

# Enabling Low-Cost Particulate Matter Measurement for Participatory Sensing Scenarios

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**Abstract.** This paper presents a mobile, low-cost particulate matter sensing approach for the use in Participatory Sensing scenarios. It shows that cheap commercial off-the-shelf (COTS) dust sensors can be used in distributed or mobile personal measurement devices at a cost one to two orders of magnitude lower than that of current hand-held solutions, while reaching meaningful accuracy. We conducted a series of experiments to juxtapose the performance of a gauged high-accuracy measurement device and a cheap COTS sensor that we fitted on a Bluetooth-enabled sensor module that can be interconnected with a mobile phone. Calibration and processing procedures using multi-sensor data fusion are presented, that perform very well in lab situations and show practically relevant results in a realistic setting. An on-the-fly calibration correction step is proposed to address remaining issues by taking advantage of co-located measurements in Participatory Sensing scenarios. By sharing few measurement across devices, a high measurement accuracy can be achieved in mobile urban sensing applications, where devices join in an ad-hoc fashion. A performance evaluation was conducted by co-locating measurement devices with a municipal measurement station that monitors particulate matter in a European city, and simulations to evaluate the on-the-fly cross-device data processing have been done.

**Categories and Subject Descriptors:** B.4.M [Hardware]: Input/Output and Data Communications – *Miscellaneous*; H.1.2 [Information Systems]: Models and Principles – *User/Machine Systems*

**General Terms:** Design; Experimentation; Measurement; Reliability

**Keywords:** Novel Sensing; Particulate Matter; PM10; PM2.5; Participatory Sensing; Urban Sensing; Mobile Dust Sensor; Air Quality; Environmental Sensing; Wearable; Crowd Sensing.

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## 1 Introduction

With ever more evidence presented we have grown increasingly conscious of the potential consequences of pollutants on our health and environment. Among these, particulate matter (PM) pollution is especially hazardous, because fine dust can pass through our lungs directly into the blood stream, disrupt the gas exchange, destroy cells and contribute to respiratory and cardiovascular disease. In order to mitigate these risks, governments around the world have put regulations into place regarding the maximum permissible levels of fine dust. The US Environmental Protection Agency (EPA) [39], the World Health Organization’s (WHO) [35] and the European Union [1] have declared different limits for the particle size classes  $PM_{10}$  and  $PM_{2.5}$ .<sup>1</sup> China has announced to regulate  $PM_{2.5}$  levels nationwide from 2016 on [41].

However, we see several issues regarding those measurements and the concentration limits. The *density of control points* (i.e. current official measurement stations) is inadequate and thus values do not always reflect our personal health risk. Today,  $PM$  concentrations are usually determined through gravimetric measurement, using so-called high volume samplers (HVS). Such certified high-precision devices are typically large, stationary and expensive and therefore very sparsely deployed, typically only few stations covering large urban areas (see Table 1). More fine-grained measurements are important, since exposure levels have been observed to vary even in close proximity, e.g. in different streets of the same

<sup>1</sup> In many sources,  $PM_x$  is often (inaccurately) described as “all particles smaller than  $x$   $\mu\text{m}$ ”. It is actually defined as “particulate matter which passes through a size-selective inlet with a 50% efficiency cut-off at  $x$   $\mu\text{m}$  aerodynamic diameter” [1]. The classes  $PM_{10}$  and  $PM_{2.5}$  roughly correspond to particles that can be breathed into and deposited in the lungs, respectively even deeper in the alveoli, where they may disrupt the gas exchange.



**Fig. 1.** Scenario: Enabling mobile, participatory PM sensing in large metropolitan areas, e.g. in Beijing, China, with cheap commodity hardware.

City	# of stations	Area
Beijing, China	18	~16,000 km <sup>2</sup> [40]
Berlin, Germany	12	~890 km <sup>2</sup> [38]
Greater London, UK	83	~1,600 km <sup>2</sup> [18]
Mumbai, India	7	~440 km <sup>2</sup> [20]
New York City, USA	13	~1,200 km <sup>2</sup> [24]

**Table 1.** Number of particulate matter measurement stations in selected metropolises.

city block [26]. Current static measurement grids can not provide the necessary resolution.

Aside from ourselves, municipal authorities have a huge motivation to reduce PM levels as well, since non-compliance to meet regulatory standards can result in strong fines: Even though currently not being enforced by the EU, the penalty for exceeding the legal limits can be close to \$1,200,000 – per day [22]. In order to be able to effectively combat high *PM* levels, cities must be able to identify hot-spots and temporary peaks in exposure. For this, both a *high temporal resolution* as well as the *timeliness of readings* are important: A possible application case could for instance be, that city governments exercise concentration-related control of traffic by temporarily prohibiting vehicular access to certain hot-spot areas. A low latency is crucial for such a reactive system.

A Participatory Sensing approach is especially well-suited to address the described aspects, as it intrinsically involves empowering citizens [9]. By providing engaged individuals with low cost measurement devices, they can quantify their individual exposure and at the same time by combining measurements of multiple people provide the necessary spatial resolution necessary for accurate city wide estimations. Suitable tools to quantify *PM* levels need to be identified or developed. We focus on *distributed, mobile* measurements of fine dust, as motivated above. Important factors for suitable devices, respectively sensors are:

- *compact*: Sensors should be small, ideally embeddable into existing ubiquitous technology like mobile phones.
- *inexpensive*: Mobile measurement solutions need to be affordable for Participatory Sensing scenarios.
- *usable*: Avoid frequent maintenance, e.g. changing filters, frequent charging, expert calibration, etc.
- *responsive*: To identify sources and to enable reactive systems, timeliness of data is important.
- *accurate*: Finally, the readings need to be meaningful.

