L(n) = \sqrt{\frac{1}{n} \sum_{\forall p} e^{p,450}(n)} \tag{5}$$

By definition, $RMSE(450) = 0$. Figure ?? shows the RMSE of all indicators when using increasing sampling intervals, i.e., a decreasing number of samples n. With lower n, we see an increased RMSE for all indicators L_{eq}, L_{10}, L_{90} (solid lines). L_{10} is subject to greater loss in accuracy, since it indicates shorter noise events that are more dependent on the placement of the samples, while the L_{90} background indicator is less sensitive to the sampling interval.

To study the effect on the soundscape classifier SC, we compare the resulting labels $SC^{p,n}$ with the truth values $SC^{p,450}$. We first look at the F1-score that is often used as classification metric. In a multi-class setting and with a micro-weighting, it corresponds to the accuracy, i.e., the quotient of correct labels to the total number of labels. It is shown in Figure ??. Since the categories in SC are ordered (see (??)), we also take the distance of the error into account, i.e., if a label hops one or even two steps. Here, we only observe errors of one step, and Figure ?? shows the percentage of wrongly assigned 15-minute periods. With $n = 225$ samples, ca. 2 % of labels are switched, and with $n = 30$, ca. 5 % of labels are assigned wrongly. (Since only one-step errors occur, results are consistent with the F1-score.)

5 LEARNING BIAS COMPENSATION

Since we expect the errors observed above to be systematic, we explore if this bias can be learned and compensated by an improved indicator $\tilde{L}^{p,n}$:

$$\tilde{L}^{p,n} = L^{p,n} + \delta(L^{p,n}, n) \tag{6}$$

For each of the indicators $\tilde{L}_{eq}, \tilde{L}_{10}, \tilde{L}_{90}$ we train a model M_L to learn $\delta(L^{p,n}, n)$. The training data consists of the measured indicators L^n, the number of samples n and is labelled with the ground truth L^{450}. We remove any 15-minute periods with missing data, and select the 15-minute periods from week 8 as test set. Through hyperparameter tuning we select a random forest regressor with 100 trees.

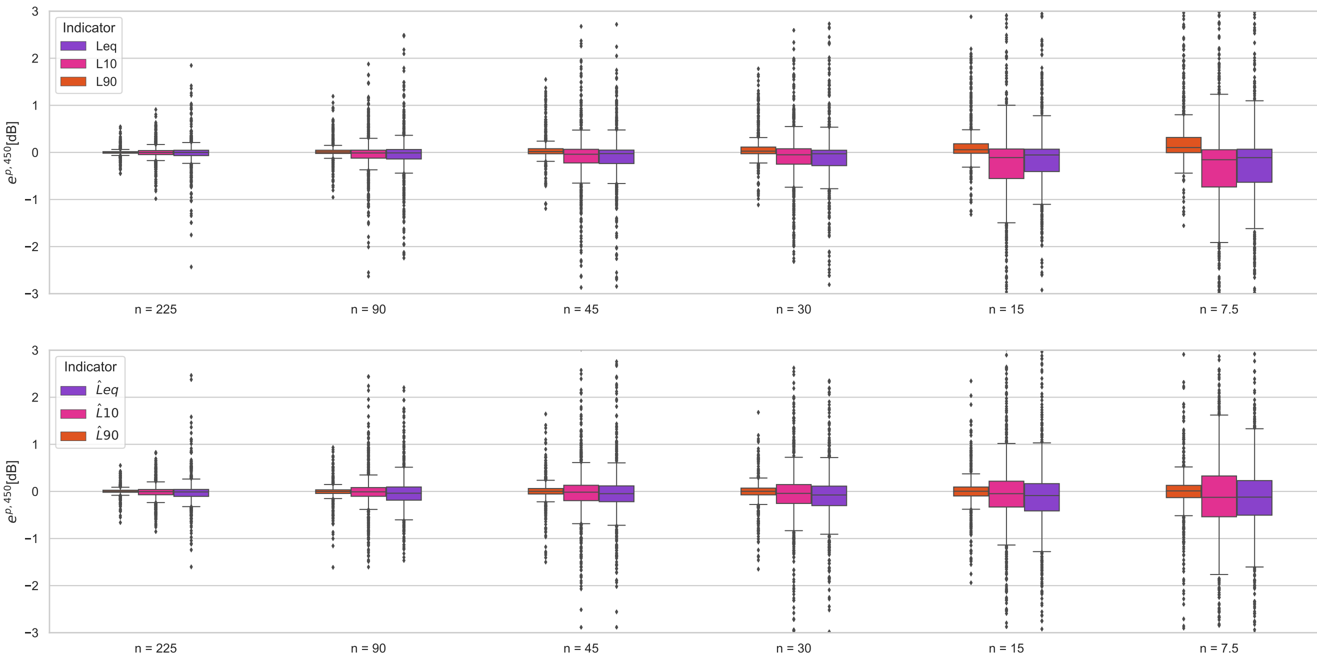

Figure 3: Errors for the noise indicators when using longer sensing intervals for monitoring. The upper row shows errors for different n without bias compensation, the lower row shows errors with bias compensation.

