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An IoT-Based System Implementing Statistical Models for the Post-Larvae Shrimp Acclimatisation Process

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Abstract. Acclimatisation of post-larvae shrimp is critical to guarantee adequate growth in freshwater shrimp farming. Acclimatisation aims to adapt shrimp from their natural habitat (seawater) to the freshwater that is in the pools where they will grow later. Acclimatisation is a challenging process because of the more frequent required monitoring, the potential harm that out-of-limit indicators could cause, and the rapid correction needed to return the monitoring indicators to their specification ranges. This research proposes an IoT-based system integrated with advanced statistical tools in the form of control charts to support the monitoring of the acclimatisation process. The proposal is to be implemented in a shrimp farming company and addresses the negative effects of the existing manual monitoring (operators taking readings and annotating in notebooks manually), the need to monitor acclimatisation proactively (with control charts) and, eventually, reduce the current mortality rate of the process. The paper reports on the design, future implementation, validation and integration with advanced statistical models, challenges, and eventual benefits of the proposed IoT-based system.

Keywords. IoT, shrimp farming, acclimatisation, analytics, control charts

1. Introduction

The advancement of Information and Communication Technologies (ICTs) has allowed the creation of tools that have strongly influenced people's daily lives. In this context, Internet of Things (IoT) technologies *"are deployed in different sectors, from agricultural in rural areas, health and wellness to smart home and smart-X applications in cities"* [1]. IoT has already enhanced several areas related to food security (e.g. precision agriculture) and has the potential to do the same for others. Aquaculture is in the latest group and is still a challenging area for IoT due to the complexity of its processes, which must be managed adequately.

This research work proposes an IoT-based system to study and eventually reduce the mortality rate in the acclimatisation process of post-larvae shrimp (*Litopenaeus vannamei*), which is part of shrimp farming in freshwater. The acclimatisation is essential

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for shrimps to adapt from seawater -their natural habitat- to the freshwater that is in the pools, where they will complete their growth later. Oxygen level, salinity, pH and temperature are the indicators that must be correctly controlled to guarantee an adequate adaption of the post-larvae shrimp and reduce mortality rates in the acclimatisation process. Research efforts have been made to study shrimp farming in their different stages. However, to the best of our knowledge, no research has been done on improving the acclimatisation process using IoT technology and analytics.

The proposal uses sensors that are installed in the raceways where acclimatisation occurs. The sensor-based data is periodically sent to a server and is the input to design and validate the statistical tools that are then used to monitor the indicators' levels in real time. This paper presents the design of the system that acquires the monitoring data from the acclimatisation raceways. It also proposes the analysis to define the appropriate monitoring tools to keep the indicators under control. The hardware integration with the statistical models, which is done through business intelligence tools to prepare and create visualisations based on the data, is also described. Finally, given the real users' digital literacy, the usability evaluation of the system is key to guarantee its acceptance. Hence, the usability evaluation of the system is also proposed as part of the research work reported in the paper. This paper reports on a research project (Contract Nº PE501082044-2023-PROCIENCIA) sponsored by the National Programme on Scientific Research and Advanced Studies (PROCIENCIA) of Peru.

The main contribution of the research work is towards closing the existing gap in using IoT-based technology and analytics to improve the acclimatisation process that strongly influences shrimp farming in freshwater. It specifically addresses the issue of the high mortality rate evidenced in the current acclimatisation process of a fish farm company, which is currently done manually affecting the quality of the data. The proposal also provides knowledge that can be used for other species needing acclimatisation in fresh-water-based farming. Aquaculture is an emerging economic sector in Peru and is an expanding sector internationally, which has doubled its size in recent years [2]. Hence, the proposed enhancements are expected to have a broader impact on the Food Security Sustainable Development Goal.

The rest of the paper is divided as follows. Section 2 provides insights regarding IoT and analytics in shrimp farming. Section 3 presents the proposed system to acquire, prepare, analyse and deliver information. Section 4 focuses more on the analysis that will be done to define and design the appropriate tools to maintain the acclimatisation process under control. Finally, Section 5 and Section 6 show the discussion and conclusions of the research work, respectively.