## 2 Related Work

Participatory Sensing has been studied intensively and applied to environmental sensing problems. Good examples for generating awareness from distributed, shared sensor readings are noise pollution maps of urban areas [29],[21]. Participatory and mobile air quality measurement projects like *GasMobile* [15] and *Common Sense* [12] have largely focused on gas sensing. Lacking COTS particulate matter sensors, fine dust has largely not yet been considered in such projects. The *PEIR (Personal Environmental Impact Report)* [19] calculates the  $PM_{2.5}$  exposure based on parameters such as the distance from known hazardous areas, e.g. freeways. While this can help people to assess their exposure, it is actually dependent on better base data. Projects like *botworld*<sup>2</sup> use simulation approaches to quantify dust dispersion more fine granularly based on coarse existing data. Neither project uses actual sensors.

Both the *OpenSense* project<sup>3</sup> [4] and *da\_sense*<sup>4</sup> make use of public transportation vehicles to measure air quality beyond a few fixed measurement stations. While *da\_sense* proposes the integration from different sources (such as infrastructure sensors, environmental WSNs or smartphones) so far no  $PM$  data is integrated. *OpenSense* on the other hand integrates the *DISCmini* from *Matter Aerosol* into the mobile measurement setup which gives a fine grained resolution for the covered tracks. Still, the *DISCmini* is an expensive commercial hand-held particle monitor, it comes at a price of almost \$15,000, making it far too expensive for larger scale participatory sensing scenarios. Other cheap devices, such as the *Personal Environmental Monitor (PEM)* [33] or the *UCB particle monitor* [10] are in principle suited for personal sensing, but have drawbacks of their own: The *PEM*'s gravimetric measurement reportedly offers good results, but readout is delayed and difficult for non-expert users, while still costing ~\$500. The *UCB monitor* is only intended for use in indoor environments.

An interesting study using bicycles as a platform to carry out mobile measurements is described in [26]. The authors conclude “that a limited set of mobile measurements makes it possible to map locations with systematically higher or lower ultra-fine particles and  $PM_{10}$  concentrations in urban environments.” They used semi-professional equipment to monitor  $PM_{10}$  levels, which is unsuitable for Urban Sensing scenarios because of its cost. [17] presented a distributed network of nodes using the low-cost *Sharp GP2Y1010* sensors in order to monitor dust, particularly in urban areas. The accuracy was analyzed against that of a gravimetric measuring device. However, the paper focused on network aspects and does not contain detailed information on the evaluation, just that the results were “calculated based on 20 measurements”. No information on the sampling frequencies or the duration of those measurements is publicly available. In [25], a wireless sensor node for indoor particulate matter sensing is presented, and its calibration and performance are discussed and evaluated. While the authors

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<sup>2</sup> <http://www.botworld.info/>

<sup>3</sup> <http://www.opensense.ethz.ch/>

<sup>4</sup> <http://www.da-sense.de/>

claim that their system “. . . can monitor the air quality in real time in large spaces, such as a subway station, at a lower cost than existing commercial products”, no details on the sensor itself or its cost are actually presented. A similar project is the *Dust sensing Project* [11] which used Sunspot nodes. While a detailed description of nodes and sampling code is available, no evaluation of sensitivity and accuracy was published.

Another interesting approach to measuring atmospheric dust in Participatory Sensing scenarios has been presented by the *Air Visibility Monitoring* [27] respectively the *iSPEX*<sup>5</sup> projects. People use their camera phones to take pictures of the sky and upload them to a central database. There, from the image, location and phone sensor data (e.g. orientation), the air pollution is calculated. Cloudy skies and indoor environments are a clear limitation to this approach. In parallel to the work presented in the paper at hand, we worked on integrating an optical dust sensor with mobile phones. The general feasibility of an approach to use the camera and LED flash as the receptor respectively the light source of such a sensor has been shown in [5]. Most of this work’s results are applicable to such a system as well.

### 3 Sensing System

A number of companies offer small, generally embeddable particulate matter sensors that could fit in a hand-held measuring device. Several small sensors are compared in [8], the results indicating that only few of those sensors actually seem suitable for the use in mobile *PM* measurement scenarios. We chose the *Sharp GP2Y1010*, a cheap commodity dust sensor, as basis for our work, as it has been used in several dust sensing projects [2,3,11,13,17,23,30]. However, none of these supply information on how they enabled accurate readings from the simple sensor – or whether they did at all. In order to do this ourselves, we conducted a series of parallel measurements with the *GP2Y1010* and a high-accuracy laser photometer as reference device, the *TSI DustTrak DRX 8533 Aerosol Monitor* [36].

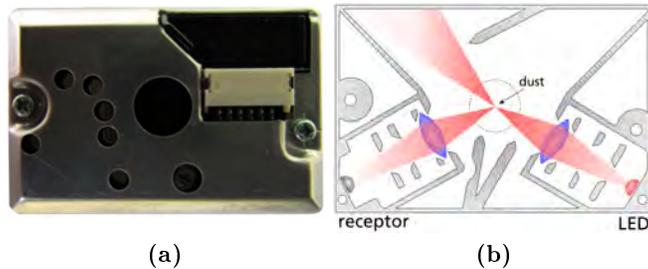
#### 3.1 Dust Sensor

The *GP2Y1010* employs light scattering as operation principle: An IR light beam is emitted into a measurement chamber. When dust is present, the light is refracted by particles and the amount of scattered light is detected. The measurement chamber is designed to be a light trap, so that only the refracted light falls onto the receptor (see Figure 2).

