Towards Aquaponics 4.0: A Framework for Automation, IoT, and Smart Systems Implementations in Indoor Farming

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

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Abstract

Aquaponics is a farming method that promises to be a good alternative against the food and environmental problem the world is facing. It is a combination between aquaculture (farming of fish) and hydroponics (growing plants without soil), being a technique to grow plants with the aquaculture effluent. This technique claims to have a high water efficiency, is pesticide-free, and reduces the use of fertilizers. All in all this technology is considered green and sustainable. Since the interest in aquaponics is increasing, the major challenge is to provide feasible and reliable solutions at the commercial scale. The concept of precision farming, usually applied in the traditional farming sense, is now being introduced, leading to the need to adopt sensing, smart, and IoT systems for monitoring and control of its automated processes. This thesis aims to support research towards a viable commercial aquaponics solution by first; identifying, listing, and providing an in-depth explanation of each of the parameters sensed in aquaponics, and the smart systems and IoT technologies in the reviewed literature. Secondly, to propose a tool that uses image-processing techniques, deep learning, and regression analysis to estimate the size of the crops as they grow using image segmentation and do a correlation between the size of the crops and their fresh weight for being modelled that will work as a performance metrics. Third, the development of a framework is presented that involves the creation of a wireless sensing module that uses sensing parameters and the connection to a database capable of storing and linking the information to a quality assessment tool. Finally, an application that adopts digital twinning in the growing beds of an aquaponics system for monitoring, in real time, parameters and hence control the aquaponics physical system is developed.

Preface

This thesis is the original work by Abraham Reyes Yanes. Three journal papers and one conference paper related to this thesis have been submitted, accepted, or published and are listed as below. As such, the thesis is organized in paper format by following the paper-based thesis guideline.

1. **Abraham Reyes-Yanes,** Pablo Martinez, Rafiq Ahmad, "Towards automated aquaponics: a review on monitoring, IoT and smart systems" *Journal of Cleaner Production, 263, 2020.*
2. **Abraham Reyes-Yanes,** Pablo Martinez, Rafiq Ahmad, "Real-time growth rate and fresh weight estimation for Little Gem Romaine Lettuce in aquaponics grow beds" *Journal of Computers and Electronics in Agriculture*. (Under Review)
3. **Abraham Reyes-Yanes,** Sofia Gelio, Pablo Martinez, Rafiq Ahmad, "Wireless sensing module for IoT Aquaponics database construction" *International Journal of Innovation, Management and Technology*, *(ICCMA2020)* (Accepted)
4. **Abraham Reyes-Yanes,** Pablo Martinez, Rabiya Abbasi, Rafiq Ahmad, "A digital Twin framework for intelligent grow beds in aquaponics systems" *Agricultural Systems*. (Manuscript Submitted)

To my Wife and Family

For their invaluable support in this journey

Without access to modern farming techniques or machinery, let alone science-based climate and weather data, farmer's livelihoods hinge precariously on a changing environment that they are struggling to understand.

-U.S. AGENCY FOR INTERNATIONAL DEVELOPMENT

Acknowledgements

First, I would like to thank God Almighty for giving me the strength, knowledge, ability, and opportunity to undertake this research study and to persevere. I found there a refuge where I could go and boost myself again day by day.

Special thanks to CONACyT (File No. 2018-000039-01EXTF-00050) and Transportes Pitic scholarships from Mexico for their financial support that made possible this endeavor. I feel oblige to take the opportunity to sincerely thanks Dr. Rafiq Ahmad (Assistant Professor) for believe in my abilities, for being understanding and for his guide during my studies. I also would like to specially thank Pablo Martinez (PhD Candidate) for his valuable guide and time invested through my research project and the LIMDA members where I fortunately found co-workers and friends to discuss research problems but also to spend spare time that somehow made this journey less heavy.

I feel privileged to have found a group of friends in this foreign country to balance my research and personal interests. Thanks to them for those afternoons and weekends sharing quality time.

I will lastly, but most important for me thank my wife and family. Thanks, Maria José, for trusted me and leaved everything behind. Thanks for your unconditional support and being such amazing wife and mother. Thanks to my parents and brothers for their warming love and support in the distance.

Edmonton July 2020

Abraham Reyes Yanes

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List of Abbreviations

TAN	Total ammonia nitrogen
AOB	Ammonia oxidizing bacteria
NOB	Nitrite oxidizing bacteria
DO	Dissolved oxygen
EC	Electro conductivity
TDS	Total dissolved solids
SL	Salinity
RH	Relative humidity
PPF	Photosynthetic photon flux
YPF	Yield photon flux
PPFD	Photosynthetic photon flux density
PAR	Photosynthetically active radiation
AI	Artificial intelligence
PPT	Parts per trillion
PPM	Parts per million
ISFET	Ion-sensitive field-effect transistor
IoT	Internet of Things
WSM	Wireless sensing module

Chapter 1 Introduction

This chapter introduces the thesis, describes the work done, and gives motivation for the research. It also defines the preliminary research questions and sets the objectives of the research project.

1.1. Background and Motivation

More than 113 million people across 53 countries experienced acute hunger requiring urgent food, nutrition and livelihoods assistance (IPC/CH Phase 3 or above) in 2018 [1]. In front of this reality, it is necessary to look for alternatives to solve this problem. The food demand the world is facing cannot be maintained by additional natural resources or land exploitation [2]. Looking for sustainable solutions that contribute to the food production and consumption, some of the alternatives that can be implemented are: (1) reduce actual meat consumption, (2) minimize food waste, and (3) modify the current food production processes [3].

In this scenario of food and environmental crisis, the aquaponics farming method come into as a solution to improve farming productivity. Aquaponics is defined as the process of growing aquatic organisms and plants symbiotically [4]. Aquaponics have attracted increasing attention because the ability to save resources, high efficiency, and low consumption. Aquaponics have become the trend of the agricultural development nowadays [5]. Any aquaponics system is defined by a recirculating aquaculture system (RAS) and a hydroponic system working together. As a brief summary, aquatic animals excrete waste, then bacteria convert the animal waste into nutrients, and plants make use of the nutrients to grow, thus improving the water quality for the aquatic animals [6].

Nowadays, the agriculture industry is the world's largest user of water, around the 70% of the total consumption, of which 70% of the water is wasted throughout their different processes [7], [8]. One person drinks around two and five liters of water daily, but it requires nearly 5000 liters of water to produce the daily diet for a single person [9]. The sustainable development strategies have become a global trend, and a circular economy is the general trend of sustainable development and the best mode of economic development [10]. Aquaponics is known as a form of sustainable agriculture because it imitates natural systems, where the efficiency of the water is dramatically increased, and has fewer environmental impacts [11]. As a sustainable, circular, efficient and intensive low-carbon production mode in the future, the aquaponics system has realized the transformation from waste to nutrients and has effectively solve the problem of environmental pollution [12].

As a modern approach, the earliest application of aquaponics, as a research area, was in the 70's and 80's. With the purpose of improving the quality of water by removing the excess of ammonia in RAS aquaculture systems, plants were used as bio filters [13]. Aquaponics research started to grow after 2010 [14]. Nowadays, aquaponics is being practiced in at least 43 countries around the world, but 84% of the practitioners use this technology as a hobby [6]. The successful development of aquaponics could guarantee a major part of a more sustainable world food supply [14]. The global application of aquaponics will succeed helping the food crisis and world sustainability as long as it becomes widely spread as a commercial alternative. Only 31% of the commercial aquaponics facilities reported to be profitable and 47% rely in others products or services for additional income [6]. As such, research challenges still exist to procure viable commercial aquaponics facilities.

A proper design and correct management of the system are the key points towards the economic feasibility and the global success of aquaponics itself [15]. The design and management of an aquaponic system is a difficult challenge when trying to achieve high yields and quality. Being a greenhouse and a symbiotic environment, the parameters, and factors (light, temperature, pH, moisture, etc.) that need to be controlled are diverse. As these systems are quite complex because of their multiple components and requirements such as disease prevention, water quality and levels, leading to inspections seven days a week 24 hour per day [16]. Estimations made by Tokunaga et al. [17] state that in aquaponic environments the labor costs are around 46% of total operating costs and 40% of total annual costs.

Precision farming is a concept that has benefited from the rise of sensing techniques, automation, computer vision, smart applications, and Industry 4.0. With the introduction of automation, smart strategies, and connectivity in the farming industry, a new door was opened for the improvement of these aquaponics systems. The expected benefits of smart automation are a significant reduction of manual labor, a more robust control of the process by increasing the accessibility and connectivity of the parameters, and using computer capabilities to make data-driven decisions [18].

Thus, due to the importance that aquaponics is getting as a future farming method, it seems like the right path to keep working in the development of tools and frameworks towards precision farming, using the concepts aforementioned (sensing, automation, etc.), to help with the scalability and economic feasibility of aquaponics in the future.

1.2. Research questions

To understand the challenges that Aquaponics faces towards it's widely adoption and contribute to this objective with the design and use of automation, computer vision systems and smart technologies; some questions are proposed. Questions that, if answered, will help the future academic and commercial contributors in the research area to enhance this technology and promote the Aquaponics scope as a feasible and sustainable food production technology.

- Which parameters are involved in Aquaponics, and which ones can control, monitor, and/or predict aquaponics system behavior to reduce manual labor?
- Which monitoring, smart and IoT technologies are currently being researched towards commercialization of aquaponics systems that could lead to an easily adoption?
- Which performance metrics are stablished for Aquaponics that increase the understanding of the process?
- How can the concept of IoT be putted in place with Aquaponics and how it benefits the limiting factors in the aquaponics technology?

1.3. Research objectives

The overall principle of this thesis is to widely promote the adoption of Aquaponics around the globe, moved by the great potential this technique offers facing the food challenges in the upcoming years. Working towards the precision farming concept, will ensure the correct understanding of Aquaponics but also open the door to the inclusion of automation and smart techniques that help reducing the inherent complexity and costly adoption of it. With this aim in mind, the general objective and three specific objectives are listed, which along the different chapters will be approached and explained in detail. The main research objective is to:

"Develop a framework for Aquaponics 4.0 to promote the use of automation, computer vision and smart technologies towards the enhancement and the widely adoption of this

farming technology as a reliable, feasible, sustainable and green option for food production''

The objectives of the framework are:

- **O1.** Bridge the gap between biological and automation experts building some knowledge ground that benefit the mutual understanding , promoting the contributions of automation and smart implementations in Aquaponics and the interest of biological experts in automation tools as a beneficial trend in the development in the area.
- **O2.** Develop smart tools using computer vision, image processing and prediction algorithms that enhance the performance metrics of Aquaponics towards precision agriculture.
- **O3.** Structure a Digital Twin framework and application for Aquaponics that encourage the reduction in labor, increase the comprehension of digital tools and supports the autonomous applications in commercial implementations.

Figure 1.1 displays a representation of the Aquaponics 4.0 concept and research steps (objectives), tools and related topics.

1.4. Organization of the thesis

Aquaponics as a farming technique promise to be one of the tools to solve the hunger and food scarcity in the world, the fact that is a green and sustainable technique, make this technique even more appealing to the research community considering the

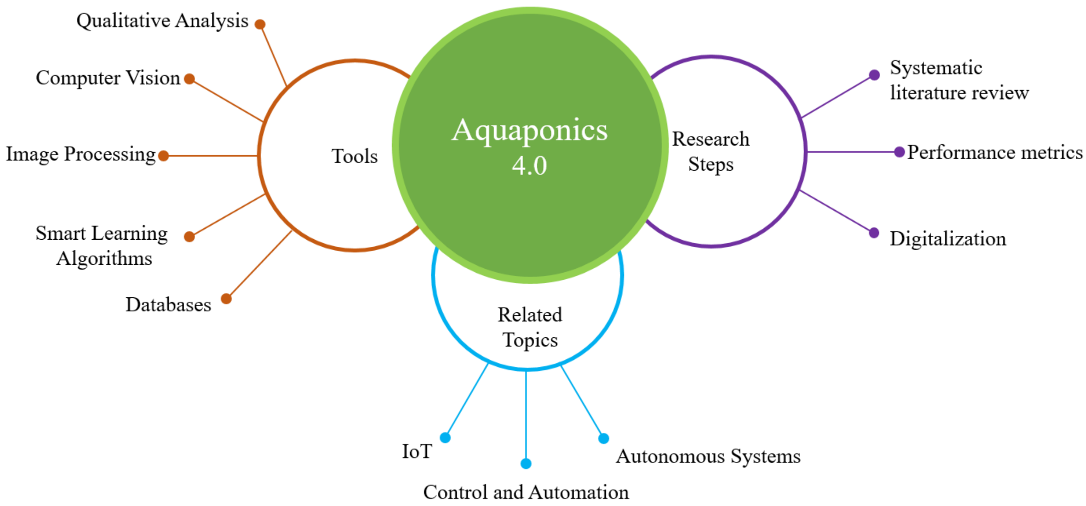

Figure 1.1 Tools, related topics and research steps in Aquaponics 4.0.

environmental problems that we as a society are facing nowadays. Even though the advantages offered by Aquaponics, it has become difficult the widely and commercial adoption since its management complexity and high costs of operation. The work shown in this thesis presents the introduction of the Industry 4.0 and automation techniques as a feasible solution to increase the understanding of Aquaponics, making an analogy of the progress achieved in other areas such as automotive or manufacturing production. Techniques such as automation, computer vision systems and prediction algorithms will not only enhance the development of aquaponics but also help to manage the complexity of the systems and reduce costs related to labor.

For the best introduction of this Industry 4.0 and automation tools into Aquaponics, it becomes necessary the mutual understanding of the both involved knowledge areas: biological and automation experts. During the analysis of the literature review, was found the existence of a huge gap between both and there was not a contribution that helped this collaboration. Chapter 2 presents the article "Towards automated Aquaponics a review on Monitoring, IoT and Smart Systems" addressing the first research objective aiming to bridge this gap and help to a well-organized and substantial future contributions.

Organically, two performance metrics were designed and putted in place to monitor the grow rate and fresh weight of the crops in Aquaponics systems as the following step to increase this Aquaponics understanding using engineering technologies. This is the base for any future contribution that could be done towards the study of optimal parameters or the system behavior under changing conditions. These performance metrics were implemented using computer vision, image processing and smart learning algorithms and are explained in Chapter 3 to fulfill the objective 2 through the article "Real-time growth rate and fresh weight estimation for Little Gem Romaine Lettuce in aquaponic growing beds".

To increase the potential understanding of the process, the IoT and modular capability was introduced to the system. Sensors to monitor the current status of the system were installed as an IoT module and a framework to send, store and analyze this values that use MySQL databases and procedures, PHP and python scripts were designed. This work was described in Chapter 4 through the article "Wireless sensing module for IoT Aquaponics".

