



Real-Time Visualization of Methane Emission at Commercial Dairy Farms

Dirkjan Schokker¹(✉), Herman Mollenhorst², Gerrit Seigers³,
Yvette de Haas¹, Roel F. Veerkamp¹, and Claudia Kamphuis¹

¹ Wageningen Livestock Research (Animal Breeding and Genomics),
Wageningen University and Research,
PO Box 338, 6700 AH Wageningen, The Netherlands
dirkjan.schokker@wur.nl

² Wageningen Livestock Research (Livestock and Environment), Wageningen
University and Research, PO Box 338, 6700 AH Wageningen, The Netherlands

³ Facility and Services (Information Technology), Wageningen University
and Research, PO Box 59, 6700 AB Wageningen, The Netherlands

Abstract. The Dutch government has set an objective to reduce greenhouse gasses (GHG) emissions to 116 Mton CO₂-equivalent in 2030. The agriculture sector aims for 11–23 Mton of GHG emission by 2050 and thus contributes to this objective. For this sector, the major contributor to the GHG emission in the Netherlands is the dairy sector. Before any mitigation strategies can be enrolled, some key facts need to be measured regarding the GHG emission on a farm. One of these key facts is the establishment of the baseline of GHG emission on a farm (and per cow). For this, we previously have built an infrastructure to measure and collect methane and carbon dioxide (near) real-time on a farm. The next challenges, addressed in the current study, were to (1) combine the private methane data, collected real-time through the infrastructure, with open source weather information, and (2) visualize both data streams for farmers, by developing an application that can be viewed on a web or mobile phone platform.

Keywords: Farm · Cow · Methane emission · Real-time · Visualization

1 Introduction

1.1 Background

The objective for the Netherlands is to achieve a greenhouse gasses (GHG) emissions reduction of 49% in 2030 (compared to 1990). In 1990, the total GHG emissions were approximately 228 megaton CO₂-equivalent. This means that in 2030, the GHG emissions has to be reduced to 116 Mton CO₂-equivalent. Five sectors have been indicated, including electricity, industry, mobility, houses, and agriculture. For agriculture the objective for 2050 is to have a 90% reduction, in other words a maximum of 11–23 Mton of GHG emission. To establish a baseline for the methane emission of a farm and of an individual cow, and more importantly to identify the most successful strategies to reduce these emissions, it is necessary to have (real-time) methane data.

This continuous monitoring of methane emission from livestock production systems, including dairy farming, is needed to understand which aspects contribute to the methane emissions and to what extent. Moreover, this knowledge is needed to develop mitigation strategies. The available data can be used to visualize the impact of these strategies.

A large intensive research program has been started in 2018 by the Dutch Ministry of Agriculture, Nature and Food [1], to identify strategies to reduce methane emission in the agricultural-sector. Part of this program involves continuous monitoring of methane, by means of sensor measurements, both at the barn and individual animal level. The research program involves several animal production domains, including dairy farms. Therefore, monitoring of methane takes place at 17 commercial Dutch dairy farms. At these farms, methane is measured by methane analyzing sensors. These so-called sniffers use a nondispersive infrared sensor (NDIR) for methane and carbon [2]. These sniffers generate a constant analogue signal that is linearly related to gas concentrations. By placing these sniffers in the milking robot, we ensured that all milking cows at a farm were monitored for their methane emission while being milked. To collate these data from several sniffers in the field and to link this information to individual barns and animals we developed a flexible infrastructure [3]. This infrastructure continuously monitors sniffer functioning and data quality to bring loss of data to a minimum, and allows for a cheap but trustworthy data transfer from the sensors to a cloud storage platform (in our case: Microsoft Azure). The infrastructure is also flexible in accepting other types of information. One can think of other sensor data, but also animal and farm data that are often stored in separate farm management programs. Another part of the flexibility of the infrastructure links to the scalability, i.e. handling data from new farms in case the number of farms, where methane is monitored, increases.

In this study we worked on two challenges. The first challenge was to combining the real-time sniffer data, which is private data, with open source weather information from IBM through Akkerweb (www.akkerweb.eu). This combination is important because it is expected that wind and relative humidity affect methane emissions [4, 5]. The second challenge was to develop a tool that visualizes the incoming sniffer and weather data, two data streams that differ in veracity, for web and mobile applications using Power BI, an interactive tool to visualize data developed by Microsoft (<https://powerbi.microsoft.com/>).

1.2 Objectives

Our objectives were (1) to integrate private methane data with open source weather data and (2) to visualize methane emission data on dairy farms in (near) real-time to in an application for web and/or mobile.