While the sensor has been used in previous work and seems promising, it was clearly not designed to provide accurate absolute readings. The *GP2Y1010* is intended for the use in air conditioners and air purifiers [31], its default detection granularity is limited to the coarse distinction between “house dust”, “cigarette

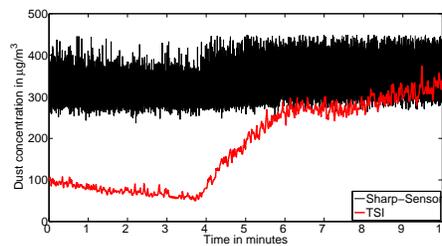
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<sup>5</sup> <http://ispex.nl/en/>



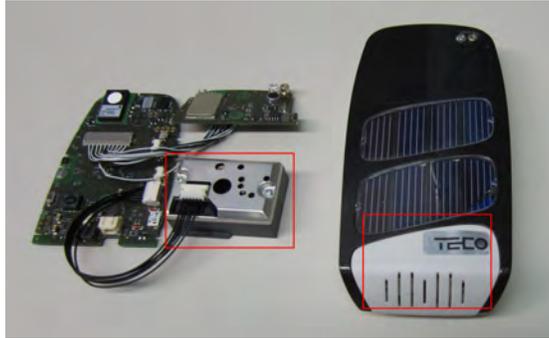
**Fig. 2.** (a) The *Sharp GP2Y1010* dust sensor, and (b) the structure of its light trap on the inside and visualization of its operation principle.

smoke”, and “no dust”. Although its data sheet shows an exemplary relationship between the dust density and the sensor’s output voltage, it states that the graphs are “just for reference and are not for guarantee” [32]. After applying an approximation of this curve to the readings of the sensor and comparing it to the measurements of the *TSI DustTrak* reference device, we can see that the sensor output is very noisy and the curves do not match (see Figure 3). This, along with the fact that different specimen of the sensor displayed strongly varying output levels, lead to experiments with signal processing and calibration.



**Fig. 3.** Raw readings of the *GP2Y1010*, computed according to the exemplary reference curve in the datasheet [32], vs. those of the *TSI DustTrak*.

After initially building our experiments on an *Arduino Mega* platform, we eventually switched to using the *TECO Envboard* (see Figure 4), as its housing protects the sensor from other possible sources of error, such as fluctuating ambient light conditions [37] or bedewing [31]. In addition to that, it carries multiple additional sensors, which we investigated regarding their use to provide supplemental data that is beneficial for our efforts to reach a high accuracy. Finally, it is equipped with micro-fans that ensure a constant air flow through the sensor, which enables continuous measurements, while reducing the risk of residual dust staying trapped in the sensor and compromising accuracy.

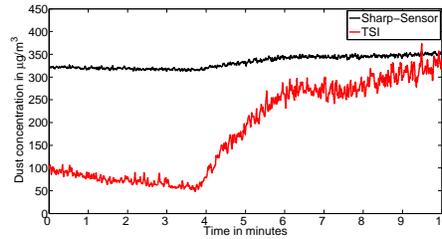


**Fig. 4.** The *TECO Envboard*, an environmental multi-sensor platform with Bluetooth interface and multiple sensors, that was used in our experiments.

### 3.2 Accuracy Improvements

We started developing our refinements by investigating the performance of the *Sharp GP2Y1010* and its ability to measure the particulate matter concentration in the air using the setup described in [8]. All sensors were used as they were delivered, using their unmodified factory sensitivity settings. We sampled the sensors at the maximum possible frequency according to the LED pulse width and waiting times documented in the data sheet [32], which resulted in a sampling rate of  $\sim 100$  Hz. The *TSI DustTrak DRX 8533 Aerosol Monitor* reference monitor sampled at its maximum rate of 1 Hz, calibrating it according to the manual [36] prior to each measurement run. We neither used impactors nor filters to keep our samples clean from coarse dust.

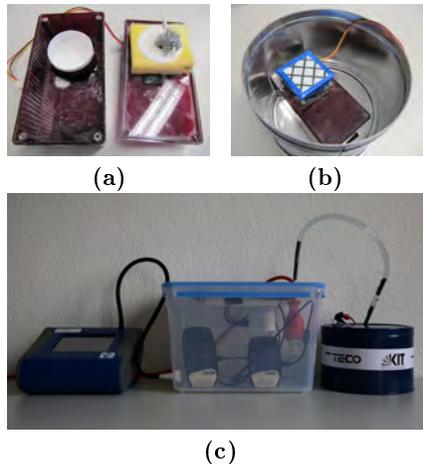
**Noise Reduction** The first step towards de-noising the sensor output was eliminating the outliers and thereby smoothing the output. Since our reference device was sampled at 1 Hz, we also sliced the *GP2Y1010* readings into windows of 1 s length and calculated the median over the 100 samples. The results are shown in Figure 5. A correlation between the *Sharp GP2Y1010* output (upper curve) and the *TSI DustTrak* measurements (lower curve) becomes more clearly visible. As the particulate matter concentration decreases from about  $100 \frac{\mu\text{g}}{\text{m}^3}$  to  $50 \frac{\mu\text{g}}{\text{m}^3}$  within the first four minutes, the *GP2Y1010* output shows a similar tendency and decreases as well, albeit only slightly. The increase in dust concentration between the fourth and the sixth minute is also reflected in the sensor’s readings. As a second process step to further reduce the noise, we applied a moving average filter with a window size of 60 s (i.e 60 data points) on the data. We separated the noise reduction into two steps, because the first one can be easily carried out in the sensing device before logging or transmitting the data. By this, we can achieve data reduction without losing significant information. The second step for further smoothing can either be carried out on the device or on a back-end system. By adjusting the window size, a tradeoff between accuracy



