Low-cost sensors for insect protein production

Pilot Report

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Background to the pilot and proposed solution

The problem the pilot sought to address

According to FAO, the world population will reach 9.1 billion by 2050. To feed that number of people, global food production will need to grow by 70%. Africa, which is projected to be home to about 2 billion people by 2050, must accelerate its farm productivity at an even faster rate than the global average if it is to avoid continued mass hunger. In Kenya, the economic review of agriculture 2021 indicates that about 35% of the Kenyan population lack access to adequate food, with an estimated 2.1M people experiencing high levels of acute food insecurity.

One possible solution to address this challenge is through insect farming, in particular, the black soldier fly larvae (BSFL) as a source of feed for farmed animals which in turn are used to provide food for humans. BSFL have the ability to convert organic substrates to high-quality biomass that is rich in protein, for animal feed. They can also produce biodiesel and bioplastics and have high biotechnological and medical potential.

While insect protein is a growth industry in Africa (for example, in Kenya, 4% of animal feed protein comes from insects), the current monitoring system for insect growth is limited in that the parameters are measured manually and the process is paper-based, which makes real-time data collection and data analysis practically impossible. Overall, there is little standardisation of best practices in production methods for smallholders, low widespread expertise in insect farming, and a lack of live data to act on when farming insects.

All this means that insect farmers lack decision making tools based on data which could help to increase yields, allow greater profitability, and develop a more widespread and mature industry.

The idea conceived for this pilot

Sanergy is a social enterprise based in Nairobi focused on waste management and circularity, that manufactures high-quality insect-based animal protein from organic waste, in the form of the Black Soldier Fly larvae. Sanergy teamed up with the International Centre of Insect Physiology and Ecology (ICIPE) to provide a comprehensive proof of concept on the use of IoT sensor technology for optimal insect-based animal protein production.

The pilot tested the use of IoT sensor technology to provide real-time data to help insect farmers continually monitor insects at all stages of their development in order to optimise production and adapt to changing environmental factors. The ultimate idea would be for Sanergy as a social enterprise to use these sensors in their in-house production, but also to work with bodies such as ICIPE to determine the kinds of sensor and service packages that could be marketed to smallholder farmers, how they can be designed for ease-of-use, and how these packages might be financed.

The context

Any IoT system has to bring together four key components to deliver a powerful solution: The hardware (i.e. sensors themselves), connectivity, data analytics and the user interface. If one of these components is malfunctioning or working sub-optimally then the entire system is weakened.

BSF farmers operate in environments that require a specific hardware (both the sensor itself and the mounting it is attached to) to ensure it is durable enough to last under larvae growing conditions, and reliable. The pilot had to explore the question of whether an iterative redesign process could work given the research time required at each stage and the possibility that durable sensor components may not be able to be locally sourced.

With regards to connectivity, as the majority of small-scale Black Soldier Fly farmers are located in remote locations where internet connectivity is not strong and/or not reliable, this was flagged as a key challenge for the pilot from the outset. So too were the battery life requirements of any setup.

The contextual challenge from the perspective of the user interface and data analytics, lay in three areas: The technical training required for smallholder farmers to configure and monitor the sensors, or approach to removing this need, designing and delivering an intuitive interface so farmers could access the right information at the right time; and the the data analytics and interpretation training that would enable them understand what the resulting data meant, especially in instances where data analytics revealed new insights that were contrary to previous experience.

ProteinMaster facility, a small-scale BSFL farms engaged by the pilot

Goals of the pilot

The pilot explored three key interrelated goals relating to the testing and scaling IoT sensor networks for BSFL farms in Kenya. This meant adopting a range of methods in order to:

1. Demonstrate that IoT sensor networks can be deployed in large and small-scale BSFL farms in Kenya, in order to gather data on critical environmental parameters for growth (pH, temperature, humidity, ammonia, CO_2 and pesticide residues).
2. Learn what a longer-term technical product and service model for rolling out the technology across BSFL farms in Kenya, and especially small-scale farms would need to consist of. Including establishing what the IoT product offering for farmers (i.e. sensors, connectivity, user interface) might need to look like, and what additional services would need to be provided to farmers in order to meet all of their needs relating to using the technology for increasing BSFL yields.
3. Validate that a sensor led approach can lead to increased yields in BSFL farms, and begin to develop a machine learning algorithm capable of predicting the effect of different rearing and environmental parameters on yields.