2 Materials and Methods

2.1 Infrastructure

Up till now, 18 sniffers were installed at 17 commercial Dutch dairy farms, using the same set-up as described by Huthanen et al. [2]. These sniffers have a nondispersive infrared (NDIR) sensor, a simple spectroscopic sensor, here used to detect methane and carbon dioxide. The sniffer sends the corresponding values every 30 s to the connected Arduino (microchip Atmel SAMD21, 32 bit Arm Cortex Arduino compatible and a uBlox Sara R410M, all NB-IoT bands, LTE-M). Subsequently, the Arduinos were programmed to push the data every 3 min to the Azure cloud. This was done via the Internet of Things (IoT) network, to avoid potential problems with low coverage of e.g. a WIFI signal.

In Azure, a Microsoft cloud platform (<https://azure.microsoft.com>), an IoT hub was built which was subscribed to the data stream, meaning getting and loading the data. Here, different alerts were coded, for example when the data stream pushed by the Arduino had down-time (out of action) or when measured values were outside a predetermined expected range, the data owner received an email [3]. To visualize the data stream from the IoT hub, we used Power BI (Version: 2.72.5556.801 64-bit, August 2019), which provides interactive visualizations to create dashboards and reports. Additionally, we integrated an additional open data source, i.e. current weather data. Here, we have used the IBM weather data, by querying the current weather via an API at Akkerweb. The following weather fields were retrieved: temperature, wind speed, precipitation (last 24 h, 6 h, or 1 h), UV strength, and the relative humidity. These values were visualized within Power BI for the city in which a farm is located. The associated city names were transformed to “latitude-longitude” by using <https://www.latlong.net/>, to ensure proper working of the API. A schematic overview of the data flows is presented in Fig. 1.

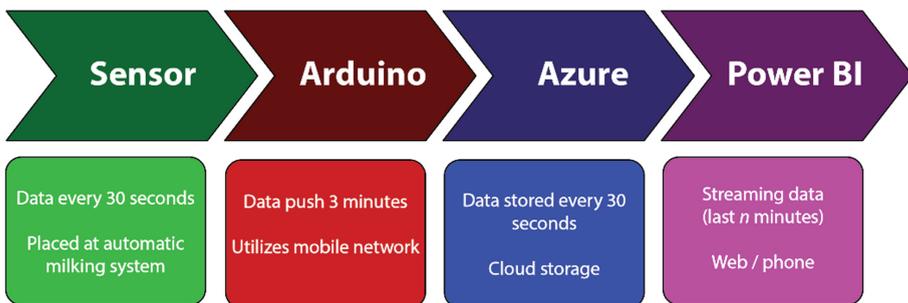


Fig. 1. Data-flow diagram. The sensor is placed in the area of the milking robot. The data is captured by an Arduino sends it to Azure in the cloud. In Azure the data is loaded into an IoT hub. Lastly the data is visualized in Power BI.

3 Results and Discussion

3.1 Methane Visualization

We were able to visualize sniffer data in (near) real-time for individual commercial Dutch dairy farms. A lesson we learned when performing the data push from the cloud Azure to Power BI is that the data needed to be in a so-called “star” schema. The center of the star has one fact table (in our case the farm) and a number of associated dimension tables (in our case methane and weather data). This star schema is needed to have a more efficient performance on the visualization side in Power BI, compared to a so called “snowflake” schema. Figure 2 shows data from one sniffer, equaling methane emission data from one milking robot unit on a farm, for a 90 min period. This figure shows fluctuations around zero, indicating the absence of a cow in the milking robot. On the other hand, a peak indicates the presence of a cow in the milking robot. From these data, it is not evident yet when one cow enters or leaves the milking robot. It would be worthwhile to combine these sniffer data to other farm management software and/or measurements, to assess more precisely when a cow enters or leaves the milking robot. When further developing this visualization application further development is needed regarding the integration of the individual cow data. The main advantages of such additional data are to have improved emissions estimates at farm level, and the possibility to generate a cow specific methane profile. This will open-up new possibilities to reduce methane emission, by feeding and/or breeding strategies, as well as management [6].

3.2 Integration with Additional Data Streams

The sniffer data may fluctuate due to characteristics of the barn. For example, its construction and air flow through the barn and the location of the milking robot may influence the measurement. Furthermore, outside weather may also exert an influence, like temperature, wind flow, and humidity. The current weather data was pulled into Power BI and subsequently visualized for the village the farm is located (for example Cornwerd, a city in the northern province Friesland, see Fig. 3).