**Fig. 5.** De-noised sensor output by averaging (median) over 1 s-windows.

and timeliness can be made.

**Calibration** Using these improvements, we attempted to calibrate the *Sharp GP2Y1010* by mapping its output to the corresponding particulate matter concentration, in order to later allow the direct calculation of the dust concentration in the air. The sensor does not feature different channels or any other means to distinguish between particles of different sizes. Instead, we derived different calibration coefficients for  $PM_{10}$  and  $PM_{2.5}$  respectively. To have a broad spectrum of dust concentrations for calibration, we built a self-made dust dispenser (see Figure 6). It basically consists of a box and fan that is connected to a small bale of steel wool (a). When the fan is turned on, the steel abrades chalk inside of the box and blows it into the outer containment (b). A filter sheet is used to prevent too much dust being dispensed at once. In the full calibration setup, the air flows through the dispenser, then into the box containing the *Envboards* and



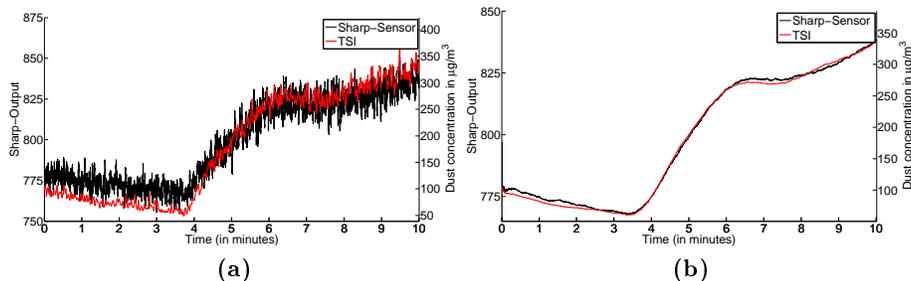
**Fig. 6.** Calibration setup: (a) dust dispenser box with chalk reservoir and steel wool, (b) outer containment, and (c) complete setup.

finally through the *TSI DustTrak* (c). This dispenser makes it possible to quickly generate high dust concentrations which will decay slowly after turning off the dispenser. By alternating dispensing and ventilation phases, we enabled readings over the full spectrum of the sensor. For the actual calibration of the sensors we performed measurements over 18 hours, again sampling the *GP2Y1010* at 100 Hz and the *TSI DustTrak* at 1 Hz. The dust dispenser was set to be turned on for 15 minutes once an hour. This led to a repeated sequence of rising and falling dust concentrations, allowing the sensors to repeatedly measure different concentrations levels.

We first applied the two de-noising steps that were described in the previous section. The second step was also applied to the readings of the *TSI DustTrak*. Based on this data, we calculated a linear scale factor  $a$  and offset  $b$  between the two curves as coefficients for the raw readings  $x$  to calculate the concentration  $\rho(x)$ :

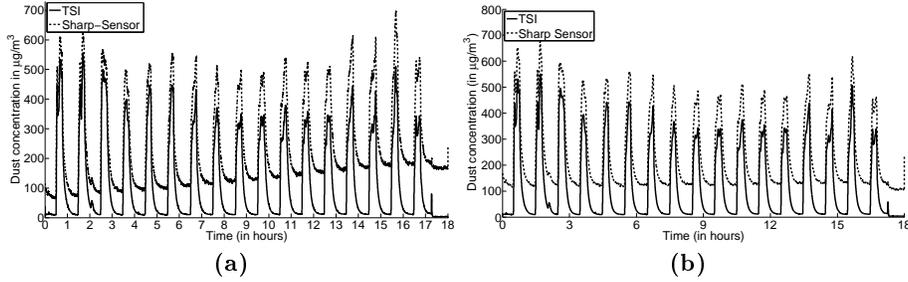
$$\rho(x) = a \cdot x + b$$

The results of these steps are depicted in Figure 7, once after the first de-noising step (a) and once after the subsequent smoothing of both curves (b). The graph's ordinate represents the time (in min) and plotted on the y-axis are the readings of the *GP2Y1010* (10-bit ADC-values, black curve), respectively the  $PM_{10}$  values measured by the reference device (in  $\frac{\mu g}{m^3}$ , red curve). These figures clearly show that it is possible to align the readings of both devices by linear calibration coefficients.



**Fig. 7.** Processing by de-noising and linear calibration: (a) slicing into 1 s windows, (b) smoothing through moving average filter with 60 s window.