Through delivering against these goals, the pilot aimed to take initial steps towards a longer term vision of creating sensor and service based packages that could be marketed to and scaled for impact with smallholder farmers in Kenya. In this regard, the focus for this pilot was largely on validating that the technology can be adapted to work in BSFL farms and deliver value to end users, and learning what a longer term product and service model for small-scale farms would need to consist of. With a view that subsequent work could focus on continuing to develop and deliver a product and service offering for smallholder farming, as well as explore what's required to take this offering to scale.

Key Activities

To realise the goals outlined above, the pilot completed a range of key activities.

To demonstrate that IoT sensor networks can be deployed in large and small-scale BSFL farms in Kenya, and can gather data on critical environmental parameters, the team deployed a wide range of sensor types in IoT networks within a range of different farms. In addition to deploying the sensors, a cloud-based dashboard was developed for hosting data, and the team monitored dashboards in order to determine whether sensors were transmitting continuous, real time data on the necessary parameters.

In addition to technically testing and validating whether IoT sensor networks could be deployed in BSFL farms in order to generate data needed to optimise farming practices, the team iteratively tested different technical approaches to setting up networks (e.g. deploying multi-sensor nodes as opposed to single-sensor nodes), in order to test which approaches were most contextually appropriate and efficient. This involved trialling different solutions, and monitoring which approaches best met the needs of farms, while also enabling the continuous transmission of real time data.

To learn what product and service model would be required to serve the needs of small-scale BSFL farmers, the pilot team conducted user research with farmers from three small scale farms, before piloting the technology and seeking feedback from farmers. The piloting phase also allowed the pilot to observe whether the technology helped inform changes to agricultural practices and improve yields within farms.

To validate that a data driven approach can lead to increased yields, the team also built a machine learning algorithm that was trained on data collected over the course of the pilot, and used data science methods to determine whether the algorithm was capable of accurately predicting the impact of different parameters on BSFL yields. With a view that in the longer term, the model could be used alongside sensors and sensor data, to provide real time insights to BSFL farmers on what changes to environmental or rearing conditions could lead to increased yields.

To conduct the activities, the pilot adopted an agile sprint methodology, where activities occurred over four sprints, and findings from individual sprints were used to inform subsequent sprint activities. In practice this involved the following core activities across each sprint:

- Sprint 1 (November 2022 - March 2021): Multiple individual experiments were conducted to test whether different sensors could reliably and consistently collect and transmit data in both large and small-scale farming environments.
- Sprint 2 (April 2022 - July 2022): The team continued to test different sensor types. They also conducted research with smallholder farmers to identify user needs and incentives for adopting technology.
- Sprint 3 (September 2022 - December 2022): The team tested and validated different technical approaches for implementing sensor networks in farms (e.g. multi-sensor nodes). Separately the team started to pilot the technology with small-scale farmers to identify needs for using IoT sensor networks.
- Sprint 4 (February 2023 - March 2023): Further tests were conducted of different technical approaches for implementing sensor networks. The team continued piloting the technology with smallholder farmers. Work was conducted to build and test a machine learning model, leveraging historical data from previous sprints.

Findings from pilot activities

Finding 1: A range of sensors can be deployed in Black Soldier Fly farms to generate accurate and reliable data on growth conditions

Key questions the pilot sought to test

Through the pilot the team sought to test whether a range of different sensors could be deployed accurately and reliably in both large and small scale BSF farms, to measure a range of parameters, in real time and in a variety of different feedstocks. In doing so, the pilot also sought to confirm that sensors were durable enough for different environmental conditions.