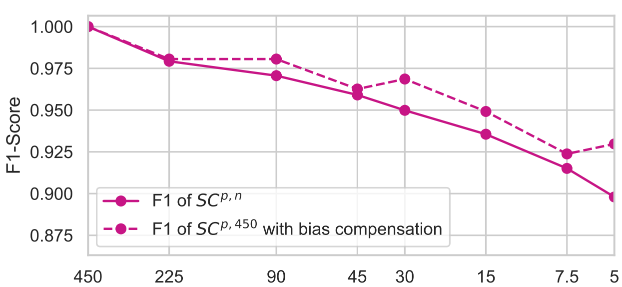

Figure 4: F1-score for the SC label.

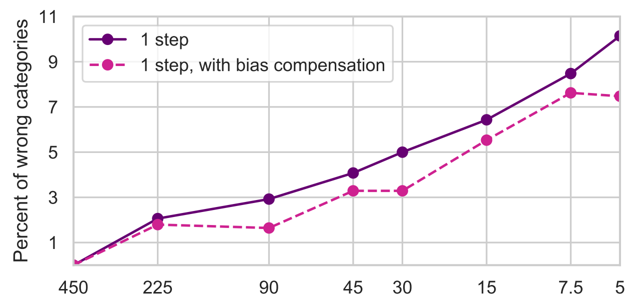

Figure 5: Percentage of switched SC labels.

The results for the RMSE are shown with dashed lines in Figure **??**, showing that the compensation reduces the RMSE in some cases for lower n. The boxes in the lower part of Figure **??** accordingly indicate a lower bias compared to the ones without the compensation in the row above. Correspondingly, the F1-score in Figure **??** shows an improved performance of the soundscape label, and Figure **??** shows a reduced percentage of categories assigned wrong.

6 PREDICTION BY MACHINE LEARNING

The task of the prediction is to estimate future noise levels based on past observations and explanatory variables, such as time. Our motivation is not only to validate the feasibility of the prediction itself, but also to estimate its inherent error, as we need it later in the discussion in Sect. **??**. For each of the numeric noise indicators and sampling numbers n, we train a separate model M_L^n. The prediction features are based on time and context, summarized in Table **??**. Each 15-minute period p is hence characterized by a feature vector x_p:

$$x^p = (weekday, hour, quarter, schedule, holiday)^T \quad (7)$$

Time is described by weekday, full hour and quarter. The binary variable *schedule* indicates hours with faculty-planned activities, and *holiday* marks official holidays, like Easter. The label for each period is the corresponding noise indicator

Feature	Values	Importance M_L^n	Importance M_{SC}^n
weekday	[0, 1,.. 6]	25%	26%
hour	[0,1,.. 23]	20.3%	28%
schedule	[0,1]	36%	24.2%
quarter	[0,1,2,3]	5.5%	8%
holiday	[0,1]	13.2%	13.8%

Table 3: Features for the prediction of noise indicators.

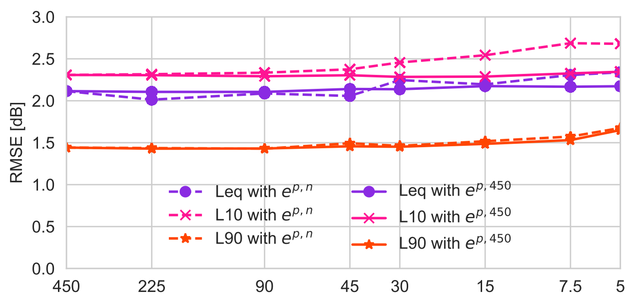

Figure 6: RMSE of the prediction of noise indicators.

$L^{p,n}$. We choose again a random forest regressor with 100 trees. The importances of the features are noted in Table ??.

For evaluation, we calculate two errors, $e^{p,n}$ and $e^{p,450}$:

$$e^{p,n} = M_L^n(x^p) - L^{p,n} \quad (8)$$

$$e^{p,450} = M_L^n(x^p) - L^{p,450} \quad (9)$$

The first one uses the indicators measured with $n \leq 450$ as truth values (i.e., uses the same n), and is hence a measure for the prediction quality. The second one compares the prediction trained on samples L^n with the truth acquired with $n = 450$. Correspondingly, Figure ?? shows the RMSE based on these two error metrics. Interestingly, there is much less dependency on n than in the monitoring case of Figure ??. We explain this with the inherent error of the prediction itself, which is in the same order for $n = 450$ as for the other n. This also explains why the error is similar when comparing the regressors trained with data from $n < 450$ and then compared with the $n = 450$ data.