Finally, the digitalization of this system and the tools implemented were done. This digitalization was designed as a mechanism to facilitate the communication between the digital tools and the human operators as a human-machine-interface. For this purpose, the Digital Twin concept was adapted to Aquaponics and developed, being able to successfully make this interaction and is shown in Chapter 5 and in the article "A Digital Twin framework for grow beds in aquaponics systems".

Finally, Chapter 6 provides conclusions and summarizes the research contributions, limitations, and future-work directions. Figure 1.2 presents the structure of the thesis.

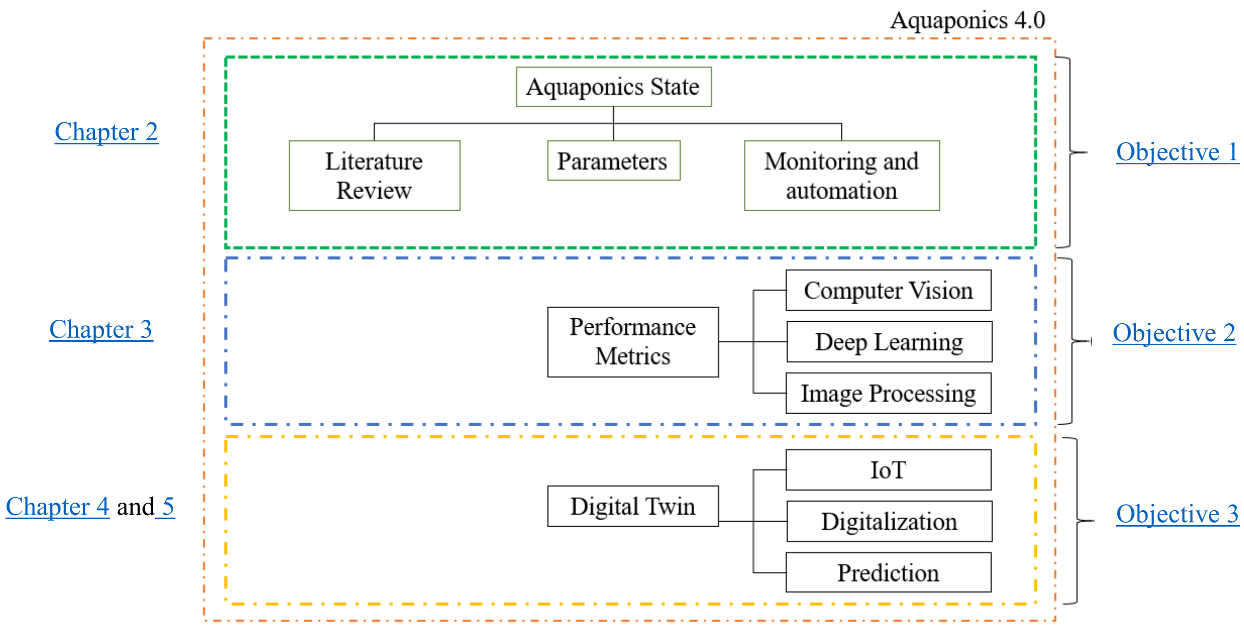

Figure 1.2 Thesis Structure

Chapter 2 A review on monitoring, IoT, and smart systems

This chapter performed a systematic literature review analysis that may be used then as a bridge between the biological and automation academics areas and serve as a guide for those interested to initiate in the enhancement of aquaponics through precision farming.

2.1. Research Methodology

The analysis is based in a comprehensive literature review of monitoring, smart and IoT systems in aquaponics. The objective of this research is to synthesize the current knowledge and approaches on monitoring systems for aquaponics. Towards this objective, a quantitative review method, e.g. systematic approach, is employed in this study. Since there are scarce publications in literature about aquaponics systems, some hydroponic systems were included in the analysis to complement the information.

The systematic analysis presented in this paper is based on a qualitative analysis of carefully selected journal and conference papers. The task was performed manually by the authors; as a result, the identified and presented articles are reviewed one by one and categorized based on their research focus and results. Publications written only in English were considered and no review articles were included in this research. The systematic review is carried out to provide a comprehensive view of existing research with the purpose of identifying gaps in the body of knowledge and provide deep understanding of the current status of the studied research area [19], [20]. Figure 2.1 displays the overview of the research methodology adopted.

Figure 2.1. Overview of research methodology.

Table 2.1 lists all the selected publications and their integration of sensors based on the researched parameters, smart approaches, and IoT technology. In summary, 21 aquaponic (A) or hydroponic (H) systems are selected from the literature and their proposed monitoring systems are evaluated in depth. Overall, 19 physical parameters are identified as being actively studied and are considered by researchers as critical for aquaponic systems. 'Smart' includes the use of machine learning, deep learning, prediction algorithms and decision-making. IoT involves, for example, remote control through web based or mobile applications.

The monitoring parameters found in the analysis are then defined, classified by water and environmental factors. Then, the importance of each of them in an aquaponics system is presented and how to measure and control them in an automated system is discussed. The admissible high and low levels for each parameter in the symbiotic (aquaculture, nitrification, hydroponic) environment are finally summarized. Then, a suggested location for each of the mentioned sensors for both coupled and decoupled aquaponics system is proposed based on literature analysis. As such, a summary of all the parameters that influence the behavior and final growth results in aquaponics systems is given. Each parameter is listed with the proposed adequate ranges for each component, namely the aquaculture, the nitrification process, and the hydroponic component. Further, the potential side effects on the system when outside of the proposed range are provided for each parameter.

Smart and IoT frameworks and techniques are presented. Some future considerations and possible applications in the areas are then proposed. A discussion part is presented where high and low levels for a sustainable equilibrium in the three components is proposed for an aquaponics environment. The authors hope that illustrating the relationship between sensors and each parameter serves as a good start to introduce automation in aquaponics at a commercial level.

Table 2.1 List of sensed parameters, smart systems and IoT systems in literature.

Author	Type	**Sensing**																	**Smart**	**IoT**
		Water									Air									
		pH	EC	T	Level	DO	NH_3	TDS	SL	Flow	T	RH	CO_2	Light	Moisture	$NO3^-$	$NO2^-$	Height		
(Wang et al., 2015)	A	×	×	×	✓	✓	×	×	×	×	✓	✓	×	✓	×	×	×	×	×	✓
(Kumar et al., 2016)	A	✓	×	✓	×	×	×	×	×	×	×	×	×	×	×	✓	×	×	✓	✓
(Kyaw and Ng, 2017)	A	✓	×	✓	×	×	×	×	×	✓	×	×	×	✓	×	×	×	✓	×	×
(Murad et al., 2017)	A	✓	×	✓	×	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	✓
(Nagayo et al., 2017)	A	✓	✓	✓	✓	✓	×	✓	✓	×	✓	✓	✓	✓	×	×	×	×	×	✓
(Mamatha and Namratha, 2017)	A	✓	×	✓	✓	×	×	×	×	×	×	×	×	✓	×	×	×	✓	×	✓
(Pitakphongmetha et al., 2016)	H	×	×	×	×	×	×	×	×	×	✓	✓	×	×	×	×	×	×	✓	✓
(Palande et al., 2018)	H	✓	×	×	×	×	×	×	×	×	✓	✓	×	×	×	×	×	×	×	×
(Mehra et al., 2018)	H	✓	×	×	✓	×	×	×	×	×	✓	✓	×	✓	×	×	×	×	✓	×
(Aishwarya et al., 2018)	A	✓	×	×	✓	×	×	×	×	×	×	×	×	×	✓	×	×	×	×	✓
(Vernandhes et al., 2017)	A	×	×	×	×	×	×	×	×	×	✓	✓	×	×	✓	×	×	×	×	✓
(Manju et al., 2017)	A	✓	×	✓	✓	×	✓	×	×	×	×	×	×	×	×	×	✓	×	×	✓
(Sreelekshmi and Madhusoodanan, 2018)	A	×	×	✓	✓	×	×	×	×	×	✓	✓	×	✓	✓	×	×	×	×	✓
(Jacob, 2017)	A	×	×	✓	✓	×	✓	×	×	×	×	×	×	×	×	✓	✓	×	×	✓
(Dutta et al., 2018)	A	✓	×	✓	✓	×	×	×	×	×	×	✓	×	×	×	×	×	×	×	✓
(Zamora-Izquierdo et al., 2019)	H	✓	×	×	✓	×	×	×	×	×	✓	✓	×	×	×	×	×	×	×	×
(Odema et al., 2018)	A	✓	×	✓	×	✓	×	×	×	×	✓	✓	×	✓	×	×	×	×	×	✓
(Elsokah and Sakah, 2019)	A	×	×	×	✓	×	×	×	×	×	✓	×	×	✓	×	×	×	×	×	✓
(Haryanto et al., 2019)	A	✓	×	✓	×	×	×	×	×	×	×	×	×	×	✓	×	×	×	×	✓
(Mandap et al., 2018)	A	✓	×	✓	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	×
(Naser et al., 2019)	A	✓	×	✓	×	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	×

2.2. Monitoring parameters

The approach to measure the recurring parameters can vary from system to system. As an example, the water pH sensing system can vary from pH test strips, some standalone sensors with LCD screen attached, or analog sensors capable of transmitting the information, wireless or not, to some controller (PLC, micro-controller, etc.). With the aim of designing a reliable, sustainable, and economic feasible system, automated sensing techniques need to be evaluated. The monitoring and control of environment and equipment through intelligent technology is the premise and foundation to ensure the stable operation of aquaponics system [10]. Along the years, different types of aquaponics systems have been proposed, adopted and explained [21], mainly categorized as coupled and decoupled systems. Figure 2.2 summarizes the proposed location of the sensors for the aforementioned aquaponics systems. In the following subsections, each parameter is introduced and its role in aquaponic systems is explained. Then, an explanation on how authors measured, used, and controlled them is given.

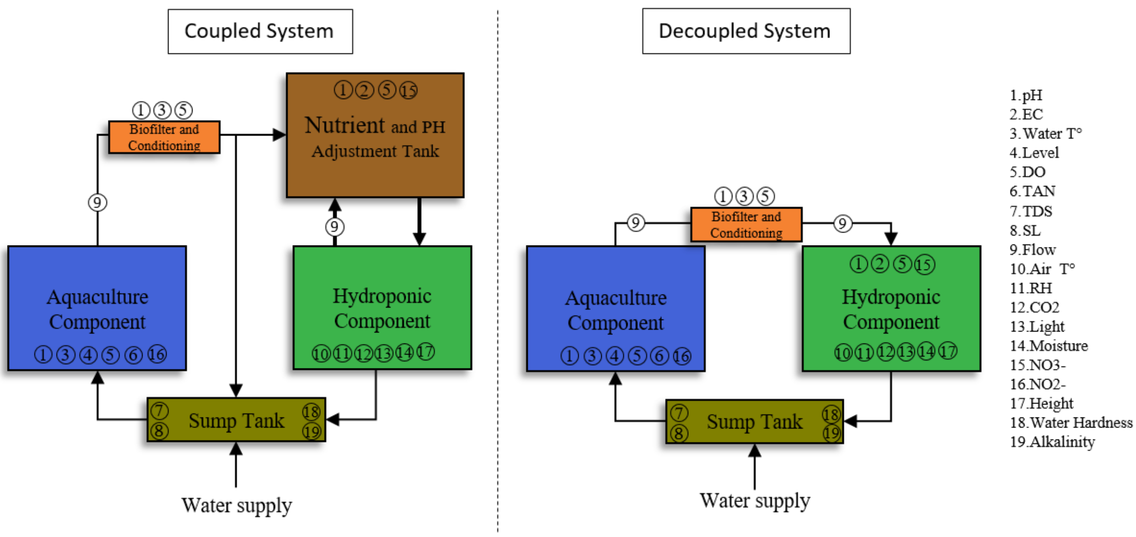

Figure 2.2 Location of sensors in a Coupled and Decoupled Aquaponics, after [4].

2.2.1. Water

The quality of the water is commonly presented as the most important factor in aquaponics processes [22]. This can be easily understood since water is used as the medium to provide nutrients to the plants. In addition, water is the most complex factor in the automation point of view because implies synchronous control of several parameters that are dependent of each other. As a combination of aquaculture and hydroponics, aquaponics is the result of mixing two well-known techniques that, nowadays, are still being widely adopted and developed individually. The RAS design in aquaculture came up for water efficiency and sustainability. However, the ammonia in the water started to accumulate at deadly levels for the fish. As such, bio filters started to be used for recirculating the water. In the other hand, the plants in the hydroponic approach need nutrients and elements that the water cannot provide without the use of fertilizers. Using fertilizers in hydroponics leads to water disposal and replacement. The dependency between these two techniques in aquaponics lies in the transformation that the water goes through between them. Technically, the plants grow with the effluent of the fish tank. However, this process is not straightforward and occurs thanks to a process called nitrification, explained below.

To ensure ideal quality standards in the water solution to favor the nitrification process and plant growth, while keeping the fishes healthy, it is theoretically necessary to maintain the correct amount of nutrients, pH, temperature, dissolved oxygen and salt throughout the whole process. The methods to measure or sense each of the parameters are varied. In the next sections, each parameter will be explained in depth.

2.2.1.1. Nitrification

Nitrogen is the most important inorganic nutrient for the plants. The nitrification process base is the ammonia, which is obtained from fish waste. It can be found in the form of ammonia (NH3) and ammonium (NH4+), where the concentration of both in the water solution is a function of the pH, the temperature and the salinity [23], [24]. The sum of both is known as total ammonia-nitrogen concentration TAN (NH4+ + NH3) [25]. The process that transforms the TAN into nitrates NO3-, which is a form of nitrogen that the plants can uptake, is called nitrification [26]. First, TAN is oxidized intro nitrite NO2- by ammonia oxidizing bacteria (AOB). This nitrite NO2- is then broken down by nitrite oxidizing bacteria (NOB) into Nitrates NO3- [23]. A typical aquaponic system consists of an aquaculture component, a bio filter for the nitrification and a hydroponic component, as illustrated in Figure 2.3[27].

When designing the hydroponic component three different choices can be made for the grow bed: (1) nutrient film technique (NFT); (2) deep water culture (DWC); and (3) media-based [21].