As the pilot progressed, and the team validated that a range of sensor types could be deployed, the team sought to test a range of technical models for installing a sensor network in BSF farms. In particular, they tested whether data from multiple sensors could be processed though multi-sensor nodes, as opposed to individual nodes. Typically, multi-sensor nodes can help to reduce complexity and cost within wireless sensor networks, as sensor nodes are typically battery powered, and the time and cost involved in replacing batteries on single sensor nodes is reduced when shifting to a multi-sensor node approach.

Through deploying and testing sensor networks in BSFL farms, the team also sought to learn about the potential barriers and complications to implementing this technology in context. They also wanted to explore how the technical implementation of IoT sensor networks would best help overcome these barriers, and might therefore be utilised in order to replicate the deployment of sensor networks across other BSFL farms in Kenya.

The methods used for testing

Separate field tests were conducted across a range of different environments, to confirm that sensors could be reliably calibrated to relay required data for monitoring purposes on an ongoing basis, and in real time. The team also sought to test that sensors were all durable enough for different environmental conditions, including the acidic conditions of the substrate many sensors were placed within. A range of sensors types were tested over the course of 3 sprints:

- In Sprint 1, 5 types of Wisense sensors were deployed simultaneously in large and small-scale farms, to gather data on substrate moisture levels, substrate temperature. ambient temperature. ambient humidity, ambient CO_2 and air flow conditions. These sensors were deployed both in large and small-scale set-ups and monitored over a period of one and a half months.
- In Sprint 2, light intensity sensors were deployed for a period of two weeks to see if they could provide continuous and real-time measurements of ambient illuminance.
- In Sprint 3, two WiSense ammonia sensors were set up inside a controlled trial setup in a larvae growhouse where another sensor type (DOL 53 NH_3 Sensor) was used to compare results.

To test whether data from sensors could be processed through multi-sensor nodes, in Sprint 3 the pilot tested two multiple sensor nodes (one from Wisense, and another from a different manufacturer which came with its own alternative battery powered sensors). The team tested whether single multi-sensor nodes could be used to process all the data outlined in each of the experiments above.

Light intensity sensors in the adult BSF rearing area. Photocredit: Sanergy

Key findings from testing:

Through deploying a range of sensors across three separate sprints, the pilot identified that sensors were able to relay real-time data on all the data parameters they intended to capture, that could help inform growth of larvae (moisture levels, temperature. ambient temperature. ambient humidity, ambient CO2 and air flow conditions, light intensity, ammonia levels). The pilot found it was possible to implement and adapt sensors for both large and small scale BSF farms.

Connectivity was an issue, which led to lapses in the ability for sensors to generate continuous data over, especially in more remote environments. Within farms there was intermittent loss of internet connection that resulted in some losses of data. The pilot team overcame this problem through redesigning the sensor nodes, to add board memory, capable of retaining data for up to 4 hours, in the event of losing internet connectivity. This enables data buffering, where data could be locally stored and then transmitted once internet connection was restored.

The distance of the sensor nodes from the gateway (which communicates with the sensors over varying protocols and then translates that data into a standard protocol to be sent to the cloud) was noted to be an issue behind lapses in connectivity. The team identified the need for the sensor nodes they tested to be positioned closer to a gateway for reliable connection, and the need for additional gateways within farms, to ensure this is possible.

Through the testing of multi-sensor nodes, the team validated that it was possible to process data from multiple sensors through a single node, with the exception of ammonia sensors. The team also identified that a larger battery capacity would be required for the Wisense multi-sensor node, as the frequency of battery replacement was every two days. An alternative multi-sensor node was also tested, but proved not fit for purpose, with regards to the environmental conditions (sensor nodes had entry points that were not properly sealed, and therefore exposed circuit board to acidic substrate conditions).

The pilot found that in the case of ammonia sensors, access to a mains power supply was a requirement for continuous and real time data transmission, due to the very high power requirements for these sensors, that couldn't be met for any significant amount of time through batteries. Relying on mains receptacle and a 5V power adaptor made it impossible to integrate the ammonia sensor in a multiple-sensor node.