However, when applying the calibration data on consecutive measurements, we encountered new problems: We discovered that the offset of the sensor seemed to “jump around” between different measurement runs, i.e. the sensor baseline de-calibrated. Also, the sensors displayed a significant drift over time. Both effects can be observed in Figure 8. The graph shows an 18-hour sampling session with the dust dispensing pattern described above. We applied the coefficients derived from a previous calibration run. In order to quantify the drift, we examined several sensors over multiple measurement runs. We found that the drifting



**Fig. 8.** (a) Drift when applying the calibration on a second 18h-measurement and (b) compensation through simple relative baseline manipulation.

behavior exhibited was nearly linear with time and very similar for multiple passes. Thus, we were able to reduce the drift by simple relative baseline manipulation. We introduced a separate calibration step for each sensor to determine its time-dependent drift factor  $k$ . Using this, we adjusted our calculation of  $a$  and  $b$ . This lead to the following new formula for calculating the concentration  $\rho$ :

$$\begin{aligned}\hat{x}(t) &= x - k \cdot t \\ \rho(x, t) &= a \cdot \hat{x}(t) + b \\ &= a \cdot (x - k \cdot t) + b\end{aligned}$$

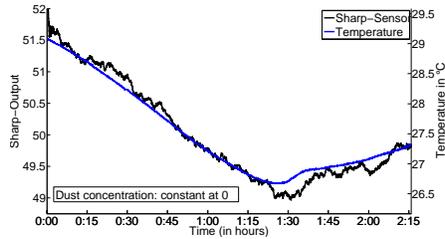
Figure 8 (b) shows the result. Still, we saw further room for improvement. In order to tackle this, we examined the effects of other parameters on the *GP2Y1010* output.

**Sensor Fusion** At this point, we switched to using the *TECO Envboard* sensor platform [6], since there is a documented temperature dependency of the *GP2Y1010* [31]. We analyzed the readings of the *Envboard*'s internal *Sensirion SHT21* digital temperature and humidity sensor. There is a very strong relationship between the readings of the two sensors (see Figure 9).

To correct for this, we again devised a linear compensation<sup>6</sup> as a function of the temperature  $T$  according to measurements taken at a reference temperature  $T_0$  of 20 °C. We introduced another calibration step after the drift compensation and before calculating the scale factor and offset, again leading to a revised formula for calculating  $a$  and  $b$ , respectively  $\rho$ :

$$\begin{aligned}\hat{\hat{x}}(T) &= \hat{x}(t) + \alpha_T \cdot \Delta T \\ \rho(x, t, T) &= a \cdot \hat{\hat{x}}(T) + b \\ &= a \cdot (x - k \cdot t + \alpha_T \cdot \Delta T) + b\end{aligned}$$

<sup>6</sup> We expect this formula to perform less well in extreme temperatures and aim at replacing the linear correction in the future.



**Fig. 9.** Measurements at a constant concentration of 0 (zero filter) vs. *SHT21* temperature readings.

Overall, the combination of these steps greatly improved accuracy of the readings. However, the already observed effect of the offset de-calibration could not completely be eliminated by this. While the scale factor  $a$  could be accurately derived from the calibration process, several independent influences lead to a shift in the offset  $b$ . The base line of the sensor output shifts not only with varying temperature, but also depending on other factors, such as changes in the measurement frequency (even though within specification). As a result, we neither sampled the sensor irregularly nor changed the fixed sampling frequency between measurement passes. We also observed shifting base levels depending on the subset of sensors that we sampled. While this may be due to device peculiarities, we decided to use a fixed set of sensors for all our consecutive measurements. Even so, we kept encountering changes in the offset between measurement runs. The offsets seemed to change randomly every time the sensors are turned off and on, even after trying to remove any residual charge. Therefore, we decided to make use of additional information we may have in Participatory Sensing scenarios to combat this problem.

**On-the-fly Calibration Correction** While all previous improvement steps took place on the device level, Participatory Sensing scenarios have the potential to further improve measurement accuracy by sharing information across devices. This can be as simple as averaging readings from co-located devices to reduce measurement errors. More sophisticated approaches may take the shape of the actual data, dispersion models, calibration age, device type, etc. into account when correcting values as well. An example for the application of instant calibration of low-cost gas sensors, either in each other’s vicinity or even multi-hop, was presented in [16]. We propose to use the data from co-located sensors to eliminate the problem of offset de-calibration that the *GP2Y1010* described above. In order to do this, we used measurements from a co-located reference point to correct the calibration of the hand-held devices. A reference point can either be a high-precision professional measurement station or another device which has a high confidence that it is correctly calibrated. The device that carries the *GP2Y1010* sensor then uses the reference values to correct its bias. As we only intend to correct changing offsets, only very few measurements have to

Device ( <i>Sensor</i> )	Detection Method	Max. Rate	Range	Price
<i>Envboard</i> [7]				
<i>Sharp GP2Y1010</i> [32]	light (IR) scattering	1Hz <sup>†</sup>	~0 - 500 $\frac{\mu g}{m^3}$	\$ ~10 <sup>‡</sup>
<i>TSI DustTrak DRX 5833</i> [36]	light (laser) scattering	1Hz	1 - 150,000 $\frac{\mu g}{m^3}$	\$ ~9,000
State-operated Measurement Station				
<i>Grimm EDM 180</i> [14]	light (laser) scattering	~10/min	0.1 - 6,000 $\frac{\mu g}{m^3}$	\$ ~35,000
<i>Leckel SEQ47/50</i> [34]	gravimetric	24h-mean	$n/a^*$	\$ ~20,000
<i>Leckel SEQ47/50</i>	gravimetric	24h-mean	$n/a$	\$ ~20,000

<sup>†</sup> Using the de-noising steps presented in this work. The maximum raw sampling rate is ~100 Hz.