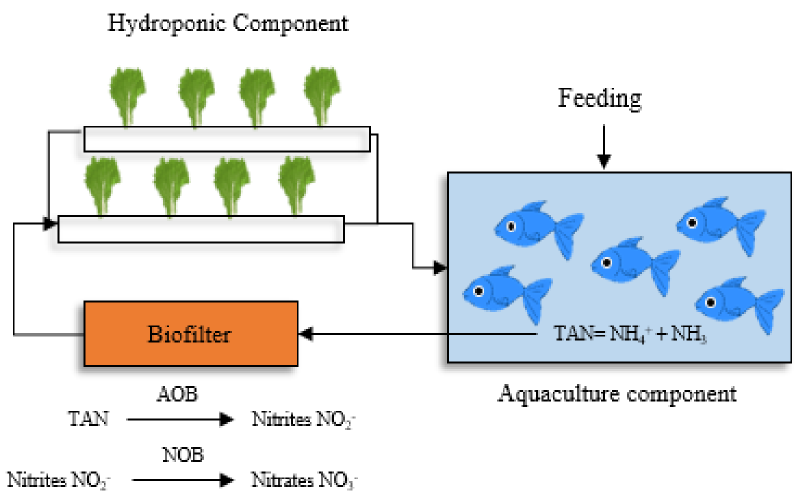

Figure 2.3 Nitrification in a CAS system with NFT grow bed, after [27].

2.2.1.1.1. TAN

Ammonia is a dissolved gas present naturally in surface and wastewaters [28]. It is a form of nitrogen found in organic materials and many fertilizers. Ten percent of the protein in fish feed will be converted into ammonia in the system water [29].Ammonia is produced by the waste excreted by fish and plays an important role in the aquaponics system, since it will serve as initial component for plants nutrients. The total ammonia-nitrogen generated in the aquaculture component can be calculated by the Equation 2.1 given below:

$$P_{TAN} = F * PC * c \qquad \text{Equation 2.1}$$

where P_{TAN} is the production rate of TAN (kg/day), F represents the feeding rate (kg/day), PC is the protein content (fractional), and c is the constant amount of excreted TAN per protein input based upon the feeding rate. The constant is empirically obtained and, for aquaponics systems, $c = 0.092$ [23]. The feeding process can be then adjusted by controlling the production rate of TAN.

Ammonia is highly toxic for fish in small amounts, and it is predominant (relative proportion increases) in the water solution when it becomes strongly acidic or alkaline. Stone and Thomforde mentioned that the desirable range for fishes of TAN is from 0-2 mg/L [28]. Somerville et al. make a difference between warm water fish and cold water fish [30]. In the first case, the optimum TAN range is <3 mg/L, and in the second one, it is <1 mg/L. For bacterial activity, namely AOB and NOB, the optimum value is <3 mg/L and <30 mg/L for plants [30].

Ammonia is colorless and odorless in small amounts, so sensing it is the best form of knowing the presence of the parameter. Usually these sensors consist of a wire electrode in a custom filling solution. The internal solution is segregated from the sample medium by a ion selective membrane, which interacts with ammonium ions [31]. To increase the ammonia measurement accuracy, it is necessary to know the pH and temperature of the water. As such, quantifying the amount of ammonia in water solutions becomes a data fusion problem between pH sensors, temperature sensors, and ammonia concentration sensors. As shown in Figure 2.2, those sensors need to be included in the water tank, as the concentration of ammonia past the biofilter can be considered negligible.

2.2.1.1.2. Nitrite

Nitrite is obtained from ammonia by the AOB. Nitrite is another form of nitrogenous waste that is deadly for aquatic life [32]. The desirable range of nitrite dissolute in water to allow fish, plants and bacteria's life is 0-1 mg/l [28]. A similar range of nitrite is required for bacterial activity and plant growth. The presence of nitrite should not be a problem if maintained in the optimal range. Nitrite concentration sensors are usually a combination of nitrite-ionized electrodes and a sensing element made of a plastic (PVC) membrane, working as an ion exchanger and reference electrode. The sensor develops an electrical potential proportional to the concentration of nitrite ions in the solution, thus providing the concentration of nitrite in the water.

2.2.1.1.3. Nitrates

Nitrate is the result of the nitrification process by NOB and is a form of nitrogen component that plants can uptake. Nitrate is relatively non-toxic to fish. Stone and Thomforde mentioned that nitrate should not cause health issues if maintained below 90 mg/L [28]. Bhatnagar and Devi recommend a normally stabilized range of 50-100 ppm. This factor is important when designing the biofilter. High amounts of nitrates could mean an under-sized bio filtration and be toxic for fishes [32]. The nitrate measurement is usually done with the same sensor that estimates the concentration of ammonia, which are commonly prepared to measure both signals.

2.2.1.2. pH

pH is a measure of hydrogen ion concentration, usually known as a measure of acidity of alkalinity of a solution. The water pH affects plant nutrient availability and the nitrification rate [15], [33]. Currently, pH measurements are obtained using three different approaches: (1) test strips (2) manual electronic probes and (3) automatic probes in controllers. Due to the aim of this paper, only the third method will be covered. A pH meter is an electric device that measures the hydrogen-ion activity (acidity or alkalinity) in some solution [34]. In the aquaculture component, the desirable range for the water pH goes from 6.5-9.5 and the acceptable range from 5.5-10, however this range can slightly vary with fish species [28]. Outside that pH range, water can alter the equilibrium of the aquaponic system. For example, fish reproduction rate may be diminished in slightly acidic environments [28]. In the hydroponics component, the optimum pH is around 6.0. A higher pH than 7.0 will cause precipitation of Fe or Mn, and a lower pH than 4.5 can cause root injury [35] and plants experience nutrient deficiencies [30].

In general, aquaponics systems are sensible to changes in the water pH. For the nitrification process, the required pH range goes from 7.0 to 9.0. An efficiency increase in the range of 8.4-8.8 was reported [36]. To adjust the pH in the aquaponics system, bases like potassium and calcium should be prioritized as they serve as base for nutrients [30], [36]. Smalls changes (< 0.3) in short periods of time (18-24 h) can highly affect the health of the fishes [30].

In an automated system, the pH meter is connected to a controller where the controller receives the change in the pH meter output (mV, mA). For the controller is necessary to calibrate the sensor. The pH meter is connected to the controller and then tested in a solution with known ph. The gotten output is then correlated to the pH units into the controller programing interface. Zamora-Izquierdo et al., developed a smart farming IoT platform that focused on pH equilibrium as an agent to ensure high yield. They used a pH meter (B&C Electronics - SZ 1093) with a range of 0-13, maximum temperature of 80°C and maximum pressure of 7 bars [37]. Mandap et al., 2018 used an ISFET (ion-sensitive field-effect transistor) in their system claiming nearly the same performance as a 0.01 resolution digital pH meter (Dr. Meter pH pen tester). In this study, Mandap et al. ended up suggesting the Atlas EZO pH Sensor, having this one significantly less percentage error than other possible tested options [38]. Nonetheless, other options still exist. Manju et al., used, in their aquaponics system, an OMEGA PHE-45P pH sensor with lower maximum temperature resistance (60°C) [9], and Kuhn et al., used an Orion 3 Star meter from Thermo Fisher Scientific to determine the pH [33].

2.2.1.3. Temperature

The temperature in the water is linked to most of the other water-related parameters in the aquaponics system. For the nitrification process, the optimal temperature is around 17-34°C [30], if the water temperature goes below this range, the productivity of the bacteria will tend to decrease and the nitrification process will not be successful. For the hydroponics component, the suitable temperature range is 18-30 °C [30]. For the fish, maintaining a correct temperature diminishes the risk of diseases. The appropriate temperature varies depending on the species: for tropical fish, the optimum temperature is 22-32 °C; while for cold-water fish species, the required temperature is 10-18 °C. Some other fishes have a wider range of suitable temperature, i.e. 5-30 °C [30]. High water temperatures can restrict plants' absorption of calcium.

The methods to measure the temperature in the water are varied. The most common practice to measure water temperature is to check the temperature range, resolution and the tolerance to the salinity. Since most of water temperature sensors cover the desired range, the sensor's resolution is the most important factor in the selection. Note that the sensor must be made to be submerged long periods and not just ‘‘waterproof’’.

Thermistors are the most common and widely used to measure water temperature. Mandap et al., Sreelekshmi and Madhusoodanan, and Mamatha and Namratha, used a DS1820 temperature sensor for Arduino controller. The temperature range in this sensor goes from - 55 °C to 125 °C and the resolution is ± 0.5 °C. Manju et al., 2017 used a LM35 IC National semiconductor temperature sensor [38]–[40].

2.2.1.4. Level

The amount of water needed in the system is determined by the size of the components, especially the aquaculture ones (fish tanks) [30]. The stocking density in the aquaculture tank highly affects the fish's growth and health and is one of the most common root causes for fish stress. The recommended amount of stocking is 20 kg of fish per 1000 liters of water [30]. It is not recommended to grow fishes for consume in tanks with less than 500 liters. In bigger systems, to mitigate changes in the water quality parameters has been reported to be easier than in smaller units.

Every aquaponics system has natural water losses for mainly four reasons: 1) fish sludge removal; 2) evaporation; 3) plant evapotranspiration; and 4) fish splashing during feeding [41]. Also, the hydroponic system consumes a daily amount of water that typically goes from 0.1% to 3%, depending on the hydroponic/fish tank ratio, water temperature, flow, plant and fish species, and the hydroponic type of system used [41].

The water level in tanks can be manually measured with sight glass or floating devices, but the automated measuring systems available are numerous. One can simply sense when the water gets to a desired level (binary output) or decide to measure the total amount of water in the tank/system (range output, usually 4-20 mA). The most advanced sensors for measuring fluid level are ultrasonic, radar or laser-based sensors.

Water level is the third most researched parameter in existing literature. Zamora-Izquierdo et al., used a Omron K8AK-LS1 water level controller with a maximum temperature tolerance of 50 °C [37]. Mehra et al., used an analog output water level sensor connected to an Arduino controller [42]. Wang et al., followed the same approach [43]. Mamatha and Namratha, used an array of sensors to determine the water level in tanks[40]. They used three probes at different levels to know when actions were needed to keep the water level as required, e.g. start pumping water when water level was low. Jacob, used a BC546 NPN transistor circuit to make an overflow level sensor in the water tank [44]. Kyaw and Ng, and Sreelekshmi and Madhusoodanan, used an ultrasonic level sensor to control the water tank levels [39], [45].

2.2.1.5. Dissolved Oxygen

Dissolved oxygen (DO) is a measure of how much oxygen is dissolve in the water available for the aquatic living organisms. The amount of Do in the water is an important parameter for the three organisms (fish, bacteria, and plants) that share the aquaponics environment. Alongside the water level, the amount of oxygen in water determines the ability to support aquatic life [46]. Oxygen is dissolved in the water at very low concentrations (in parts per million or ppm) and has been reported to be the parameter that has most immediate and drastic effects on aquaponics [30].

In natural environments, oxygen is produced by photosynthesis in aquatic green plants and algae. It is of high importance to monitor the dissolved oxygen in any aquaponics system because its level varies dramatically in short periods of time (24 hours) [46].

There is a strong relationship between temperature and the DO, as warmer water can hold less oxygen. When fishes are eating, the consumption of DO increases and it needs to be compensated in some cases. Further, the nitrification process is an oxidative reaction; thus, it depends on the existing dissolved oxygen to happen. When the levels of oxygen are low, the bacteria will stop to break down the ammonia and nitrite, increasing potential health's risks for fishes and plants. Optimum levels for nitrifying bacteria's go from 4 to 8 mg/L [30].

Plants use their leaves to absorb oxygen during respiration, but still need to absorb oxygen through their roots [30]. For the hydroponics component, plants need high levels of DO, typically >3 mg/L[30]. When oxygen is low, plants' roots start to die, and some fungus may appear. In the aquaculture component, most of the fish species require a DO concentration >5 mg/L [47]. In cases of low concentration, fish production of TAN will diminish [32]. In small sized systems, dissolved oxygen is expensive to measure since there are no low-cost methods available. In this case, manual visual inspection of the fish is the most common approach, i.e. red zones around the eyes or fish swimming close to the surface are indicators that DO levels are low. When using DO sensors, it is necessary to be aware that DO measurements are affected by temperature, pressure, salinity, and some compensations may be needed. The two methods available to measure DO concentration are optical and electromechanical, if excluding laboratory-based methods such as colorimetric approaches and Winkler titration.

The optical sensors measure the interaction between the oxygen and certain luminescent dyes. When DO is present, the returned wavelengths are limited or altered due to oxygen molecules interacting with the dye [48]. The existent electromechanical option to measure the dissolved oxygen concentration can be galvanic and polarographic. Inducing voltage to polarize (or not) the system, the presence of DO is measured by the change in the electrical signal.

DO concentration measurement systems are expensive, and as such, few publications that target such parameter exist in the literature. Odema et al., connected a DO sensor to a Modbus and used TCP/IP technology to transfer the data [22]. Mandap et al., successfully used an Atlas DO probe with a capacity range of 0-100 mg/L, a maximum pressure of 3,447 kPa and maximum depth of 343 meters, in an aquaponics system [38].

2.2.1.6. Electro-Conductivity

The electro-conductivity (EC) is a measurement of the ability of a medium to conduct electric current, and in the case of aquaponics systems, it is highly correlated to salinity (amount of salt concentration in the water) [9], [49]. Therefore, fish population is the most sensible to changes in the EC. It also relates to how fresh the water is and low levels could indicate unbalanced systems [49]. High levels of EC indicate that water is polluted, and it may cause death of the fish population.

A minimum salt content is desirable though to help fish maintain their osmotic balance [28]. The optimum range for fishes is 100-2000 μS/cm, but a wider range has been found acceptable (30-5000 μS/cm) [28]. A measurement of the electro-conductivity in the hydroponic component can be used as an estimator of the water nutrient content if added to a pH measurement. However, such measurement would not be able to differentiate between all the different nutrients.

Day by day, measurements of water EC may provide insight on nutrient consumption. Thus, it may help maintain consistency with each crop cycle, and ensure maximization of nutrients use without over-fertilizing [50]. A method to control the nutrient solution in the hydroponics system through EC monitoring was proposed [35]. For example, Enshi-shoho nutrient solution was used to provide control over EC, as it has a known EC of 2400 μS/cm.

The electro-conductivity meters usually employ a potentiometric method and four platinum electrodes. Some current is applied to the outer pair and the potential between the inner pair is then measured. Nagayo et al., suggested the use of this parameter in their work [49].

2.2.1.7. Total Dissolved Solids

Dissolved solids are naturally present in water. TDS levels represent the content of inorganic salts, organic matter and other dissolved materials in water [51]. Typically an optimum amount of TDS in water for fish life is inferior to 1000 mg/L, although values below 2500 mg/L have been found acceptable [28]. High amounts (>1000 mg/L) of TDS can cause a toxic medium for most fish species.