Through the experiment the team therefore validated that it was technically possible to deploy IoT sensor networks to collect data in both small and larger scale BSFL farms in Kenya. In particular, the pilot identified that a technical model that adopted a large battery powered multi-sensor node presented the greatest promise for further replication across other BSFL farms in Kenya, assuming access to either WiFI or mobile networks is also available (so that data can be transmitted to cloud based servers). However, as the pilot found that ammonia sensors in particular had to be powered through a mains electricity supply and connected to a separate node, this could present barriers to the deployment of these particular sensors in environments that suffer from a lack of access to consistent power.

Finding 2: Farmers can adopt sensors, and engage with and use sensor data to increase BSFL yields. However, there are some barriers to adoption that need to be considered when scaling the solution.

Key questions the pilot sought to test

In addition to deploying a range of sensor types in BSFL farms and testing the technology works, the pilot sought to test whether through providing smallholder farmers with access to a dashboard presenting the data from sensors, they would be able to understand the data generated, incorporate data into their own production methods, and ultimately whether actions taken in response to sensor data led to increased yields.

In exploring these questions the pilot also sought to understand the specific needs and barriers of smallholder farmers to engage with, understand and benefit from sensor derived data, as well as understand what might be required to encourage adoption of the technology for smallholder farmers.

Methodology / activities undertaken

In Sprint 2 and 3 of the pilot, a dashboard was developed that was able to collect data from sensors, and present back readings to farmers. This included data on NH3, light intensity, multiple substrate-sensor nodes and multiple ambient-sensor nodes. The dashboard software was sourced from Odoo, an open source enterprise resource planning (ERP) system.

During these sprints, sensors were deployed on a small-scale BSFL farm outside Nairobi, run by Zihanga LTD. The sensors and dashboards were then tested with these farmers, to learn what farmers needed in order to effectively utilise the data from the dashboards, and ultimately test whether farmers could use the data to improve yields. This involved an iterative process of working closely with three farmers to seek their feedback on the usability of the sensors and dashboard, providing support to address any barriers to using the sensors and dashboard, and seeking feedback on the extent to which the sensors and dashboards had helped to increase yields.

Key findings / outcomes from testing:

Through working with farmers over a period of many months, the pilot was able to validate that farmers were able to engage with sensors and dashboard and use the technology and information in order to increase BSFL yields.

As Nicholas Ndekei, Chief Executive Officer at Zihanga LTD, who tested the technology on his farms commented;

"Before we used to hatch our eggs in the traditional methods and would lose up to 40% of our production. The IoT forces you to quantify more things, and forces you to know what you need to do and how to do it. We saw an increase, we're getting 90% of production."

Through supporting farmers to adopt sensors, and a data-driven approach to farming, the pilot also learned about several critical barriers that farmers had when adopting the technology, that the pilot ultimately identified solutions to address.

An initial learning from working with farmers was that the complexity of installing and especially calibrating sensors presented a barrier to adoption. Without technical support from the pilot team from ICIPE and Sanergy, farmers would not have been able to install and calibrate the sensors within their farms.

According to Nicholas Ndekei, the Chief Executive Officer of Zihanga Ltd, *"configuration of the IoT sensors took a significant amount of time and without the technical support from ICIPE and Sanergy, which came as part of the practical training in the use of Iot sensors, we wouldn't have been able to do it on our own".*

The team validated that direct installation and calibration support can play an important role in overcoming this barrier to adoption, but also identified other potential options that could be explored in the future to resolve this problem - such as developing pre-calibrated sensors, and devices which can be very easily installed by farmers themselves, as part of a "plug and play" model. Alternatively, remote calibration support could form part of a potential longer-term solution.