We also trained a model M_{SC}^n to predict the soundscape classifier. We use the same training data as for M_L^n, but use the soundscape categories as labels, and use a random forest classifier as a model. Similar as with the monitoring use case, we show in Figure ?? the resulting F1-score for the classification. The solid line shows scores when labels are compared to truth values determined by the same n, and the dashed line when the truth values are $n = 450$. Figure ?? shows the percentage of mispredicted labels. Similar to the regression above, the error is higher compared to the monitoring case, due to the inherent prediction error. However, we see again

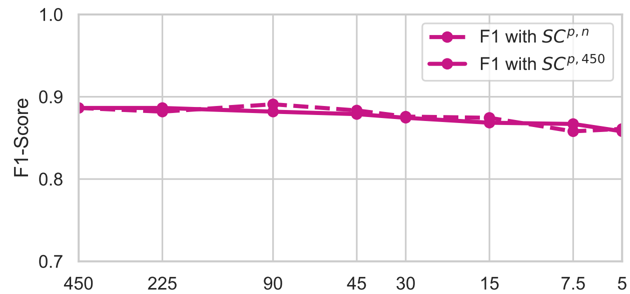

Figure 7: F1-score for the prediction of the SC label.

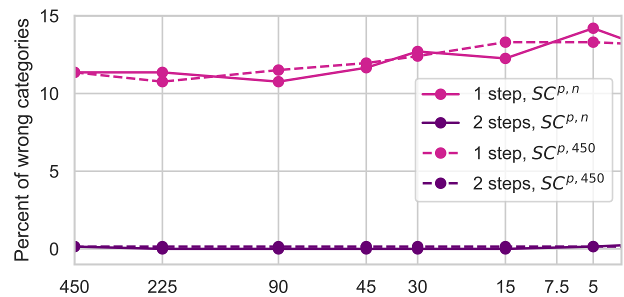

Figure 8: Percentage of mispredicted SC labels.

that the error depends less on n for the prediction than for the monitoring use case.

Figure ?? illustrates the performance of the predictor for L_{eq} for one randomly selected day of the test period by showing the actually measured data and the predictions using the models trained with data sampled with different values for n. In the lower part, the figure shows the soundscape labels for each 15-minute interval. The upper row shows the labels measured with $n = 450$, the ones below the predicted ones, based on data sampled with different values for n.

7 ENERGY-ACCURACY TRADEOFFS

The results of the experiments and use cases from above provide the context to discuss the energy-accuracy tradeoff for noise monitoring in working environments. In Sect. ?? we studied how the accuracy of various indicators and labels develops when the sensing interval is extended. As expected, using longer sampling intervals and hence collecting less data decreases accuracy, but also decreases energy usage considerably. However, we also observe that the accuracy only drops moderately compared with significant gains in energy-efficiency. Hence, the required accuracy should be seen in connection with system resources, the actual user requirements and for which decision the data is used. This gives a system a broad range of tradeoffs so that it can increase its overall performance. In the following, we will discuss