As sensing units, TDS meters are commercially available. Usually used to measure TDS in potable water, TDS meters are similar to EC meters. In fact, the same sensor used to measure EC can be used.

2.2.1.8. Salinity

The salinity (SL) indicates the amount of salt concentration in the water [49] and is a driving factor that affects the density and growth of the fishes [32]. Salinity is often derived by the electro-conductivity measurement, just like TDS. The desirable range of SL varies with each fish species. The most common adoption was given by (Garg and Bhatnagar, 1996 for the common carp and its range goes from 0 to 2 ppt (part per trillion).

2.2.1.9. Water hardness

Water hardness is a measure of the concentration of existing positively charged calcium and magnesium salts in water solution. Calcium and magnesium are essential to fish metabolic reaction, namely bone and scale formation, thus, relevant to fish growth [32].

Whereas low levels of water hardness only cause stress in fishes, high levels could be lethal since it increases water pH, resulting in a low nitrification and nutrients absorption rate for plants. The desirable range for water hardness goes from 50-150 mg/L, but >10 mg/L is acceptable for most species [28].

Water test kits can be used to manually measuring water hardness, relying in test tablets or paper test strips. However, water hardness is usually determined qualitatively by the TDS or EC measurements [52]. Some colorimeters or spectrophotometer sensors are used when lower measurements than 4mg/L $CaCO_3$ are expected.

2.2.1.10. Alkalinity

The alkalinity is a measure of the concentration of bases, typically carbonate and bicarbonate in aquaponics systems. Water hardness and alkalinity are often confused as alkalinity measures the negative ions (carbonate and bicarbonate) and hardness the positive ions (calcium and magnesium). Alkalinity is usually referred as the water ability to resist changes in pH or the capacity to neutralize acids. Low levels indicates that even small amounts of acids can cause large change in the pH [32], high levels of alkalinity cause non-toxic ammonia to become toxic. Desirable ranges of alkalinity go from 50 to 150 mg/L $CaCO_3$ [28].

2.2.1.11. Flow

Water flow through the aquaponics system is extremely important to estimate the capacity of filtration (solids) and bio-filtration (nitrification), as well as to determine the nutrients availability for the plants. It is recommendable that the flow in the system is maintained constant to avoid stress in the fishes and to avoid nutrient deficiencies in the plants. Most importantly, it is needed to measure the flow between the filters and the grow bed.

The flow rate will vary depending in the hydroponic system adopted. In NFT-based systems, flowing water in the channels ensures that the roots receive large amounts of oxygen and nutrition. The recommended water flow for NFT should be lower than 1-2 L/min [30]. In the media-based technique, a siphon is used to filtrate the water through the media. The recommendation is to set the flow rate to be able to filter the entire water fish tanks every hour through the grow beds. In the DWC-based systems, the water flow is mostly due to gravity. As such, water needs to flow during approximatively 1 to 4 hours through the channels to guarantee adequate replenishment of nutrients. The growth of the plants in DWC systems benefit from high flow rates and turbulent water because plants' roots absorb more nutrients.

Optimal water flow is calculated from channel size and water capacity. Once the requirements are set, a flowmeter will be useful to guarantee water flow throughout the system and enable detection of major problems, i.e. obstructions in the piping system. A flowmeter is a device capable of measuring the amount of water that is passing through a pipe. It exists four types of different flowmeters: 1) mechanical; 2) vortex; 3) ultrasonic; and 4) magnetic. Murad et al., use a water sensor to detect the water flow into the fish tank through the siphon outlet in a media grow bed [8], and Kyaw and Ng, put a flowmeter between the fish tank and the grow beds [45].

2.2.2. Environment

The parameter related to the air conditions in contact with the plants are analyzed in this section. To obtain and maintain balanced and safe optimal crops in the system and to ensure the stable and healthy growth of fish and vegetables it is necessary to monitor and control some environmental parameters[10]. Namely, the air temperature, where the ranges changes between the plant species; the light intensity, which depends on the growth stage of the plant; the air humidity, the air content of CO2 (carbon dioxide), and the media moisture, in case of adopting a media base as the hydroponic component.

2.2.2.1. Air Temperature

The air temperature influences the health of plants. The suitable temperature for most of the vegetables commonly grown in aquaponics systems is 18-30 °C. At higher temperatures, leafy greens bolt and begin to flower and seed [30]. Further, the air temperature is responsible of a correct transpiration of the crops.

The factors that have taken into consideration when selecting air temperature sensors are: 1) temperature range; 2) contact or contactless; 3) sensing element; and 4) calibration method. For measuring the air temperature in aquaponics systems, a thermistor has been the recurrent option as the air temperature and humidity are measured together. Sreelekshmi and Madhusoodanan, used a DTH11 thermistor [39]. Vernandhes et al., used a DHT22 thermistor, which is a more accurate sensor and has a larger range of temperature values than the DTH11 [53].

2.2.2.2. Relative Humidity

The relative humidity is an expression for moisture in the air. Most of the grown crops in aquaponics systems need humid air for thriving, thus the relative humidity needs to be well managed. The humidity in the air can be measured in different ways: 1) mass of water in unit volume of air; 2) unit mass of air; or 3) partial pressure of water vapor in the air [54]. Air humidity can be also expressed as a proportion of the air-water saturation or relative humidity (RH).

Warm air has a higher moisture-holding capacity than cooler air. To maintain control of the level of humidity, a good control over ventilation and heating systems is necessary. The ventilation system allows the exchange of the moisture inside the greenhouse with drier air from outside the facilities. The heating devices are necessary to warm up the outdoor air to the optimum growing temperature and increase the capacity of the air to hold moisture. To increase moisture on indoor air, it is common to use moisturizers.

The optimum level of RH varies depending in the type of crop and the growth stage of the plants. The most common considerations are 50%-80%, but those depend on the indoor temperature. An excess of RH in the air would interfere with the plants' transpiration and prevent roots and stems to supply an adequate quantity water to the leaves.

As mentioned previously, air RH is usually provided by the air temperature sensor. However, individual sensors can be used: Wang et al., used a DTH11 capacity humidity sensor to measure RH values in an aquaponics systems [43].

2.2.2.3. CO2

The carbon dioxide is an essential component of the photosynthesis, vital chemical reaction for plants sustain. In mass production indoor systems, it is possible that plants use all the CO2 available in the air. As such, artificial addition of CO2 and control of its levels is necessary.

The optimum range level for most of indoor crops is within 340-1300 ppm [55]. However, a smaller range may be needed for some crops. For example, 800-1000 ppm of CO2 in air is necessary to grow tomatoes, cucumbers, peppers, or even lettuces. Depending on the type of crop, the lighting conditions, air temperature and RH, different CO2 air concentrations are needed.

Elevated CO2 also leads to changes in the chemical composition of plant tissue. The extra carbon molecules may be dissolved in the systems' water, forming carbonic acid, HCO3-. This would provoke a decrease in the water pH. Recommended levels of carbonic acid must be less than 5 mg/L to enable proper fish growth [32], [56]. More than the indicated level is toxic for aquatic life.

The commercially available sensors that measure CO2 concentration in the air are infrared gas sensors (NDIR) or chemical gas sensors. Nagayo et al., used a MG811 sensor to measure the CO2 content in the air of their proposed system [49].

2.2.2.4. Media Moisture

Media moisture is the soil water content in the media base. This measurement is only necessary when is used the media-base type in the hydroponic component. For this type of hydroponic component, it is good practice to implement a moisture-soil sensor to guarantee that the media has correct amount of water for the plants. More plants die due oversaturated root than of drought. It is highly recommendable to check for the water holding capacity of the soil selected in order to set the parameters for the sensor system. Werner did an analysis for traditional farming using different types of sands, loams, clays and combinations. After sensing using a tensiometer (0-100 centibars), he found that the optimum ranges vary from type to type of soil, going from 30-60 centibars (Werner, 2002). Traditional meters are electrical resistance blocks, tensiometer and time domain reflectometry (TDR). Another soil-moisture sensor works under capacitance and measure the dielectric permittivity of the water in the medium and is the sensor commonly adopted in Hydroponics due the simplicity. In this case, Vernandhes et al., used a FC-28 as a soil-moisture sensor. Since various materials for the media base are used and their levels are not fixed, no generic recommendation can be provided for this parameter [53]. Nevertheless, interested people can find the appropriate levels after selecting the media base and crops to farm.

2.2.2.5. Light Intensity

Sunlight is critical for plants but is unavailable or limited in indoor facilities. Artificial lighting is placed in aquaponics systems as a substitute to provide light to the plants. Light is usually measured in terms of its intensity (lux). However, plants use a limited part of the light spectrum called photosynthetically active radiation (PAR). It designates the spectral range of solar radiation that photosynthetic organisms can process.

Most of the plants do not require PAR regulations and grow independently of lighting conditions, but some light sensitive crops, i.e. lettuce, salad greens, and cabbages, can bolt, seed and become bitter and unpalatable with high levels of PAR [30]. Additionally, with low light intensity, the growing rate of plants is greatly diminished. Contrary to plants, water does not need direct light radiation and it is paramount to isolate any water system to help maintain the water temperature and prevent algae growth. Further, the nitrifying bacteria are photosensitive organisms during the initial formation of the bacteria colonies. For new aquaponics systems, it is recommendable to cover the area from direct light for the first 3-5 days.

Different equipment can be used to obtain PAR measurements; however, research has shown that using a photosynthetic photon flux (PPF) and yield photon flux (YPF) specific PAR meter is the most accurate measuring sensor for narrow spectrum radiation sources, such as artificial lights [58]. In efficient light systems, a balance between correct PAR usually given in photosynthetic photon flux density (PPFD) and the right light intensity (lux or lumens) must be reached. In general, crops need between 14 to18 hours of light per day. The amount of PPFD that plants need vary from its growth stage and type of plant, but an average optimal range of 600-900 PPFD is required [59]. To measure the radiation intensity of a lighting system, a light dependent resistor (LDR) can be used. From such measurement, PPFD can be estimated. Both, Mamatha and Namratha, and Sreelekshmi and Madhusoodanan, used an LDR to successfully measure the ambient light intensity [39], [40].

Table 2.2 shows the summarized levels and the parameters just introduced.

Table 2.2 Parameter ranges and potential effects in aquaponics systems

Parameter	Aquaculture Range	Nitrification	Hydroponic Range	Low Level Effect	High Level Effect	Ref.
pH	6.5-9.5	7.0-9.0	4.5-7.0	Fish reproduction rate is diminished. Root injury and plants experience nutrient deficiencies.	Plants experience nutrient deficiencies.	[36] [35] [28]
Water T	5-32 °C *	17-34 °C	18-30 °C	Increase the risk of diseases in fishes.	Increases the risk of diseases in fishes.	[30]
Water Level	1000 L per 20 kg of fish	-	-	Fish stress leading to grow health issues.	Plants experience nutrient deficiencies.	[30]
DO	4-5 mg/L	4-8 mg/L	>3 mg/L	Plant roots may die, and some fungus can start to grow. Fish stop to eat. Bacteria will stop nitrification process.	-	[30] [47]
EC	100-2000 µS/cm	-	-	Loss of nutrients in the water. Indicates unbalanced systems.	High levels of EC indicate that water is pollute and may cause death of the fish population.	[28]
TDS	<1000 mg/L	-	-	-	Toxic for most aquatic life, especially fish.	[28]
Salinity	0-2 ppt	-	-	-	Affects the density and growth of the fishes.	[60]
Water Hardness	50-150 mg/L $CaCO_3$	-		Fish stress.	Increase of pH , resulting in a low nitrification and nutrients absorption rate for plants	[28]
Alkalinity	50-150 mg/L $CaCO_3$	-	-	Poor status of water body. Low ability to neutralize acids, risk of high ph.	Cause non-toxic ammonia to become toxic. Fish stop breathing.	[28]
TAN	0-2 mg/ L	<3 mg/ L	<30 mg/ L	-	Highly toxic for fish.	[30] [28]
Nitrites	0-1 mg/ L	0-1 mg/ L	0-1 mg/ L	-	Highly toxic for fish, plants and bacterial activity.	[28]
Nitrates	50-100 ppm	-	-	Nutrient deficiencies in plants	Toxic for fishes.	[32]
Flow	-	-	1-2 L/min*	Low availability of nutrients.	Low availability of nutrients	[30]
Air T	-	-	18-30 °C	Incorrect transpiration of the crops.	Leafy greens bolt and begin to flower and seed. Increases transpiration of the crops. Reduces efficiency of water supply to the plants.	[30]
RH	-	-	50%-80 %	Curled leaves and dry leaf.	Inadequate supply of water to plants. Causes mold and fungus growth.	N/A
CO_2	-	-	340 ppm-1300 ppm	Decrease in plants photosynthesis.	Changes in the chemical composition of plant tissue.	[32] [55][56]
Bed Moisture	-	-	-	Not enough nutrient availability in plants. Drought.	Plants will start to wilt, and roots start to dye due a lack of oxygen.	N/A
Light Intensity	-	-	600-900 PPFD	Decrease in plants' photosynthesis.	Carbon limitation in plants.	[61]

2.3. Smart Systems

Intelligent or smart systems is a broad concept in the academic world with the purpose of optimizing production by making use of cutting-edge information, communication and computing technologies [62]. The opportunity to use smart systems in industrial applications came from the research developments in artificial intelligence (AI) in general. Some misconceptions have been made in this research area when naming proposed systems as “smart”. Usually, researchers tend to label as smart a system that is just automated or wireless. A machine that work under input signals, comparison between signals and ranges, triggers and output cannot be called smart and is just an automated system. Smart is a concept more related to the Industry 4.0 itself and involves complex logical process, algorithms and it is not limited to basic logical operators. The adoption of the smart systems in the farming is going towards the concept of precision farming, which looks to apply only the water and nutrients that plants need [63]. This concept was analyzed and presents a dominance of heuristic approaches over the quantitative working methods when applying tools from the Industry 4.0 [64].

König et al., presented a review of aquaponics as an emerging technological innovation system where changing the food production technologies themselves was proposed as one way of creating more sustainable food systems [2]. The immersion of smart techniques in aquaponics is helping to minimize production times, reducing the need of labor, lowering the expertise need it to regulate the systems and enhance the quality of the products. When managing a farming system, the adoption of Cyber-Physical systems is increasing. These systems are presented as collaboration levels between self-configuration (machines), local (analysis of the production system) and extended (collaboration between different actors as clients, farmers, etc.). The usage of advanced learning techniques (machine learning), can support and expand this concept [64] .