A second critical barrier identified by the pilot related to the uptake of sensor monitoring data from the dashboards. The pilot identified that despite providing farmers with some initial training in sensor monitoring, data collection and analysis, they were not able to make a direct link between the data they saw and the actions they could take to optimise production. The team discovered this because the farmers were questioning their own ability to understand what the data meant, especially in instances where data analytics revealed new insights that were contrary to their previous experience. This prompted ICIPE and Sanergy to provide continuous training to Zihanga Ltd on data analytics and interpretation, and by the end of Sprint 3, the team were confident that Zihanga Ltd had built powerful data analytics capabilities and were also able to explicitly link data to actions. The pilot therefore validated the need for more thorough and ongoing training to help farmers in their context adopt the solution.

In addition, the team identified that performing in-house data analytics, and providing farmers with more direct actionable insights to improve and optimise BSF production, was another approach which proved effective in encouraging farmers to use data to optimise production methods.

Overall, the pilot was able to validate that smallholder farmers could adopt the technology and use it to deliver increased yields on their farm. However, for this to be possible, the pilot also learned about the barriers faced by smallholder farmers to use the technology, and the need for solutions such as comprehensive training on how to use the sensors, and support installing and calibrating the sensors.

Over the course of the pilot wider barriers to scaling the solution amongst smallholder farmers were also identified – including around awareness and cost of devices which increased over the course of the pilot due to external factors. At this stage, the pilot has yet to explore solutions to these barriers, and further work is required to develop a cost model for scaling the solution, including validating the cost-benefits for farmers to invest in the technology, and identifying a viable payment model and price point for providing sensor-based products and services to farmers.

Finding 3: Machine Learning algorithms can be used to predict yields and identify optimum growth conditions for BSFL farms

Key questions the pilot sought to test

A critical question the pilot sought to explore was whether an AI model could be developed that could identify through machine learning techniques, what environmental conditions were optimum for insect growth. In the immediate term, the team sought to build a solution which interpreted data relating to feed (type, depth, feeding rate), amount of larvae added and length of beds. In the longer term, the pilot team aspires to develop a solution that could also interpret data from sensors, and provide accurate feedback to help farmers improve yields.

Methods used for testing:

In Sprint 4, the team developed a data science model using data on growth conditions and yields from sensors on a smallholder farmer test site, as well as data collected from other sites.

The model was trained on a number of variables. The output/target variable was the mass of wet larvae harvested (kg per meter) at the end of the rearing cycle.

Against this target variable, the model was trained on a number of input variables, in order to establish the influence each variable had on the mass of wet larvae harested. Input variables included:

- Feed formulation type
- Length of beds (rearing platforms in which larvae is grown)
- Amount of young larvae added in the first phase of production
- Feed depth
- Feeding rate
- Cycle time in each rearing phase

The process used to train the model involved conducting rigorous testing within a BSF factory between February and September 2022, where BSFL was routinely harvested (it takes approximately 10-17 days to harvest the larvae), and the team recorded data on different input and output variables for each harvest, which was then used to train the model. Data was processed before it was used to train the algorithm to account for missing variables, duplicates and outliers. The algorithm was developed to identify the correlation between given input parameters and the amount of BSFL harvested, and was tested by the team using data science methods to determine its accuracy.

Key findings from testing:

The team built and tested a machine learning algorithm that was able to study rearing conditions data and predict the expected weight of BSF larvae to be harvested with a high degree of accuracy. The algorithm was also able to rank the variables that contributed most to the prediction of the expected larvae weight.

The results established that the top five ranked important features that inform optimal production are:

1. Length of the beds
2. Feed formulation used
3. The average number of young larvae loaded in each bed
4. Feed depth
5. Cycle time.

The team believe the algorithm shows promise for supporting precision farming, and could be used to guide farmers toward tuning those production system parameters, that according to the order of the ranking identified by the algorithm, and suggested optimum levels, can further optimise the production of BSFL. Detailed findings from this experiment have been published as a journal article, within the Insects journal.[1]

The team also believes the algorithm shows promise to be trained with sensor data, to identify how further environmental parameters (moisture levels, temperature. ambient temperature. ambient humidity, ambient CO2 and air flow conditions, light intensity, ammonia levels) also affect BSFL yields. In the longer term, a model trained on sensor data could inform realtime precision farming of BSFL, through predicting and informing farmers who have adopted sensors in their farms on what changes of conditions could lead to optimum production.