2. IoT and Analytics in Shrimp Farming

The International Telecommunication Union defines IoT as *"a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable ICT"* [3]. IoT has great potential to integrate diverse technologies and provide services to improve the performance of different economic sectors. The complexity of engineering IoT-based systems lies in their *systems of systems* typification, which makes them challenging to design, implement and maintain [4].

IoT has great potential to benefit aquaculture by using sensors to monitor relevant indicators and actuators to influence the species' habitat and proactively improve their growth. The data obtained from IoT-based systems can also be analysed to gather insights regarding the species' behaviour and their interaction with external factors influencing their growth. Thus, using analytics on aquaculture IoT-based systems presents an opportunity to improve the growth process and obtain better results in shrimp farming.

Research has been done to study IoT-based systems and statistical models for shrimp farming. In the post-larvae stage of shrimp farming, IoT has been used to monitor the influence of different feeding patterns on their growth performance, considering their weight variation and other organoleptic characteristics [5,6,7,8]. Ref. [9] proposes an IoT-based system for automating the culture of aquatic organisms, with a specific focus on its application in biological research and aquaculture. The system reduces manual procedures and simplifies larval culture, obtaining comparable results to manually operated systems. Statistical models have also been developed to aid in monitoring shrimp growth. Ref. [10,11] propose models to generate timely control charts supporting the identification of growing ponds needing attention by analysing the shrimps' weight profiles. Ref. [12] presents a real-time monitoring framework for aquaculture ponds, in which sensor nodes were developed to measure critical water parameters. A mobile application to generate alerts based on these measurements was also proposed.

IoT technology has been used to monitor the shrimp growth process, including the post-larvae stage. Nevertheless, IoT-based systems supporting the acclimatisation process for growing shrimp in freshwater have not been reported in the literature. This issue is critical because prompt corrections are needed during acclimatisation. Moreover, despite the existence of statistical models for shrimp growth, advanced statistical techniques have not been applied to monitor post-larvae shrimps during the acclimatisation process. Finally, existing statistical methods for shrimp growth have focused on analysing shrimps' weight profiles. External indicators, like those needed to analyse the acclimatisation process, have not been included in the generation of control charts to monitor shrimp growth.

This research addresses the gap described above by proposing an IoT-based system to monitor the acclimatisation process of post-larvae shrimp. The use of IoT technology in the acclimatisation process is convenient because of the shortest monitoring timespans and the more timely corrections required. The data gathered by the system is then used to design the statistical models supporting decision-making in the acclimatisation process. The models will be integrated into the system using Tableau software, which allows rapid prototyping and facilitates the following system validation with real users.

3. An IoT-based System for the Post-Larvae Shrimp Acclimatisation Process

The research project occurs in a freshwater shrimp farming company, whose process is described as follows. The first stage occurs in the company's laboratory, where the larvae are produced. The second stage is the post-larvae acclimatisation process, in which shrimp adapt from their natural habitat (seawater) to the freshwater habitat, where they will grow later. This adaptation takes place in cylindrical raceways (pools) of 30 cubic meters, where the post-larvae shrimp live for ten days, and the water gradually changes its salinity until it is below 0.5 parts per thousand. The shrimp is then sent to freshwater in the pre-breeding and breeding stages, where the main goal is to increase their weight.

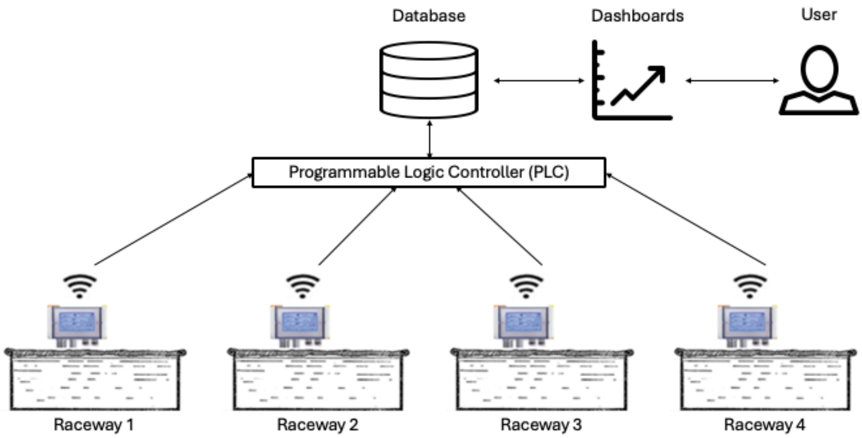

Figure 1. IoT-based system to implement in the acclimatisation process.