2.3.1. Parameters prediction

In all the literature reviewed, only one smart application was found for aquaponics systems. Kumar et al., developed an autonomous wireless aquaponics system. The smart component of the system relies in the application of regression techniques to predict future values for some of the sensed parameters (nitrate and pH) and make smart decisions with the outputs [65].

Smart applications in hydroponics, in the other hand, have more contributors and developments using deep neural networks, predictions, decision making have been made. Mehra et al., trained a deep neural network to predict pH, humidity, light intensity, temperature, and the water level in hydroponic tanks' sensors outputs. Then, this trained neural network was installed in a Raspberry Pi to control the outputs depending on the sensed values [42]. Pitakphongmetha et al., used an artificial neural network with the pH, electro conductivity, temperature, humidity, light intensity, and plant age, as inputs to predict the pH and electrical conductivity. Then, the error between predicted values and sensor outputs was used to monitor and control the parameters [66].

2.3.2. Quality and growth rate

The use of Convolutional Neural Networks is commonly used in quality assessments of the crops. A monitoring growth rate of lettuce using deep convolutional neural networks was implemented in a hydroponics system by Lu et al. [67]. Moving forward, this image prediction models can be used to monitor some parameters in the aquaculture component, e.g. the health of the fishes based in the known physical reactions of some parameters, (i.e. red areas in the eyes when the level of ammonia is dangerous), turbidity of the water for triggering the filter or cleaning, etc. The image processing and prediction techniques based on images is not found often in the literature of Aquaponics.

2.4. IoT systems

Internet of Things (IoT) is looking to dismiss the bridge of connectivity issues between systems. One of its main objectives is to make industrial machinery capable of communicating between each other and provide a framework where data-driven decisions can be taken without human intervention. The enhancement of the network capacity, with the 4G and 5G technologies, increases the feasibility of IoT implementations and leads to the creation of new communication hardware, protocols, and frameworks. The communication between devices and interfaces is currently less limited, increasing the flexibility, interoperability, and integration of complex communication systems into complex industrial scenarios such as aquaponics. In farming, IoT technologies are being implemented with very different objectives, including: improve GPS systems, weather predictions, inventories, producer-consumer information, and so forth. In our review, 71% percent of the publications used an IoT technique in their proposed system. The findings are categorized in three different sections: 1) monitoring interfaces, 2) remote applications and 3) wireless technologies. In some cases, combinations of these categories were found.

2.4.1. Remote monitoring interfaces

Monitoring interfaces are commonly an environment (interactive or not) that displays some of the interested parameters in the process to the user or stakeholder. This visualization process is key to final decision making. IoT technology enable these monitoring interfaces to display values through wireless networks, even in real-time.

Manju et al., designed a web application that showcased a dashboard connected to a microcontroller to monitor selected aquaponics' parameters [9]. In the same year, Dutta et al., connected a Raspberry Pi to all the system measurement units, then the sensors' data are sent to a web-based platform where it is stored and displayed [68]. A year later, Elsokah and Sakah, programmed an iOS application that allowed to monitor the system environment continuously by obtaining data directly from the systems' microcontrollers [69]. The direction of these collaborations is heading towards the real time reliability and mobility (not only web based but also application for mobile devices).

2.4.2. Remote control applications

Remote control applications are defined based on their capability to signal system actuators to interact or change certain parameter. Such applications are a step forward from only monitoring the system, as presented in the previous subsection. For example, with remote control applications (web-based or applications), operators can turn on/off water pumps or lights when necessary, change values of critical timers to modify the plants' growth process, and so forth.

From the reviewed papers, Nagayo et al., implemented a GSM Arduino-based monitoring and control system that can send alert messages to operators when measurements are outside specific ranges. A graphical user interfaces is designed to display the information and data could be extracted from the system [49]. The collaboration of Pitakphongmetha et al., was using Blynk, a multi-language platform that enables remote control of different microcontrollers (i.e. Arduino, Raspberry Pi) [66]. The next year, Aishwarya et al., integrated a GSM receptor with a microcontroller in an aquaponics system. As such, operators can send messages to the receptor so that real-time control over the water supply or temperature is achieved[70]. Vernandhes et al., used an Arduino connected to a web server through an Ethernet Shield. A user interface was created to allow real-time monitoring and control of the water-related sensor measurements, i.e. switch on or off the exhaust, pumps, and mist makers [53]. Odema et al., created an IoT-based aquaponics system that allows remote monitoring and control of the system parameters. The authors used a Modbus TCP standard protocol to pull measurement data from the sensing nodes of a supervisory computer [22]. Haryanto et al., designed a system with a microcontroller connected to an Ubuntu IoT Cloud. The system could be accessed to monitor and control the parameters automatically based on the sensed inputs[71]. The authors in this section added the controlling parameter into the scenario. Currently, the visualization of the parameters in the system is not enough and is necessary to control such parameters for a better system.

2.4.3. Wireless technologies

The wireless technologies are rarely presented alone and are mostly linked to the two past sections (remote monitoring or control interfaces). Nevertheless, was found that some contributors were focus in develop/apply some wireless technologies into Aquaponics to improve the connectivity. Wang et al., designed an architecture to monitor and control an aquaponics system with Arduino and sensors information. Data is efficiently stored on WRT nodes and transmitted to an OpenWrt server using a Wi-Fi data transmission module[43]. Kumar et al., designed an aquaponics system using the 6LOWPAN protocol and a wireless sensor network (WSN)[65]. Murad et al., used GSM technology to send notifications if pH and temperature values go out of range [8]. Mamatha and Namratha, used a data logging platform, ThingSpeak, to store all the information from an aquaponics[40].

Sreelekshmi and Madhusoodanan, developed a web-based monitoring system using ThingSpeak IoT platform with Arduino Uno and an ESP8266-01 Wi-Fi transceiver [39]. Jacob used a Raspberry Pi along with a Wi-Fi dongle to give internet connectivity to the system. The system uses cloud-based platforms (Pubnub, Cloudinary, and Dweet) to store and control the diverse parameters of the aquaponics system, i.e. motors and lights, with an IoT dashboard using Freeboard [44]. The use of wireless technologies in sensors or a transmission of data opens the door to improvements in the monitoring and control of parameters.

2.5. Discussion

2.5.1. Overview

The success of an aquaponics system relies on a correct management and implementation of sensors, IoT techniques and smart systems. This paper aims to summarize through bibliometric analysis the necessary and proposed solutions available in the literature to support commercial availability. Moreover, this paper targets to ease the introduction of automation, smart technologies and IoT in aquaponics systems by simplifying the selection of sensors based on biological needs.

An automated system had proven in other mature areas (i.e. automotive, manufacturing, construction etc.) to increase the productivity, reduce the human error and reduce time and amount of labor. Extrapolating it to Aquaponics will lead to fulfill the concept of precision farming with the inherent attributes such as improving resources utilization (water, electricity, fertilizers) reducing human intervention, reduce field expertise and even accelerating the grow time of most of the crops since the ideal environment can be automatically maintained.

Introducing sensors is a mandatory step in working towards the fully or semi-automation of this systems. Here the importance of having a guide for those planning to dive into the automation of aquaponics systems. Table 2.3 summarizes the parameter ranges; optimized to avoid potential threats to the aquaponic system. Figure 2.4 shows the direct correspondence found in the literature between sensors and the aquaponic parameters.

Table 2.3 Optimal parameters range for aquaponics systems.

Parameters	**Aquaponic**
pH	6.5-7.0
Water T	17°C -30°C
Water Level	.02 kg/L
Dissolved Oxygen	>4 mg/L
Electro-Conductivity	100-2000 µSiemens/cm
Total Dissolved Solids	<1000 mg/L
Salinity	0-2 ppt
Water Hardness	50-150 mg/L $CaCO_3$
Alkalinity	50-150 mg/L $CaCO_3$
Total Ammonia-Nitrogen	<2 mg/L
Nitrites	<1 mg/L
Nitrates	50ppm-100 ppm
Flow	1-2 liters/min *
Air T	18°C -30°C
Relative Humidity	60%-80%
CO_2	340 ppm-1300 ppm
Light Intensity	600 PPFD -900 PPFD

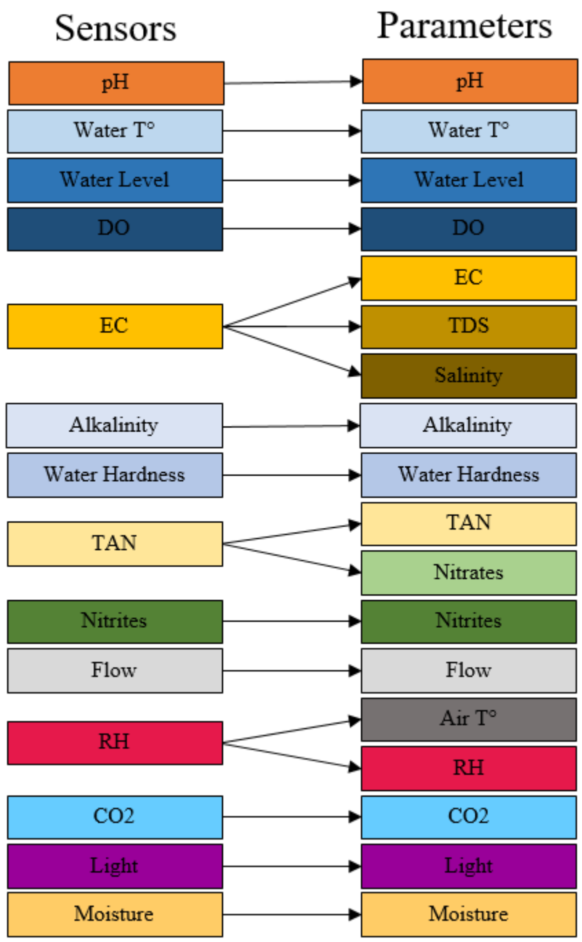

Figure 2.4 List of all parameters found in literature and their correspondence.

2.5.2. Control Strategies

The analysis of the mentioned literature showcased a consistent use of micro-controllers, such as Raspberry Pi and Arduino, in aquaponic systems. Overall, three different levels of control strategies were noted.

The most basic control strategy can be understood as a local approach with external communication. Murad et al. kept the automation and deployment locally [8]. Several sensors were used and controlled with Arduino. The system was locally controlled and connected to a GSM (Global System for Mobile) communication interface, capable to send notifications or alarms as predefined actions based on sensors levels.

A step further implies to gather and analyze information wirelessly through cloud servers. Wang et al. utilized an Arduino and a WRTnod to monitor the data acquisition and manage the aquaponic system built [43]. The sensor acquisition module built consisted in temperature, humidity, light, water level, and DO sensors. The data was sent wirelessly to the control and management center, whose function was to store the data, process it, and send it to a remote server. Once the information was stored in the server, users were able then to analyze the information and make decisions in regard to the state of the air and water pumps, lights, and so forth.

Finally, complex control strategies found in literature aimed to achieve autonomous systems through a variety of smart techniques that go from linear regression to more complex prediction models, such as neural networks. Kumar et al. included in their system wireless sensor network devices (temperature, pH and nitrate sensors) [65]. The network had a 10-meter communications range with a transfer rate of 250 Kbits/s. The authors used this time the run-time platform IBM Mote Runner1 as the sensor network. A cloud data storage system was used to store the data from the sensors, then, trend analysis helped to predict the next time series values of the variables. A regression technique was implemented to make predictions about nitrate and pH values, aiming to create an autonomous aquaponic system regarding the control of these two parameters.

However, no discrete or event-triggered control strategies were found during the analysis as authors tend more to apply distributed control systems (DCS). Those missing strategies are key to the implementation of Programmable Logic Controllers (PLCs) in such environments and would require further research.

[1] www.zurich.ibm.com/moterunner/

2.5.3. Current Limitations and Future Work

Some limitations were encountered in the current body of knowledge. Based on Table 2.1, Figure 2.5 displays the concurrence of the parameters in the reviewed literature.

It is important to note that while some parameters have been thoroughly researched, i.e. pH or water temperature, some other parameters are being neglected by the automation academic community. With varying degrees of effect in the aquaponics system, research is needed to provide practitioners of a clear impact of each of the listed parameters. An effort is then required to draw precedent in certain parameters, while keeping improving past contributions.

Regarding IoT systems, their implementation has influenced the success of other industries, i.e. automotive or aerospace, thus working in the use of those technologies in aquaponics to aim towards precision farming seems to be an accurate solution for the feasibility of such farming systems. Nonetheless, the available solutions are still primitive, with a widely spread use of micro-controllers and commercially available software that would limit its industrial application, economically speaking.

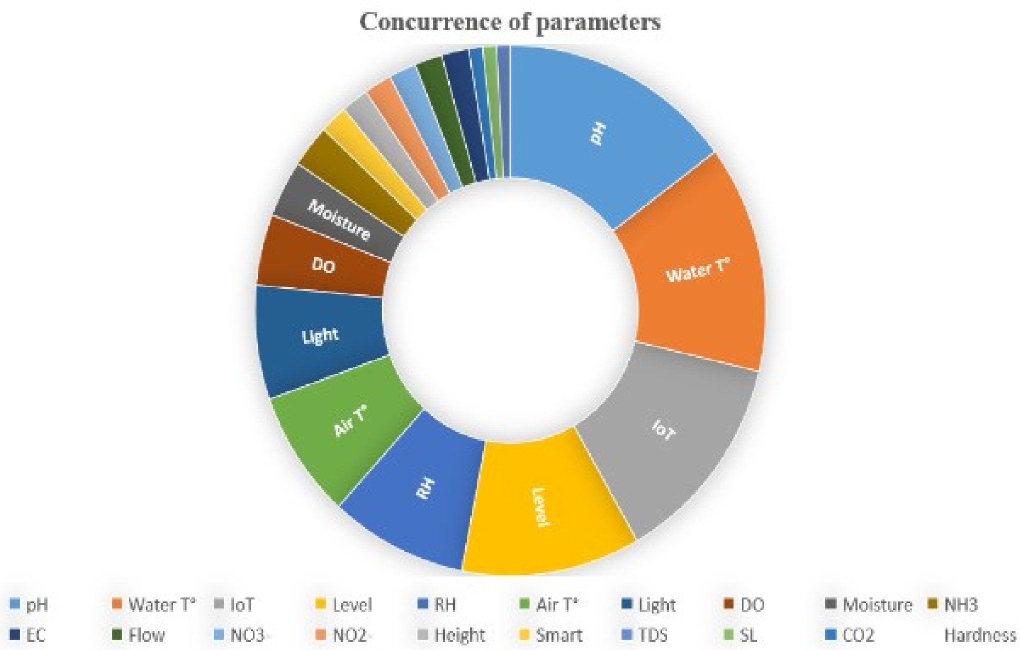

Figure 2.5 Concurrence of parameters in the proposed systems.