<sup>‡</sup> Cost of the analogue sensor. Additional costs for the data logger platform.

\* Gravimetric measurements do not have an upper bound except their total filter capacity.

**Table 2.** Comparison of measurement equipment used in the different evaluation settings.

be transmitted from the reference device to achieve notable improvement. We show the potential improvement by simulation in the next section of this paper.

## 4 Evaluation

Aside from the hours of measurements we made throughout the process of improving the sensors’ accuracy, we conducted two longer measurement sessions in order to evaluate the performance of our system under operating conditions: Firstly, we did a controlled indoor evaluation of the calibration. Secondly, we co-located the sensor platforms with official state-owned measurement stations. Thirdly, we simulated on-the-fly calibration correction for all evaluation runs and discuss the possible improvements. In addition to our sensor boards and the reference device, we obtained the data from the officially approved measurement equipment that is used in the state’s monitoring stations. Table 2 shows an overview of the measurement equipment that was used in the test. It is noteworthy that the *GP2Y1010* dust sensor costs only a fraction of the reference devices. This section shows how well our improved readings compare to the accuracy of the professional equipment.

### 4.1 Lab Evaluation (Indoor)

The first session was an indoor evaluation of our processing steps. In contrast to the prior calibration, our sensor platforms were only co-located with the reference meter, but not sampling the exact same air flow (see Figure 10). We measured the indoor particulate matter concentrations using six *TECO Envboards* and the *TSI DustTrak*, which was only sampled every fourth second, since the maximum sampling frequency is limited by the internal logging space (18 h at 1 Hz) and we intended to validate our refinements over a longer period of time (three days). The measurements of the  $PM_{2.5}$ -concentration are shown in Figure 11 (a).

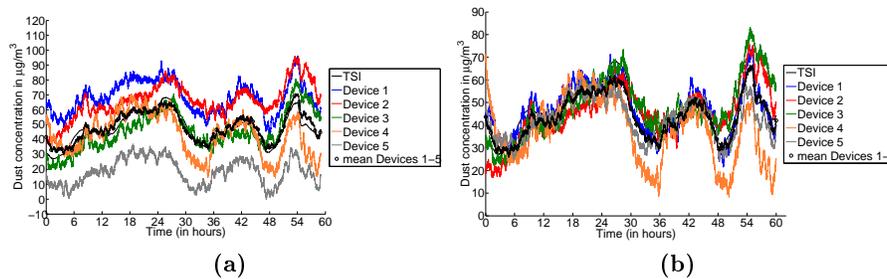
As expected, it is clearly visible that the readings from the calibrated hand-held devices show a strong correlation to those of the reference device, the scale



**Fig. 10.** Setup of the indoor lab evaluation: Six *Envboards* and the *TSI DustTrak* as reference.

factor calibration was successful. However, it can also be observed that the problem of offset de-calibration persisted. The *TSI DustTrak* measured an average of  $46.8 \frac{\mu g}{m^3}$  over the 60 hours, the *Envboards* measured averages between  $18.5 \frac{\mu g}{m^3}$  and  $68.5 \frac{\mu g}{m^3}$ . This can be already considered to be very accurate in light of the intended use of the *Sharp GP2Y1010*. Further calculations lead to even better results: By simply taking the mean of the five devices, we arrive at a very close match to the values measured by the *TSI DustTrak*. However, this is not generalizable and only limited trust can be put into the values of a single device.

This is why we continued to simulate the on-the-fly calibration correction we presented earlier. Figure 11 (b) shows the dust concentrations measured by the hand-held devices after applying the on-the-fly calibration step. We randomly selected three consecutive data points from the reference device and “transmitted” them to the mobile devices, which in turn “calculated” the difference between the locally measured values and the reference value in order to adjust their offset accordingly. This notably improved the accuracy of the devices. Similar to

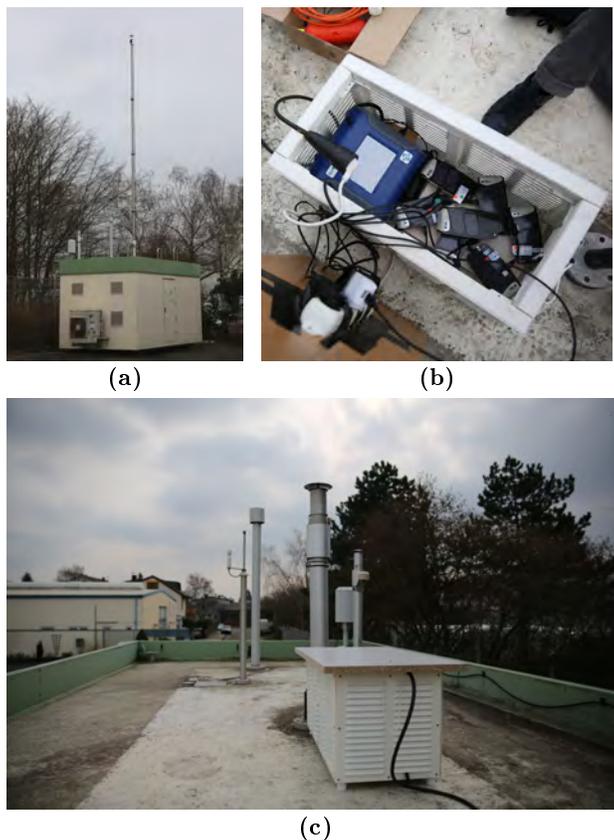


**Fig. 11.** Indoor  $PM_{2.5}$  evaluation: (a) calibrated *GP2Y1010* sensors against the *TSI DustTrak* reference, (b) values after on-the-fly correction.