While developing this part, we experienced Power BI was not yet optimally designed in handling the data streams. Mainly because Power BI is designed to visualize data from data warehouses and the new data was appended to the database. Power BI will load the whole database each time after a refresh. In our case we have combined data streams from private and open data, simultaneously. The methane data stream was loaded into an SQL database in the cloud and subsequently a subset of the data was pushed to Power BI. Power BI was subsequently used to developed a prototype application for both web and mobile (Fig. 4). This application now demonstrates the cumulative methane emission per day, which resets every day (122.63 K in Fig. 4). Additionally, the methane emissions from the last 60 min are visualized, as well as the current outdoor temperature (°C), relative humidity (%), and wind-speed (km/h).

The current study faced the challenge to combine private data, collected near real-time with open source data. This combining of different data sources, with a variety of formats, scale, and veracity will become increasingly important in the future. For

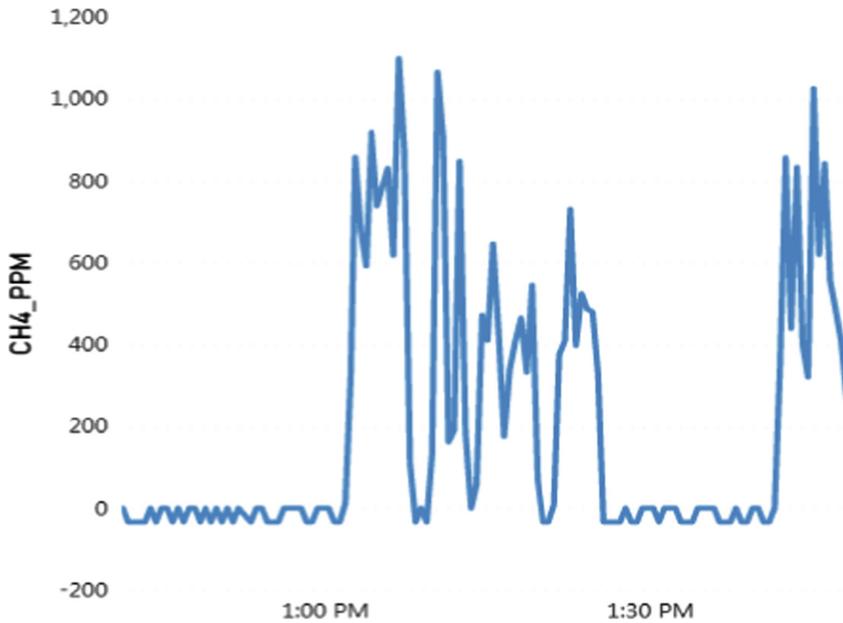


Fig. 2. Results of the last 90 min for a single sensor. The x-axis depicts the time, here from approximately 12.30 PM to 2.00 PM. Whereas the y-axis depicts the concentration methane in the air, in parts per million (CH4_PPM).

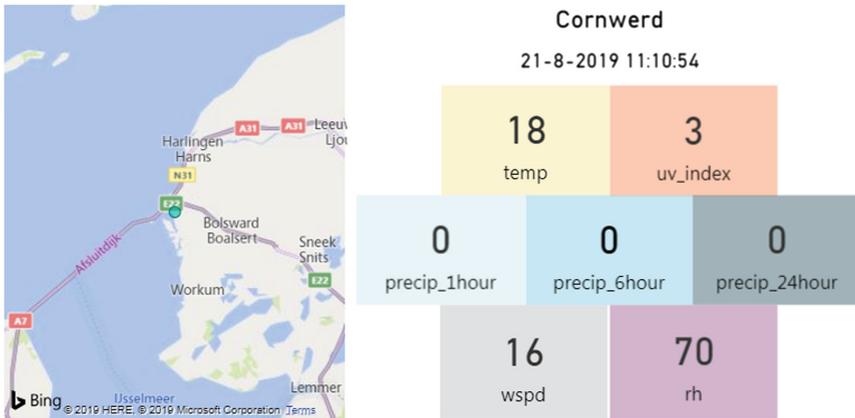


Fig. 3. Overview of the current weather of a participating farm, here in Cornwerd. The left panel shows the location on the map of the Netherlands, whereby the view is zoomed in on the province of Friesland. The right panel shows the city name, data, time and below the temperature in degrees Celsius and the UV-index. Furthermore, the precipitation of the last hour, previous six hours, or past 24 h, and the current wind speed, and the relative humidity.