When moving to commercial-industrial levels, the adoption of the adequate equipment becomes mandatory. Migration towards controllers and sensing equipment that are more robust, such as a Programmable Logic Controller (PLC), is necessary to promote automatic aquaponic solutions to commercial production. Nowadays, monitoring off-the-shelve equipment can be purchased, capable of giving real-time data, namely parameters such as temperature, pH, electroconductivity (EC) and relative humidity (RH) currently used to improve yield performance and quality of crops in greenhouses. Nevertheless, these systems cannot deal with closed-loop feedback systems that may, potentially, control external variables and/or hardware, which are necessary to push aquaponics towards smart technologies. On the same page, some monitoring systems are commercially available for correspondent systems in aquaculture. These are capable to measure parameters such as temperature, dissolved oxygen (DO), and pH, with the same limitations aforementioned. When planning aquaponics' control systems, high flexibility is needed. Since the complexity and interaction between parameters, as well as the cross-incidence (i.e. variations in temperature levels yield variations to pH levels), is high and sometimes difficult to predict or still unknown, it is then necessary to have a control system flexible enough to control and monitor the variety of sensors and equipment shared (and not) between this two technologies (aquaculture and hydroponics).

The introduction of advanced industrial control systems, such as PLCs, together with wireless networks and data servers in aquaponics can highly impact the development of this industry. PLC offers high flexibility when dealing with variety of sensors, motors, pumps, and other hardware needed in the aquaponics industry.

At last, water is the most important and complex parameter in an aquaponic system. Aquaculture alone have been one of the fastest growing food production industry, with an average rate of 8.5 % annually over the last 30 years. Promoting the adoption of the hydroponics technology as a business opportunity to the aquaculture sector will exponentially expand the aquaponics impact. To achieve this, it is necessary to enhance the research of the water treatment strategies towards a feasible and easy to adopt business model. Even though some research efforts have been made in this area that can contribute to the popularization of aquaponics, further research is required to provide a real stimulus towards the commercialization of such systems. For example, Lie et al. reported the performance of a immobilized biofilm treatment in aquaponics pilot scale [72] . Boxman et al. recently evaluated the water treatment capacity, nutrient cycling, and biomass production of a marine aquaponic system [73] and Calone et al. investigated the implications of water management through a series of experimentations in aquaponics systems [74] .However, even in this research area, it is still necessary to move towards the goal of adopting smart technologies. Further studies about the use of monitoring systems of the parameters in the bio filtration unit is necessary, monitoring and controlling parameters such as pH, water temperature and DO become mandatory in this stage since the microbial activity is highly related to this levels and the nitrogen availability in the whole system. Currently, no smart system has been designed towards the quality of water in such conditions, and the development of a smart system that involves water within the aquaculture, bio filtration, and hydroponic components is becoming necessary.

2.6. Conclusions

Research contributions in the topics of aquaculture and hydroponics are increasing and attracting attention from researchers and practitioners. A systematic analysis was presented to explore the status and global trends of aquaponics systems, focusing on their relevant sensing parameters, smart and IoT technologies. This paper presents a study of the field as a whole aiming to simplify the decision making regarding the setup of sensors in aquaponic systems and provide a clear image of the research trends in smart aquaponics. The final purpose of this work is to create a bridge between biological and electrical engineering knowledge to enable aquaponic development as a sustainable source of food. This paper contributes by giving aquaponics experts' technical knowledge about automation, IoT and smart systems; and automation expert's knowledge regarding the biological processes happening in aquaponic systems. Creating a bridge towards scaled up aquaponics systems will accelerate contributions in the area and enable viability in commercial solutions.

Chapter 3 Real-time growth rate and fresh weight estimation for leafy crops

In this chapter, the application of smart systems for monitoring, quality control, and condition assessment of the crops is researched. Early detection of plant stress is critical to minimize both acute and chronic loss of productivity [75]. Computer vision is highly suitable to perform growth and quality assessments since it's a non-contact, rapid, environmental-friendly, and accurate method for non-invasive evaluation in fruits and vegetables [76]. Contributions that make use of new technologies to enhance the growth and quality of the crops are necessary. The main aim of this contribution is to propose a system that is able to monitor the current state of the crops using computer vision systems and, automatically, estimates the growth rate and fresh weight as key performance metrics that can impact and promote future applications of smart technologies in this area. Through this work, a literature review and research methodology are presented. After this, the setup for the experimentation and the results are introduced. Finally, a conclusion of the work done and the relevance to the agricultural community is explained.

3.1. Literature review

Vast contributions have been made in performance metrics in agriculture; however, few of them target hydroponic systems, and even less related to aquaponics. Computer vision systems and deep learning approaches represent a suitable solution to solve the request of evaluation tools and can be applied to the whole production system of aquaponics. In one hand, computer vision has provided great results in other industries [20], increasing productivity by providing a deeper understanding of the underlying issues [62]. On the other hand, deep learning approaches have accurately supported modeling of complex scenarios, showcasing the capabilities of artificial intelligence [77].

Reviewing some of them, Pietro Cavallo et al. created a classification algorithm for quality evaluation of table grapes using computer vision. They categorized the quality of the grapes in five different levels using image-processing techniques by analyzing color levels in images. In addition, they used machine learning techniques to simplify the tuning and configuration of the algorithms. In the end, they proposed models that extract features from digital images. Those features allow them to predict the grape quality with good performance, overcoming linear model' limitations [76]. Flora Yeh et al. developed an automated growth measurement system for leafy vegetables in a hydroponic system. In this work, lettuce was recorded with a camera that moves along each channel. After applying image processing techniques to detect contours and estimate each plant' area and height, growth curves were given by the authors [78]. Jung et al. analyzed two different image-processing methods for the measurement of fresh lettuce weight. This analysis was done correlating the images of the leaf area with the weight of the lettuce using regression algorithms [79]. Mortensen et al. developed a methodology to perform lettuce segmentation in 3D point clouds for fresh weight estimation [80]. Lu et al. developed an application to monitor growth rate of lettuce using deep convolutional neural networks (MASK-RCNN) in systems that used NFT channels. Further image processing analysis was done to estimate the leaf area and its growth rate [67]. In a more recent generic context, MASK R-CNN has been used to segment crops successfully [81]–[84].

Even though the aforementioned contributions help to further understand the growth and quality assessments of different crops, these are not planned to work as an online mechanism for training databases in smart applications. Further, those works that include smart techniques for leaf segmentation (i.e. Lu et al. [67]), it can be expanded by adding fresh weight correlation, which is a demanded metric by the agricultural community [85], as well as to adapt the proposed approach to work with several plants simultaneously (multi-instance analysis segmentation). This work aims to present a feasible option for those interested in determining the growth rate of leafy crops based on deep learning multi instance-segmentation algorithms and estimate the fresh weight of the crops using prediction tools.

3.2. Research methodology

An automated system was developed to monitor the growth rate and estimate the fresh weight of little gem romaine lettuce in aquaponic grow beds using deep learning techniques. The methodology is divided into three sequential modules: 'Model Building', 'Model Prediction - Correlation' and 'Parameters Estimation.' The first one refers to the training of the model using MASK RCNN and involves the (1) image training database, (2) images pre-processing and (3) model training. The second module aims to perform the segmentation of leaves in the grow beds environment, and it consists of three phases: (1) image acquisition, (2) manual measurements for ground truth, and (3) model prediction. The third module makes use of the second block for feature extraction. The steps to estimate the desired parameters are the following: (1) image conditioning; (2) features extraction; and, (3) growth rate and fresh weight estimation.

First, in the model building the image database to train our segmentation model is constructed robustly, which includes images of a variety of leafy vegetables that gives to the model enough variation to perform segmentation and not only our selected crop, but can be extended to spinach, basil and other types of leafy vegetables. Once this images are gathered, the images are segmented and labeled and then used for training our model. This training is just done once, since the trained model can be used every time without the needing have repeating this process.

In the second module 'Model Prediction - Correlation' this trained model is used to predict the location of the crop and segment each of the instances in the image and refers the use of the experimentation part. Before this happens, the experimentation images (not the same as the ones used for the training part) need to be taken through a pair of cameras in the experimentation setup and some manual measurements are performed to validate the results of the model (correlate pixel values to real units i.e. mm).

The last and third module named 'Parameters Estimations' refers to the tools used to condition this images (remove distortions), perform the pixel-value task, extract features (i.e. height, area, etc.) and calculate the growth rate and fresh weight estimation. The overview of the research methodology is presented in Figure 3.1. Each element of each module is presented in the following subsections.

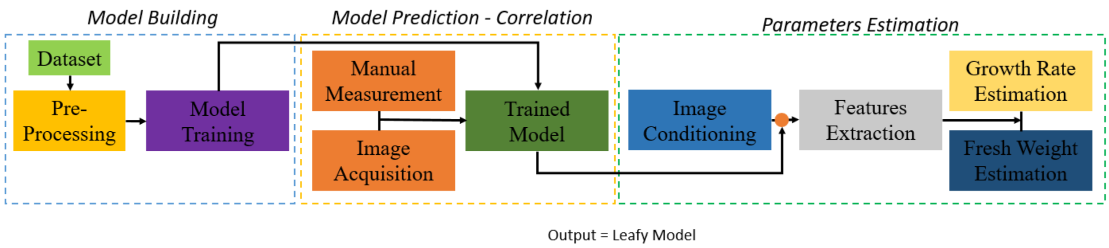

Figure 3.1 Overview of research methodology.

3.2.1. Model building

The objective of the first module is to train a model that will be used to determine the growth rate and fresh weight of plants in later steps. The steps for building the model are explained next.

3.2.1.1. Dataset and pre-processing

The image dataset was constructed using a variety of images from diverse sources. This involve the use of images from side and top view that were recorded along the growing process with the purpose of using them in the training process. With the objective of increasing the model flexibility to recognize and segment plant leaves no matter the background, i.e. indoor or outdoor environments, the database is complemented with images of leafy vegetables in different growth stages and in different scenarios obtained through Google search engine. A total of 1350 images were gathered between these two methods. In order to train the model and to provide the algorithm with the necessary data for training purposes, the images need to be consistently sized, label and manually segmented. The software used was Label Me [86] and a total of 3150 instances were obtained. Figure 3.2 shows some images from the training database.

Figure 3.2 Sample database set of images

3.2.1.2. Model Training

Traditionally for two-dimensional images, crop segmentation is performed using color, intensity, textures and morphological operations [80]. This project implementation, instead, make use of the MASK-RCNN framework proposed by He et al. for object instance segmentation [87].

For this purpose, the image database is divided into training and validation image sets. During the training process, the algorithm weights the extracted features from the training data and, then, tests the model results against the validation data. As such, unbiased estimation of the trained model performance is obtained. The MASK-RCNN model performance had a training loss of 0.21 and a validation loss of 0.31, as shown in Figure 3.3. Here can be seen how the loss (error) of the model during the prediction

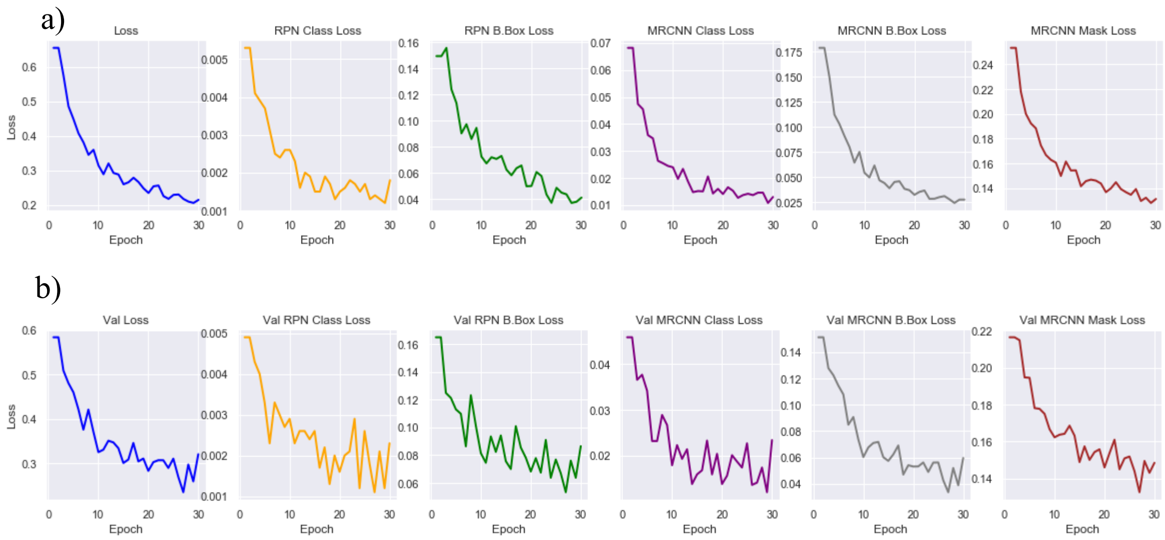

Figure 3.3 Model training results: a) training data; b) validation data.

is getting smaller with the training epochs (runs). The ‘loss’ graph stands for the overall loss, and the others make reference to the steps of the model during the region proposal network (RPN) step, classification, bounding box prediction and masking head step.

3.2.2. Model Prediction-Correlation

During this stage, the model trained is used to perform prediction of the leafy masks in real time with images retrieved from the experimental setup where little gem romaine lettuce is being grown. The main steps for this purpose are the image acquisition of the images, manual measurements and the mask prediction.

3.2.2.1. Image acquisition and manual measurements

The acquisition of images that show plants at different growth stages is necessary. For this purpose, two different cameras are scheduled to take pictures of a growing bed every 30 minutes from 6:00 hrs. to 18:00 hrs. The cameras take pictures of 1920×1080 pixels, from both top and lateral view of the plants. Each of the pictures has three plants in them. The manual measurements were taken twice a day at 8:00 hrs. And 16:00 hrs during the same period (15 days). These measurements were (1) width, (2) depth, (3) height and (4) weight using a caliper and a digital scale with a resolution of 0.01 g. To ensure the consistent weight record and reduce errors related to varying moisture content in the rockwool, this measurements were performed consistently at the same time of the day and under the same conditions (30 seconds drying process before weighting). Also, the wet rockwool was weight alone at the beginning and at the end of the process, a relation between the rockwool alone and the plant without rockwool at the end of the experiment was calculated to then derive the plant weight during the experimentation. The experimental setup that show the cameras used is shown in Figure 3.4. A schematic of the manual measurements performed is shown in Figure 3.5.