Figure 1 shows the IoT-based system that will be implemented in four raceways of the acclimatisation process. Sensors will be installed in the raceways to monitor oxygen level, salinity, pH and temperature. These data will be sent to a centralised database, which will be managed in MySQL. For this, a Programmable Logic Controller (PLC) will periodically acquire the data from the sensors through a Modbus RS485. The data obtained from the PLC will be sent to a server implementing the Data Acquisition Toolbox to process the data, which will be stored in a MySQL database. The data will be used to develop statistical models that will be implemented as control charts to monitor the acclimatisation process proactively. The models will be developed in R, and their implementation in the system will be done using the integration tools of Tableau Desktop for RServer. Dashboards implementing control charts will be provided to the users monitoring the acclimatisation process.

Control charts will allow the system to alert users when the acclimatisation process is out of control, and their monitoring indicators (oxygen level, salinity, pH and temperature) are more likely to go out of their control limits. This last statement is especially critical because the system will not only alert in case the indicators breach their process specification limits but will proactively alert when the system is out of control and the indicators have more chances to surpass their control limits. By doing this, the system will proactively provide alerts. Control limits in the control chart are set based on the variability of the data itself. The control limits define the expected range of normal process variation to distinguish between common cause and special cause variation in a process.

Four raceways will be monitored using the current manual process, which is described as follows. One operator is in charge of monitoring up to 10 raceways. The operator visits each raceway with sensors that are used to obtain the current oxygen level, salinity, pH and temperature. These readings are manually annotated in a notebook, along with the raceway identification number, date and time. If the indicators exceed their specification limits, the operator manually changes the conditions to return them to their specification range. This monitoring process is repeated every hour. These four manually monitored raceways will be the control group to compare the mortality rates obtained in the raceways where the IoT-based system is implemented.

Randomisation among the eight raceways that will be part of the experiment must be avoided. For this, the shrimp assigned to each raceway must come from the same laboratory batch, and the amount of shrimp in each raceway should be similar. Food intake must also be monitored to ensure that shrimp receive an approximately similar amount of food. Finally, the method to monitor the amount of shrimp in the raceways must be the same. In this case, two options are considered: (a) monitoring the weight of a specific volume of raceway water and (b) using an already validated image processing tool implemented in the company to monitor the amount of shrimp in the raceways. The moment the shrimp are put inside the eight raceways must be similar, as well as when shrimp are fed, and the mortality rate is calculated.

4. Analytics to Control the Acclimatisation Process

The analysis uses three months of data from the IoT-based monitoring system. The exploratory analysis will include regression models and clustering to identify the variables better correlated with shrimp survival. Statistical functional and multivariate analysis models will be then used to monitor the variables. These models will be the basis for the control charts design. The functional analysis fits with the case study because the environmental variables and survival data are better represented by a functional relationship of the variables over time.

In statistical process control, the term profile monitoring refers to monitoring variables with a functional relationship. The approach for profile monitoring consists of developing an average statistical model representing all profiles under the process in control. Each profile represents a data path of a variable in a raceway. Thus, a new profile is analysed by comparing it with the estimated model (average statistical model) using a distance measurement to determine if the new profile is under control [13,14]. The variables must also be analysed together. Each variable must provide its data profile, which represents a high-dimensional problem that adds more complexity to the study.

The classic control chart methodology will be used to generate the charts (Shewhart and Exponentially Weighted Moving Average charts) to monitor data separately. If the assumptions to apply this methodology are not met, data transformation will be done to ensure that these assumptions are met. Hotellings T^2 is another option to simultaneously monitor two or more continuous quality characteristics.