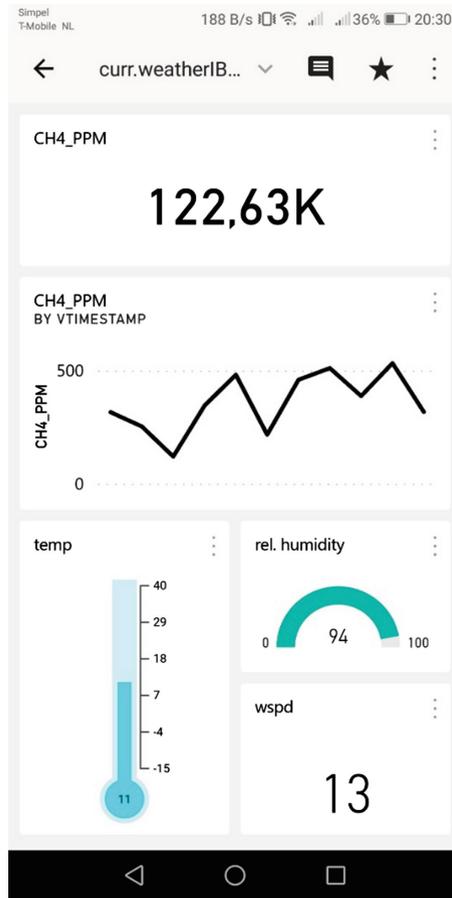


Fig. 4. Prototype of the mobile phone app.

example, when developing digital twins (of e.g., a farm) it can be expected that a plethora of sensors will monitor different aspects of the farm; including individual feed intake, animal health status, animal behavior, and GHG emission. Our study contributed to that future by exploring the possibilities to retrieve data real-time, combine it with open source data, and to visualize it for farmers. Moreover, combining the sniffer methane data with other information like age of the cow, which is a factor known to influence emission [7, 8]. Such information would be an addition to our application, to better interpret the sniffer data or to enrich the visualizations by coloring per age group. In addition, further development is needed regarding the application (web and mobile), particularly to integrate the individual cow data. The main advantages of such additional data is to generate a cow specific methane profile. This will open-up new possibilities to reduce methane emission, by feeding and/or breeding strategies, as well as management [6].

4 Conclusion

To reduce the GHG emissions on dairy farms in the Netherlands, it was necessary to first establish a baseline of GHG emissions per farm (and per individual cow). To do so, we built a data infrastructure for real-time collection of methane measurements. Subsequently, we have shown (near) real-time visualization of methane measurements, enriched with open source (weather) data. Visualization is performed on an interface via a web and mobile phone. The current methane data stream is visualized, as well as the cumulative amount of methane per day per farm. Additionally, the current weather data is integrated to enrich the methane data and possibly identify influences, e.g. wind speed, on the methane measurements. The data handling for visualization could be enrolled on 100 farms in the near future.

Acknowledgement(s). This research was conducted by Wageningen Livestock Research, commissioned and funded by the Ministry of Agriculture, Nature and Food Quality, within the framework of Policy Support Research theme “Data driven & High Tech” (project number KB-38-001-004 Smart and Privacy conserving infrastructures). Data used for this study was collected within the Climate Envelop project of Ministry of LNV.

References

1. Schouten, C.: Agriculture, nature and food: valuable and connected. The Netherlands as a leader in circular agriculture. N.a.F.Q.o.t.N. Ministry of Agriculture, Editor (2018)
2. Huhtanen, P., et al.: Comparison of methods to determine methane emissions from dairy cows in farm conditions. *J. Dairy Sci.* **98**(5), 3394–3409 (2015)
3. Kamphuis, C., de Haas, Y., van den Bergh, E.: A flexible data architecture to automate collection of (near) real-time methane sensor data at commercial dairy farms. In: Scientific Symposium FAIR Data Sciences for Green Life Sciences, Wageningen (2018)
4. Saha, C.K., et al.: The effect of external wind speed and direction on sampling point concentrations, air change rate and emissions from a naturally ventilated dairy building. *Biosyst. Eng.* **114**(3), 267–278 (2013)
5. Schmithausen, A.J., et al.: Quantification of methane and ammonia emissions in a naturally ventilated barn by using defined criteria to calculate emission rates. *Animals* **8**(5), 75 (2018)
6. de Souza, W., et al.: Mitigation of enteric methane emissions through pasture management in integrated crop-livestock systems: trade-offs between animal performance and environmental impacts. *J. Clean. Prod.* **213**, 968–975 (2019)
7. Ramirez-Restrepo, C.A., Clark, H., Muetzel, S.: Methane emissions from young and mature dairy cattle. *Anim. Prod. Sci.* **56**(11), 1897–1905 (2016)
8. van Gastelen, S., Dijkstra, J., Bannink, A.: Are dietary strategies to mitigate enteric methane emission equally effective across dairy cattle, beef cattle, and sheep? *J. Dairy Sci.* **102**(7), 6109–6130 (2019)