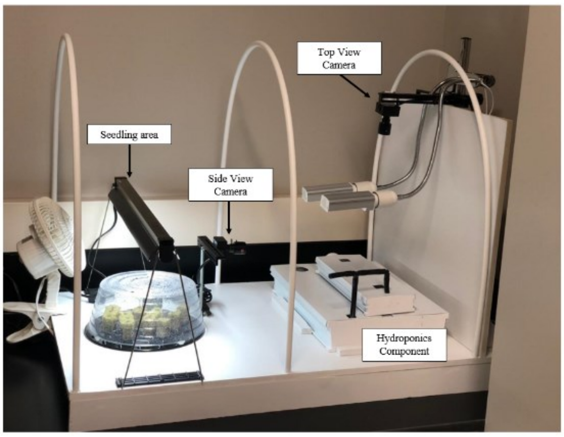

Figure 3.4 Experimental Setup

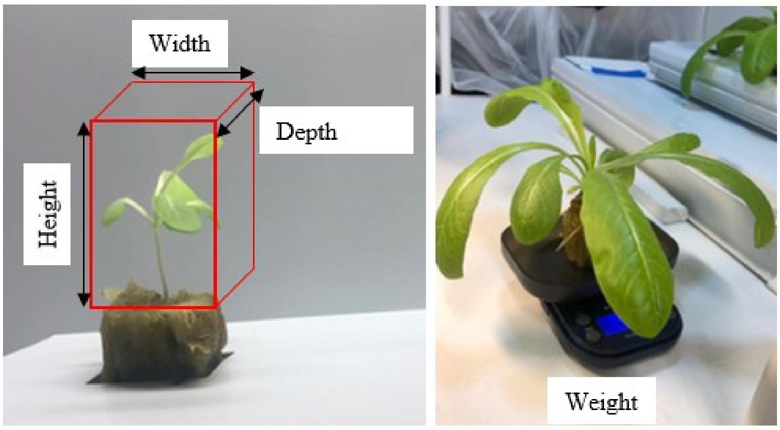

Figure 3.5 Manual measurements

3.2.3. Parameters estimation

The third module aims to perform feature extraction using the model output from the second module and estimate growth rates and fresh weight. Here, the images first need to be conditioned to avoid errors due distortions and proceed with the features extraction from the masks. The steps that this module follows are explained next.

3.2.3.1. Image conditioning

The image conditioning is needed to correlate the image pixel value with the actual measurements. To avoid errors due to radial and tangential distortion, both cameras need to be calibrated. Radial distortion makes straight lines appear to be curved and tangential distortion makes images appear closer than expected. This process was performed following standard camera calibration [88]. This calibration process finds an accurate relationship between a 3D point in the real world and its corresponding 2D image projection (pixel). The calibration images were analyzed using the OpenCV library and programmed in Python language, to find the camera parameters (internal and external) and distortion matrices. To find the projection of a 3D point onto the image plane (2D), first the transformation from world coordinate system to the camera coordinate system using the external parameters (rotation and translation of the camera) needs to be done. Next, using the internal parameters (focal length, optical center, and radial distortion) of the camera, the 3D point is projected onto the image plane. Equation 3.1 to Equation 3.4 show the equations that relate 3D points with radial and tangential distortion, respectively, for the x and y directions.

$$xr_c = x(1 + k_1r^2 + k_2r^4 + k_3r^6) \qquad \text{Equation 3.1}$$

$$yr_c = y(1 + k_1r^2 + k_2r^4 + k_3r^6) \qquad \text{Equation 3.2}$$

$$xt_c = x + [2p_1xy + p_2(r^2 + 2x^2)] \qquad \text{Equation 3.3}$$

$$yt_c = x + [p_1(r^2 + 2y^2) + 2p_2xy] \qquad \text{Equation 3.4}$$

The camera matrix, $\boldsymbol{CM}$, is then defined to remove the distortion created by the lenses of a specific camera and depends on its intrinsic parameters. Intrinsic parameters are the focal length (f_x, f_y) and optical centers (c_x, c_y). This camera matrix is shown in Equation 3.5.

$$\boldsymbol{CM} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \qquad \text{Equation 3.5}$$

To associate the coordinates of the segmented leaves of both cameras, they need to be converted to a common reference frame. Considering each camera as a pinhole, the relationship between a 3D point $\boldsymbol{M} = [X, Y, Z]^T$ and its image projection $\boldsymbol{m} = [u, v]^T$ is given by:

$$\widetilde{\boldsymbol{m}} = \boldsymbol{CM}[\boldsymbol{R}\ \boldsymbol{t}]\widetilde{\boldsymbol{M}} \qquad \text{Equation 3.6}$$

here $\tilde{x}$ denotes the augmented vector by adding 1 as the last element, and $(\boldsymbol{R}\ \boldsymbol{t})$ are the rotation and translation matrices from each camera to the common reference frame. Figure 3.6 shows the original image and the undistorted results using this approach.

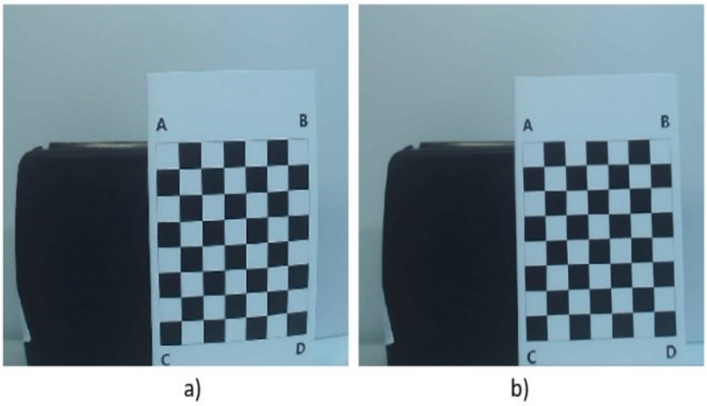

Figure 3.6 Distortion correction results: a) raw image, b) undistorted.

3.2.3.2. Features extraction

The prediction in the experimental dataset to locate and segment the leafy vegetables is implemented with the trained model from the first module. The features of these plants are determined through the predicted masks obtained. Essentially, a set of matrices with the pixels locations that belongs to the segmented plant (interested area) are retrieved from the prediction and further work need to be done with this data to process it and give it a useful meaning in our case. For this purpose, the image's moments are used. An image moment is a particular weighted average of the image pixels' intensities or a function of such moments, usually chosen to have some attractive property or interpretation. Image moments are useful to describe objects after segmentation. For example, after calculate this image moments we can easily derive features as centroid in x and y direction or area of the interest pixels. In order to derive our growth rates and predict the weights a set of features of the plants need firsts to be obtained. A list of these features are listed in Table 3.1. To calculate this features, the following steps are implemented. First, from the prediction process, the mask and a bounding box for each instance are obtained.

Table 3.1 List of features extracted

Plant Features	
Side view area	A_{side}
Height	H_{side}
Width	W_{side}
Centroid Side	C_{xys}
Top view area	A_{top}
Centroid top	C_{xyt}
Depth	D_{top}

As explained before, the masks are a set of matrices that contain the pixels that belong to the area of the object. The bounding boxes are retrieved from the model in the form of coordinates of opposite rectangle corners. In our case, three masks and three bounding boxes are retrieved from each image, one for each plant. Second, the contour for each mask is calculated using Green's theorem, as suggested by Suzuki et al. [89]. Green's theorem provides the relationship between a curve C, and a region D bounded by C, as shown in Equation 3.7.

$$\oint_C (L\,dx + M\,dy) = \iint_D \left(\frac{\partial M}{\partial x} - \frac{\partial L}{\partial y}\right) dxdy \qquad \text{Equation 3.7}$$

where C is a positive oriented, piecewise smooth, a simple closed curve in a plane, and D is the region bounded by C, L and M are functions of (x, y) defined on an open region containing D that have continuous partial derivatives. A schematic that presents the relationship just mentioned is shown in Figure 3.7.

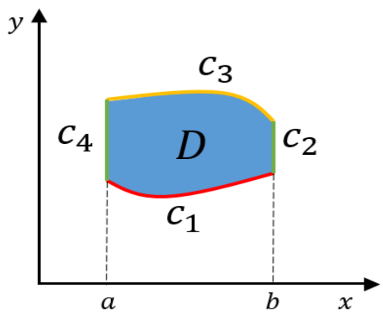

Figure 3.7 Green's theorem visual representation

Using the location of the pixels (interested area) in the matrix retrieved that can be seen as the region D, the Green theorem is then used to calculated the contour from each of the segmented instances in terms of bounding curves C. Now, a matrix that contain the points of the curve that bound the segmented pixels is calculated and can be used for the following calculations. From the obtained contours, the moments are calculated in order to estimate the area and centroid of the masks. The formulas of the moment of any plant shape image, in grayscale, follow Equation 3.8, where $I(x, y)$ are the pixel intensities, following the process suggested by Suzuki et al. [89] as implemented in OpenCV.

$$M_{ij} = \sum_{x}\sum_{y} x^i y^j I(x, y) \qquad \text{Equation 3.8}$$

From the Equation 3.8 can be calculated several combinations of i and j where each of them represent a specific feature of the image, by definition M_{00} represents the area of the leaf shape. Then, our first moment to calculate is M_{00} (pixels units) where the value is directly adopted as the area of this specific contour or plant. Our next feature to obtain is the centroid. To calculate the centroid, two more moments needs to be determined:M_{10} and M_{01} which are the pixels weighted averaged in x and y direction. The relation of the centroid components $\{\bar{x}, \bar{y}\}$ can be now derived by the quotient of M_{10} and M_{01} divided by the M_{00} area .This relationship is shown in Equation 3.9.

$$\{\bar{x}, \bar{y}\} = \left\{\frac{M_{10}}{M_{00}}, \frac{M_{01}}{M_{00}}\right\} \qquad \text{Equation 3.9}$$

The calculated moments for each contour are then M_{00},M_{01} and M_{10}. Next, the centroids for the side and top view are derived from the moments based in Equation 3.9 and are used to locate the masks and bounding box retrieved and assign them to the correspondent plant (i.e. plant 1, plant 2, plant 3). The area from the correspondence between the area of a contour and the moment M_{00}. Fourth, the height, width and depth are calculated from the dimensions of the bounding box retrieved before, as shown in Figure 3.8.

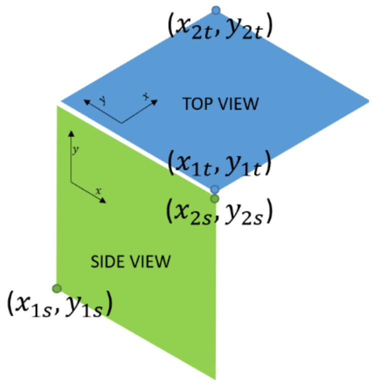

Figure 3.8 Bounding boxes schematic

The width, height, and depth are obtained from the coordinates, as shown in Equation 3.10 to Equation 3.12.

$$w = \frac{(x_{2s} - x_{1s}) + (y_{1t} - y_{2t})}{2} \quad \text{Equation 3.10}$$

$$h = y_{2s} - y_{1s} \quad \text{Equation 3.11}$$

$$d = x_{2t} - x_{1t} \quad \text{Equation 3.12}$$

3.2.3.3. Growth rate and Fresh weight estimation

Growth rate estimation is obtained using the variations in area for each plant at time i. Equation 3.13 presents the mathematical calculation for the growth rate based in the area a:

$$GR_{i>0} = \frac{a_i * 100}{a_{i-1}} \qquad \text{Equation 3.13}$$

The trend obtained is then used to estimate the growth rate in percentage units. On the other hand, the weight estimation is performed using linear regression techniques to correlate some features extracted using our proposed approach with the manual weight measurements. Linear regression tries to match the population to a set result, as shown in Equation 3.14 where Y_i is the objective population, β_0 is the population intercept, β_1 the slope coefficients, X_1 the variable, and ε_i the random error. The results and comments from both are being introduced in the results section.

$$Y_i = \beta_0 + \beta_1 X_1 + \varepsilon_i \qquad \text{Equation 3.14}$$

3.3. Results and findings

To validate the proposed methodology, a new batch of plants are grown. These plants are monitored for 15 days and the leafy vegetable chosen is Little Gem Romaine Lettuce. The side and top cameras take pictures at the same rate as in the model training stage: one picture every 30 minutes from 6:00 hrs. to 18:00 hrs. In total, 750 pictures (375 side view and 375 top view) with three plants each one.

3.3.1. Experimental Setup

The experimental setup consists in a wooden structure that holds a cover of polyethylene film to maintain the humidity in the system and the following components:

- 1 CropKing ® NFT Desktop System.
- 2 ELP 1080P Webcam (2.8 -12 mm HD Varifocal Lens)
- 1 Growth Light (T5 high output bulb, full daylight spectrum, 24 W).

- 1 Camera Ring Light (56-LED Lamps, 3000-35000 Lux)
- 1 Raspberry Pi controller
- 1 4-Channel Relay Module

The two cameras are connected to the Raspberry Pi via USB and programmed to take pictures at the intervals mentioned before. In order to control either the ring light (camera light) and the grow lights a 4-Channel Relay module was used as an interface to the Raspberry Pi. The growth lights were programmed to work at on/off intervals of 12 hours. As the hydroponics component of our system a CropKing® NFT Desktop System was used. Figure 3.4 shows the experimental setup built for the experimentations. Figure 3.9 shows a schematic of the connections between the cameras, growth light, ring light and 4-Channel relay module used.

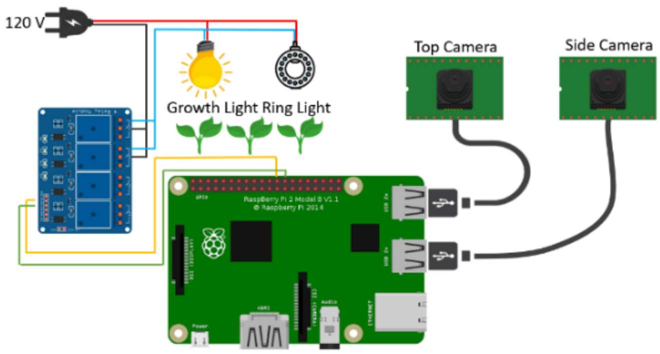

Figure 3.9 Connections schematics

3.3.2. Model training

As aforementioned, the training of our model capable of recognizing leafy vegetables is achieved using MASK-RCNN implementation repository from Waleed Abdulla [90]. Figure 3.3, introduced before, shows the training and validations loss (error) of the proposed model. The proposed approach uses first a region proposal network (RPN), which is a framework that generates several anchors (boxes) that are then evaluated by a regressor to check the occurrence of the target detection, in this case, the plants. A binary classifier returns then object/no-object scores, and the highest scored region is finally passed to a classifier that predicts the class (in our case is BN (background) and Leafy). Figure 3.10 illustrates the regions proposed for a sample image.