Non-parametric modelling can also be applied to this case study. Simpler non-parametric models, like Locally Estimated Scatterplot Smoothing (LOESS), and more complex ones, like Gaussian Process models, will be used in this case study. The challenge of the LOESS is the need for resampling to estimate the probabilistic control limits because no distribution supports the estimation. In this context, the main benefit of using Gaussian Process models is that, despite being non-parametric, it allows probabilistically quantifying the predictive limits given that the predictive variance can be quantified. Estimating these models with their limits can be used as monitoring control charts.

A comparison of the parametric and non-parametric models previously mentioned will be performed, using metrics such as Root Mean Squared Error (RMSE) and R-squared to measure the error in model predictions within an evaluation process that includes training and validation process iteration. Residual analysis will also be performed to evaluate the models.

5. Discussion

IoT-based systems can improve the acclimatisation process of freshwater shrimp farming by automating data acquisition of the indicators to monitor and the actuators to keep the indicators in their required value range. IoT technology replaces manual readings and notebook annotations that negatively influence data quality, reaction capacity to correct process malfunctioning, and other facts affecting shrimp mortality.

Improving the acclimatisation process is key to guaranteeing appropriate shrimp growth in freshwater in the next stages of the shrimp farming process. Monitoring the acclimatisation process is challenging because it requires more frequent control due to the potential harm that out-of-limit indicators could cause. For instance, a breach in the temperature specification limit promotes White Spot Syndrome, which is the most damaging disease in shrimp farming. Thus, monitoring the acclimatisation process in real-time benefits the process because the out-of-limit indicators can be detected faster to take reactive measures. However, spotting out-of-limit indicators means the damage has already been done to the process.

This paper proposes using analytics in the form of advanced statistical models to monitor the acclimatisation process proactively. The proposed models will be used to generate control charts and provide alerts when the process is out of control. These statistical tools are to be integrated with the IoT-based system in order to work with real-time data, which implies a challenging real-time transformation of the data to meet the required assumptions of the statistical techniques.

The use of control charts are the first step in studying analytics applied to acclimatisation. Currently, there is not enough reliable data to study the application of other techniques requiring more data, like machine learning predictive models. However, considering the implementation of the IoT-based system and its performance over the years, the data gathered by the system will be used to explore more data-demanding techniques to monitor the acclimatisation process proactively.

The proposal's validation to ensure its reliability requires a comprehensive approach due to the system's different components. The sensors' readings will be compared to the manual sensors currently used. The integration of the sensors with the statistical models using Tableau Desktop and RServer will be tested in a controlled environment (laboratory) and *in situ*, in which the whole system will be tested under real conditions. A human-centric approach will always be considered to ensure the eventual system adoption. The validation of the statistical models is explained below.

Once the statistical models are identified, a validation process will be conducted to asses and determine the one with the best results for this particular process. Cross-validation (CV) will be used to evaluate the statistical models, which implies the dataset will be divided into training, validation, and test sets. Models are trained on the training set and tuned using the validation set. Iterative improvements are made based on these results, and once satisfactory performance is achieved on the validation set, the model's performance is evaluated on a test set. One strategy to increase the model's reliability involves extending the refinement process to testing. This process includes implementing fine-tuning of fixed parameters or hyperparameters, depending on whether the model is parametric or non-parametric, and validating the refined model on new test data.

Finally, the research project includes the usability evaluation of the IoT-based system integrated with the proposed control charts. This evaluation considers real users operating the system and whose decision-making the system will support. The usability evaluation is critical given the digital literacy of real users who do not have experience using IoT-based systems and supporting their decision-making in advanced statistical models. The Technology Acceptance Model (TAM) will be used to design the tools to evaluate the system's usability. The results will be used to improve the system, considering real users' needs and perceptions of the system's usability and ease of use.

6. Conclusions

This research studies IoT technology and analytics to support monitoring the acclimatisation process of freshwater shrimp farming. The IoT-based system aims to improve the performance of the process, which is currently monitored manually. Analytics are proposed as advanced statistical methods for generating control charts to monitor acclimatisation proactively. The integration of the analytics component as dashboards with the IoT-based systems is also described through the use of Tableau Desktop integrated with RServer. The main challenges and benefits of implementing the proposed system in a shrimp farming company are described, as well as the future work that includes the system's validation in a real environment, its usability evaluation with real users and the eventual use of more data-demanding predictive models.

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