$PM_{2.5}$ , the  $PM_{10}$  curves of the hand-held devices show the same general behavior. Without on-the-fly calibration, the offsets were a little larger, and the simple mean did not fit as well. After simulating on-the-fly calibration, the gain was comparable to the  $PM_{2.5}$ -case.

## 4.2 Field Evaluation (Outdoor)

For our field evaluation, we co-located several *Envboards* with an official state-owned station that measures different types of background pollution. Our measurements took place in the late Winter 2012/13. We used the same, unaltered devices as in the lab evaluation, the only difference being that we placed them inside a small, well ventilated box in order to shield them from rain and snow (see Figure 12). We added the *TSI DustTrak* as well. This setup was then placed on the rooftop of the measurement station, next to the air inlets of the other

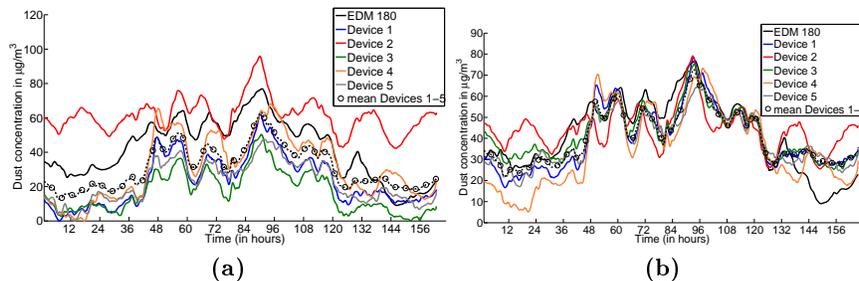


**Fig. 12.** Field evaluation: (a) state-operated measurement station, (b) equipment in weather protection box, and (c) installment on rooftop.

samplers, and logged for seven days continuously. After retrieving our setup, we compared the data of the official measurements to our own.

The state uses three measurement devices at the station, one optical and two gravimetric (for details, see Table 2). The *Grimm Technologies Model EDM 180 PM Monitor* is a laser scattering aerosol meter that has “the European Equivalence Approval for  $PM_{10}$  and  $PM_{2.5}$  as well as the US-EPA Approval for  $PM_{2.5}$ ” [14]. It measures the  $PM_{10}$ ,  $PM_{2.5}$  and  $PM_1$  levels at a maximum frequency of ten samples per minute. Usually, the state is not interested in such a high temporal resolution, so that only 15 or 30 minute averages are recorded. Their main aim is to be able to release timely readings of the 24 h-means before the gravimetric measurements are analyzed in the lab. The gravimetric readings in the station are gathered by a pair of *Leckel SEQ47/50 High Volume Samplers (HVS)* [34], one for  $PM_{10}$  and one for  $PM_{2.5}$  measurements. It takes between one and three weeks before the data from the gravimetric measurements is available, since the filters are periodically collected and weighed in the lab. The resulting data is then also used to perform a backwards correction of the time series data from the *EDM 180*, since experience has shown that even the certified optical measurements show a deviation of within  $\pm 10\%$  accuracy. However, since we expressed our interest in data with a higher temporal resolution, the state supplied us with 1 min-averages of the sampled values.

The  $PM_{2.5}$ -concentration over the seven days is shown in Figure 13,  $PM_{10}$  in Figure 14. The devices show the same phenomenon as in the indoor experiment. The *GP2Y1010* is able to detect the changes of the dust concentrations but the values have a constant offset to reference values. Additionally, some inaccuracies regarding the scale factor are also visible. The transfer of the indoor calibration coefficients to the outdoor scenario did not work as smoothly as we had hoped. One explanation for the observed deviation could be that the temperature outside was as low as  $-5^\circ\text{C}$ , much lower than we went when characterizing our sensors’ temperature dependency. We assume that the simple linear correction we used is inadequate at “more extreme” temperatures. Aside from the continuous measurements, we also looked at 24 h-means of each device, as this is the quantity that is currently relevant for regulatory purposes. The results are shown



**Fig. 13.** Outdoor  $PM_{2.5}$  evaluation: (a) calibrated *GP2Y1010* sensors against the *TSI DustTrak* reference, (b) values after on-the-fly correction.

in Figure 15 and Figure 16 respectively. We can see that on-the-fly-calibration achieves improvement in the outdoor scenario as well. This is especially true for the 24-h-means which can be brought down to a very small error, both individually or when averaging over multiple devices.

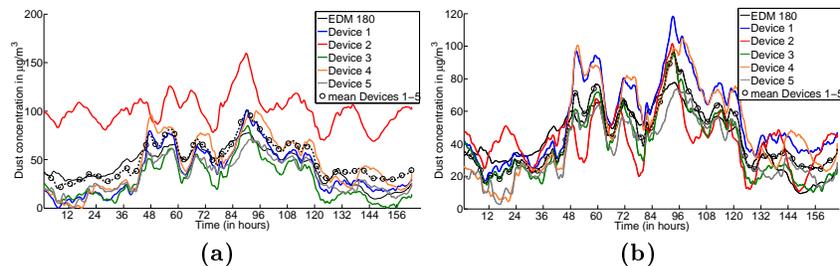
## 5 Conclusions

In this work, we have presented and evaluated particulate matter sensing technology for the use in Participatory Sensing scenarios. We investigated a cheap commercial off-the-shelf (COTS) dust sensor, the *Sharp GP2Y1010* in terms of its accuracy and presented several calibration, processing and sensor-fusion steps, that lead to meaningful readings from the sensor – which originally is only intended for the coarse distinction between “dust” or “no dust”. We showed, that in a Participatory Sensing scenario, devices equipped with the sensor can use information from co-located devices in order to stabilize and improve their readings. This distributed or mobile measurements at a price at least one order of magnitude lower than that of current hand-held solutions.