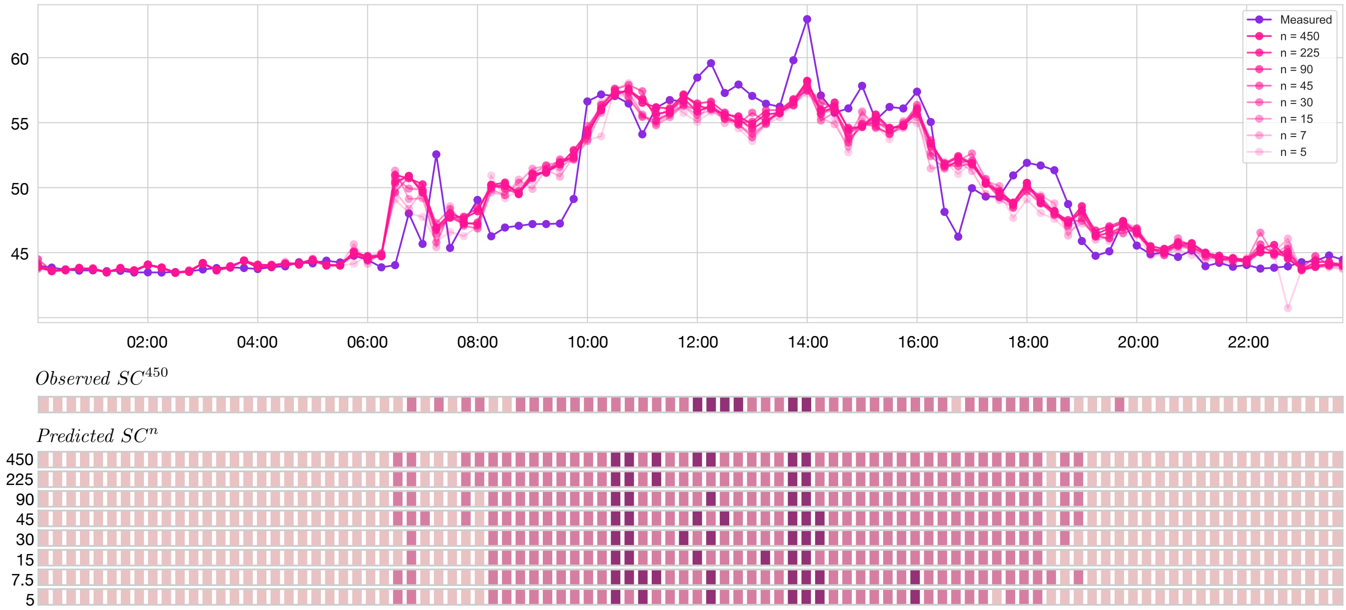

Figure 9: Randomly selected day to illustrate prediction performance. The upper graph shows the observed values for L_{eq}, and the prediction done with data based on different n. The lower graph shows the observed soundscape label, with the predicted soundscape labels for different values of n below. ■=*good*, ■=*fair*, ■=*poor*.

them to estimate potential performance gains when letting a system adjust its sampling intervals.

For the *monitoring* use case one may consider the accuracy of the measurement equipment which is in this case ±0.5 dB. Most errors when sampling with $n = 225$ instead of $n = 450$ fall below this order, while the energy consumption is cut to around 50%. Arguing further, a difference of 3 dB is barely noticeable for humans (see, e.g., [**?**]). Looking at the boxplots of errors in Figure **??**, this suggests that just sampling with $n = 30$ samples in a 15-minute interval leads to an acceptable performance, which also leads to the system only using around 7% of the energy compared to sampling with $n = 450$. Further, the presentation of information to users in more abstract form also gives room for lower accuracy. The soundscape label is based on intervals of the individual indicators, and occasional flips in a category seem acceptable. As we see in Figure **??**, less than 5% of the soundscape labels change one step up or down when we sample with $n = 30$, while only requiring around 7% of the energy. With bias compensation, one could even select $n = 15$.

When the use case is soundscape *prediction*, the inherent, irreducible error of the prediction is much larger than the error introduced by using fewer samples. When we consider Figures **??** and **??**, the system trained with $n = 30$ samples shows almost the same performance as the one trained with $n = 450$ samples, but uses only around 7% of its energy. Figure **??** illustrates the effect of using less samples for a specific day, and shows the inherent prediction error in comparison to the relatively insignificant changes due to lower n.

We further argue that the considerations of sampling intervals as above should happen autonomously by the IoT systems, which should learn to select a proper sampling interval based on its specific context and the phenomenon to observe. In this specific example, the system can, for instance, sample with less accuracy at night-time, holidays or weekends when working conditions are less relevant to the users. When nodes are using energy harvesting and their energy budget varies, adaptation can help to ensure energy-neutral operation [**?**]. By giving a node the option to adjust its sampling interval and hence the energy consumption, it can instead of just failing in low-energy situations, predict future energy intake (see [**?**]), plan ahead and strategically allocate energy to maximize its long-term application performance. In [**?**], we presented such a planning strategy using reinforcement learning, which can take the energy-accuracy consideration presented here as input. We expect that this technique can learn even more complex policies, and also take more aspects into consideration than just the sampling interval. In addition, a node could autonomously decide in which situations it should gather training data, i.e., use its shortest sampling interval to gather data with the highest accuracy. With the bias compensation in Sect. **??**, we showed how a system can improve its performance when working in low-energy situations by knowledge in the form of training data acquired earlier. This adds to the degrees of freedom an IoT node can use to optimize its energy consumption.

8 CONCLUSION

We presented the use cases of monitoring and prediction of noise indicators for working environments, and studied how their accuracy depends on the sampling interval. We showed how IoT nodes can further compensate bias through learning. The considered use cases make it possible to discuss the energy-accuracy tradeoffs for such a system, which can result in significantly lower energy consumption while offering suitable levels of accuracy. This is an important factor in making IoT-based solution for noise monitoring scalable and economically feasible, as lower energy consumption allows ever smaller devices, which are easier to deploy and operate.

In this paper, we explored the energy-accuracy tradeoff for the domain of noise, but the principle of accuracy-energy tradeoffs extends also to other domains. For future IoT systems we see the need and possibility to let a system do this tradeoff constantly and autonomously, establishing autonomous adaptive sensing that leads to smarter IoT solutions. Instead of wasting energy on acquiring data of little significance or with accuracy levels that are not relevant, IoT nodes should be able to autonomously decide what the best accuracy levels in a given situation are.

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