[1] Muinde, J.; Tanga, C.M.; Olukuru, J.; Odhiambo, C.; Tonnang, H.E.Z.; Senagi, K. Application of Machine Learning Techniques to Discern Optimal Rearing Conditions for Improved Black Soldier Fly Farming. Insects 2023, 14, 479. https://doi.org/10.3390/insects14050479

Conclusion

Through implementing and testing IoT sensor networks in BSFL farms in Kenya, the pilot was able to technically demonstrate the feasibility of using smart sensors to inform data-driven approaches to farming in small-scale farms. They were also able to surface learning on different technical approaches for deploying sensors and setting up sensor networks, and have begun to identify a technical model which is appropriate for the context, which includes the use of battery-powered multi-sensor nodes, and temporary local storage of data from sensors, to overcome barriers relating to connectivity and power.

Through developing a machine learning algorithm, the team were able to validate that a data-driven approach can enable the prediction of BSFL yields based on specific parameters, and in theory can therefore be used to support farmers to optimise methods and improve yields. Through piloting a data driven approach with smallholder farmers, improvements to yields were also observed. Further piloting of sensor technologies with smallholder farmers, and training of a machine learning algorithm is required to fully demonstrate the potential for the solution to inform improved agricultural yields, and deliver an machine learning model which is increasingly precise in identifying the changes to environmental and rearing parameters that could lead to greatest yields.

As well as validating the viability of deploying smart sensor technology within the Kenyan BSFL context, the pilot also explored what's required to scale the technology to smallholder farmers in Kenya. The pilot validated that with additional support to help install sensors, and train farmers on how to use sensors and sensor data within farming processes, farmers were able to effectively use the technology and improve yields.

The pilot has begun to identify critical components of the product and service models that could be made available to smallholder farmers to scale the technology. This is likely to include a combination of battery powered sensors deployed via multi-sensor nodes, alongside online dashboards (underpinned by machine learning, and capable of surfacing both raw data and recommendations to farmers), as well as services to help farmers adopt the technology, including training and installation/calibration. Further work is required to fully identify a product/service offering, confirm that it meets the needs of smallholder farmers, and test its longer term viability. There are a number of other outstanding critical questions, relating to the feasibility of scaling the technology to smallholder farmers in the Kenyan context, that also need to be explored through further work. In particular, further work is required to identify and test what appropriate business models, price points and payment models could be used to scale the solution.

Recommendations for further work

Having demonstrated the proof of concept, the next step would be to conduct a number of activities necessary in order to bring a viable product / service offering to the market for smallholder farmers in Kenya. This would involve:

1. Validating sensors can meet fundamental design requirements of farmers.
2. Further developing and training the Machine Learning algorithm on sensor-based data, to identify which environmental parameters have the greatest influence on yields. Further iterating dashboard so that it integrated with the machine learning algorithm, and is intuitive and easy to use.

3. Further work to develop the business model for scaling the technology to smallholder farmers in Kenya, including conducting a market assessment on willingness to pay, payment models and product options for farmers. Fully understanding what's required technically, operationally and financially to deliver a product / service offering at scale, and validating feasibility and sustainability.
4. Finalising a product package which includes sensors and access to an online dashboard (underpinned by machine learning and data analytics), and a service package which meets all the wider needs of smallholder farmers for adopting the technology for increased yields (training, maintenance, installation/calibration, advisory, financial services).

PHOTO CREDIT: ZIHANGA LTD

Photo 1: Sensors deployed at Zihanga Ltd, a small-scale BSF farm in the outskirts of Nairobi city.

Photo 2: Dried BSF Larvae as an end product of organic waste valorization.

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