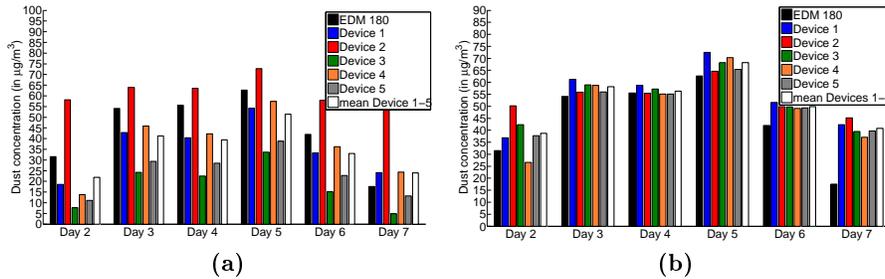
## 6 Future Work

While we are already excited by the presented results, there are still open issues and further work can be done to build on this work.

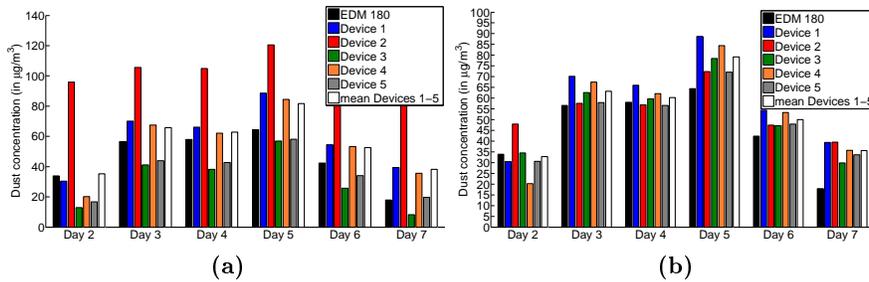
- *Other Influences*: While this work shows that calibration procedures and temperature correction already enable meaningful readings from the cheap *GP2Y1010*, other factors of influence should be examined as well, such as humidity, air pressure, etc. It is to be expected that high levels of humidity can have an impact on the sensor readings as any light scattering sensor will detect a higher particle mass due to condensation effects. It has already been shown that the reference device that we used is sensitive to high humidity and that this can be compensated [28]. For the experiments in this work however, humidity was not an issue as it did not exceed medium levels.



**Fig. 14.** Outdoor  $PM_{10}$  evaluation: (a) calibrated *GP2Y1010* sensors against the *TSI DustTrak* reference, (b) values after on-the-fly correction.



**Fig. 15.** Comparison of 24 h-means for  $PM_{2.5}$  before (a) and after (b) applying the on-the-fly calibration.



**Fig. 16.** Comparison of 24 h-means for  $PM_{10}$  before (a) and after (b) applying the on-the-fly calibration.

- *Sensor Improvement:* Although we have gotten very much out of the simple *GP2Y1010* sensor already, some problems persist. The issue with the offset de-calibration (“jumping offsets”) has not been solved on a single-device-level. Further experimentation might eliminate it, enabling accurate readings on an individual device. The integration of a dust sensor in the replaceable back shell of a smartphone would be a beautiful solution requiring no hardware modifications at all, and maybe even eliminating some of the sensors peculiarities. Other worthwhile steps should include miniaturization efforts or even completely novel sensor designs to eventually enable the embedding of  $PM$  sensors into smartphones.
- *User Calibration:* An issue with the presented calibration approach is that a normal consumer usually will not be able – or willing – to perform the necessary calibration steps, which directly affects the data quality. This work already presented algorithms where systems re-calibrate each other by exploiting periodic proximity to reference stations. In an actual urban sensing application with sufficient participants, the presented calibration could also be easily “virtualized”, i.e. new devices could learn their calibration curves (e.g. using machine learning techniques) once they enter the measurement grid. The need for explicit calibration by the end user would vanish.

- *Actual Mobility*: While intended and generally suitable for mobile measurements, so far, we evaluated only the performance of the sensor at fixed locations. Experiments that assess the impact of mobility need to be carried out.
- *Incentivisation*: Another important aspect of Participatory Sensing is motivation, i.e. users need incentives to deploy sensors, collect data and ensure its quality. *Gamification* approaches may be beneficial to persuade people to participate, once sufficiently cheap measurement devices are available to the public. By analyzing both sensor and game data on a higher level, new ways of persuading participants, e.g into taking measurements at certain low-coverage points, could be developed within such gamified environmental sensing systems.

## 7 Acknowledgments

We thank Zarko Peranić, Manfred Juraschek, Johann Steinberger, Mr. Gauss and Mr. Röhrl of the *Landesanstalt für Umwelt, Messungen und Naturschutz Baden-Württemberg (LUBW)* for supporting our outdoor evaluation.

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