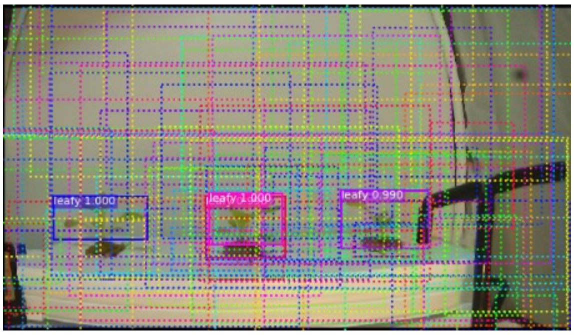

Figure 3.10 Overview of RPN step results

Secondly, the Mask-RCNN algorithm runs the mask head after retrieving the refined bounding boxes and it's identified class from the RPN stage. Figure 3.11 shows the three masks obtained for a sample image and Figure 3.12 shows the final masked image with its classification results and confidence scores.

Figure 3.11 Mask results for the sample image

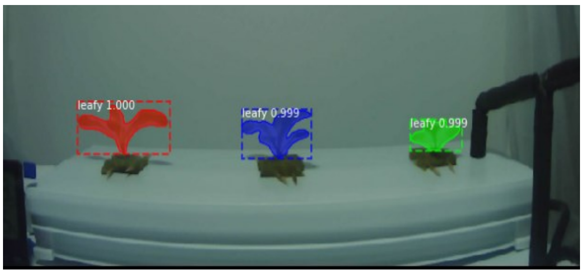

Figure 3.12 Segmentation for the sample image

3.3.3. Features extraction

First, images are undistorted using the calibration process aforementioned. Following the research methodology, a database is constructed where the plant features from Table 3.1 are listed for each of the plants for the duration of the experiment.

The plant's height, depth, and width estimated using the proposed model are compared with the manual measurements obtained from the experimental setup. Figure 3.13 the comparison between this manual and masked values for each plant. Herein can be observed the increasing trend in the dimensions, matching with the growing behavior of the plants (increase in size). Also, the estimation error for each dimension per plant can be visualized. It can be noted that important errors in estimation occur at the later stages in the plant's growth. After analyzing the masked images, it is noted that leaf's start to interfere with each other. In other words, occlusion in partially responsible for the discrepancies between measurements, especially for plants 1 and 2 after day 11. This effect will be discussed later in Section 5.2. To measure these discrepancies, the root mean squared error (RMSE) between manual and masked dimensions is used (see Equation 3.15). Table 3.2 lists the RMSE calculated using Equation 3.15 for each measurement per plant.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=0}^{k}\left|p(x_j - y_j)\right|^2} \qquad \text{Equation 3.15}$$

Table 3.2 RMSE of manual vs estimated dimension

Instance	Height	Depth	Width
Plant 1	11.31 mm	30.22 mm	28.70 mm
Plant 2	10.61 mm	24.53 mm	21.81 mm
Plant 3	14.71 mm	22.34 mm	12.31 mm

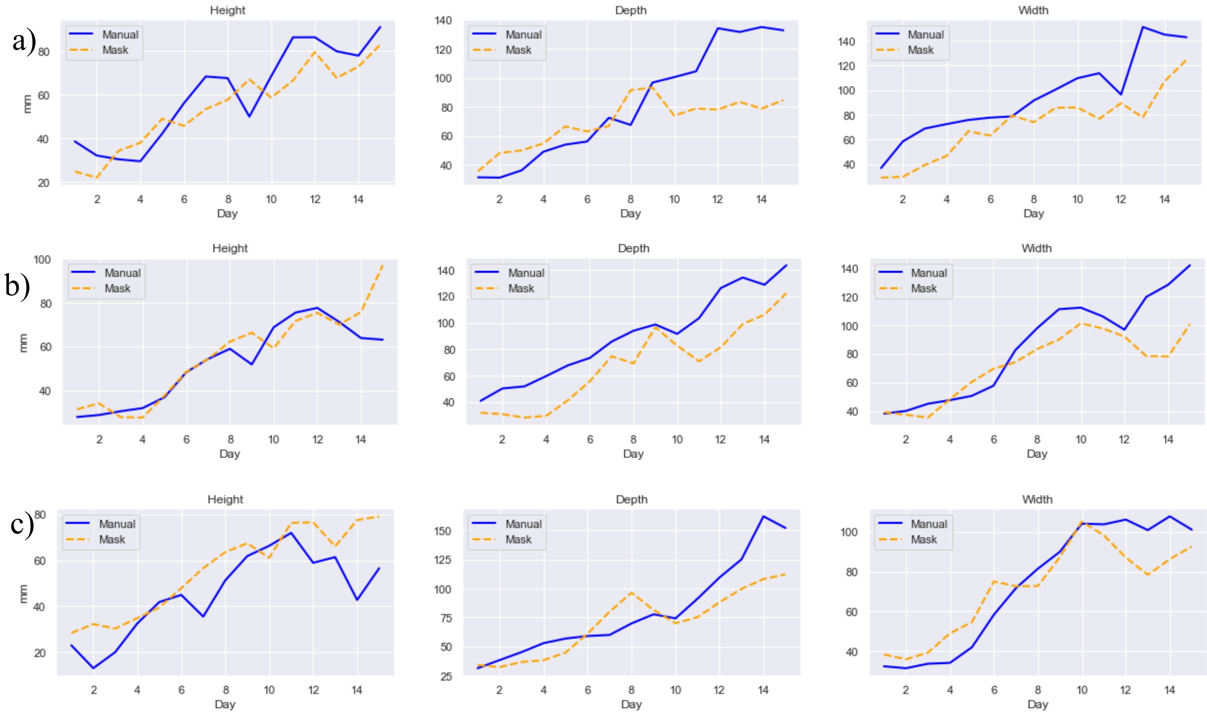

Figure 3.13 Manual vs. image estimations: a) Plant 1; b) Plant 2; c) Plant 3

3.4. Growth rate and fresh weight modeling

3.4.1. Growth rate

Recall that the main objective of this paper is to present a novel approach to determine the growth rate and weight of leafy crops during the growing stage as an online system using deep learning multi-instance segmentation .On each of the subplots (Figure 3.13), it can be noted the increasing trend of the dimensions by either manual means or estimated through the proposed vision-based method. This reflects that the model can capture and estimate the growth rates of each plant individually during the experimental setup. This analysis is performed with the purpose to validate the method's results, its estimations, and compare the trends to visualize opportunities regarding the accuracy of the model based on each of the views obtained during the experiment.

Using Equation 3.13, Table 3.3 presents the average growth rate of each one of the plants depending on the view selected. For the selected crop, reported growth rates in literature are around 21% on average [67].

Table 3.3 Estimated average growth rate per plant

Plant	Side View	Top View
Plant 1	18.17 %	18.09 %
Plant 2	16.21 %	16.31 %
Plant 3	21.06 %	19.93 %

Then, for each view, Figure 3.14 shows the detected size (in area) of each plant as it grows over time. The growth rate may then be visualized and differences in growth between them can be spotted. Furthermore, a fitting model (continuous line in Figure 3.14) can recreate the growth rate of the selected crop as a function of time. This line is obtained by minimizing the mean square error, degree 2, as shown in Equation 3.16.

$$MSE = \frac{1}{n}\sum_{j=0}^{k}\left|p(x_j - y_j)\right|^2 \qquad \text{Equation 3.16}$$

A polynomial fit of n = 4 is then obtained from the data collected and presented in this study. The obtained coefficients that model crop growth following a polynomial equation, as shown in Equation 3.17 are listed in Table 3.4.

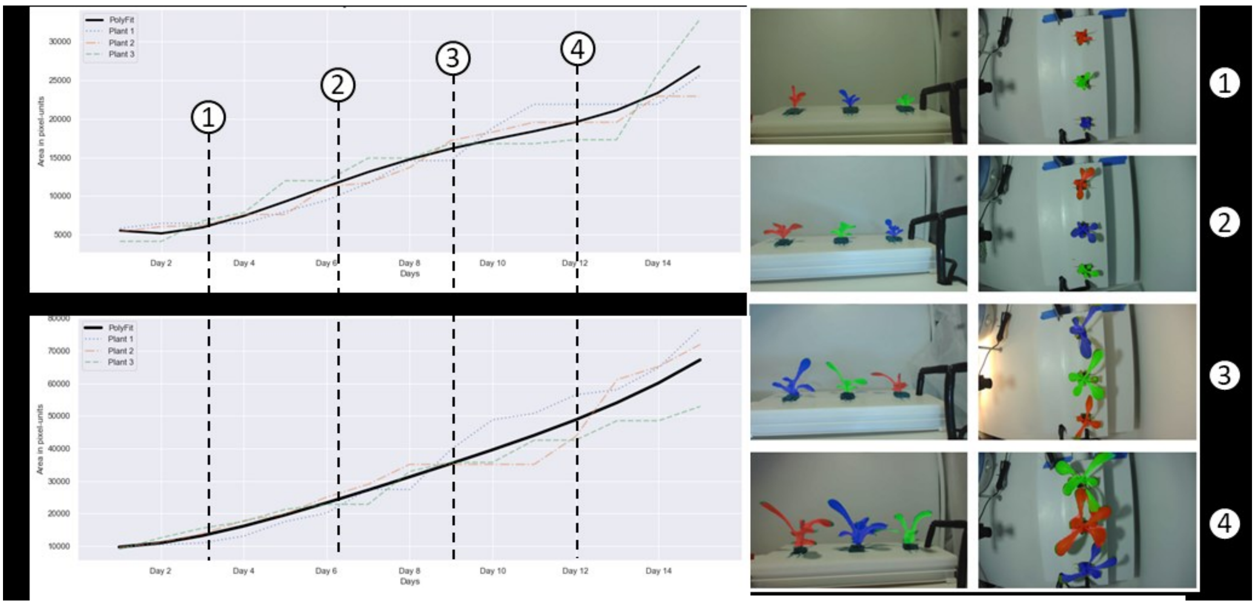

Figure 3.14 Growth rate results and fitting trends: a) side view; b) top view

$$p(\mathrm{x}) = p_1 x^n + p_2 x^{n-1} + \cdots + p_n x + p_{n+1} \qquad \text{Equation 3.17}$$

Table 3.4 List of the obtained polynomial coefficients.

Coefficient	Value
$\boldsymbol{p_1}$	+3.23 e+00
$\boldsymbol{p_2}$	-1.03 e+02
$\boldsymbol{p_3}$	+1.10 e+03
$\boldsymbol{p_4}$	-3.00 e+03
$\boldsymbol{p_5}$	+7.52 e+03

3.4.2. Fresh weight

A database is constructed as a base for the fresh weight model. The database consists in seven parameters in total: height, depth, width, side area, top area, volume, and weight. The first five are obtained from the feature's extraction process explained in Section 3.3.2.2 and listed in Table 3.1. The volume is calculated from the height, depth, and width. The final parameter (reference weight) will serve as the prediction output.

An exploratory data analysis (EDA) is initially performed to visualize the data distribution and decide the best approach to obtain a prediction model. Based on Figure 3.15 a linear regression approach is then decided for the weight prediction model for

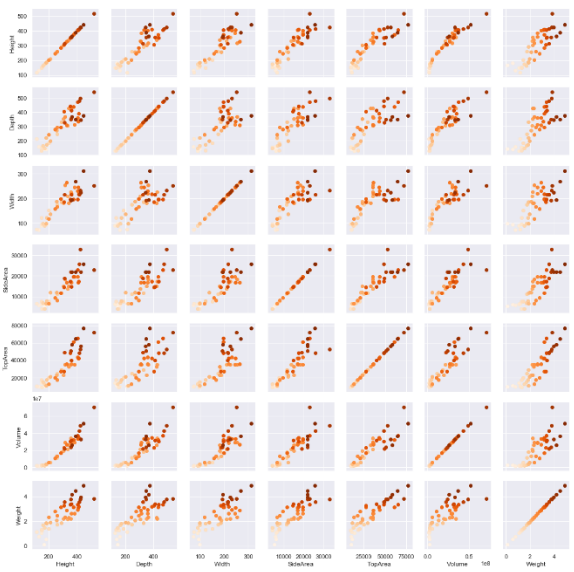

Figure 3.15 Correlation heat map for weight prediction.

further steps, as most independent variables have a quasi-linear relationship with the objective variable, the plant's weight.

The linear regression equation for the model is shown next in Equation 3.18, where β represents the coefficients from the models and X the independent variables.

$$Y = \beta_0 + \beta_1 X_2 + \cdots + \beta_n X_n \qquad \text{Equation 3.18}$$

A correlation matrix is then calculated and shown as a heat map to identify the R-squared (R2) measure of the parameters. R2 is a statistical measure that represents the proportion of the variance for a dependent variable, the weight in this case, by each one of the other independent variables, and is shown in Figure 3.16 as a heat map.

Figure 3.16 Correlation heat map for weight prediction.

For the construction of the linear model, the first step is to divide our data between inputs, 'X', and output, 'y'. By empirically selecting different sets of inputs, the regression analysis provides estimates for the output parameter, which is later compared to the real results. As a starting point, aiming to simplify the model while maintaining good prediction accuracy, the model is estimated excluding one by one those parameters with smaller R2 values.

The model is constructed using the scikit-learn library in a Python environment. The provided data is split into training and validation sets in a 70%-30% proportion. Table 3.5 lists the different RMSE achieved with the simplification of the model dropping different parameters based in the results shown in Figure 3.16.

Table 3.5 RMSE with different Criterions.

Criterion	RMSE
All Parameters	.52 g
All except Depth	.54 g
All except Width	.66 g
All except Volume	.42 g

Since our loss function (RMSE) needs to be minimized, the model obtained by using all the parameters except 'Volume' is selected. Other combinations of input parameters were tested, in addition to the ones presented in Table 3.5; however, those models obtained worse RMSE and therefore are not presented. For the selected model, the coefficients calculated are shown in Table 3.6.

Table 3.6 Linear regression Coefficients

Coefficient	Value
β_1 Height	- 0.000859
β 2 Depth	+0.001044
β 3 Width	+0.005135
β 4 Side Area	-0.000007
β 5 Top Area	+0.000042
β 0 Intercept	+0.246012

The results of the model using the coefficient values are then evaluated versus the true values to visualize the result of the predictions. These results are shown in Figure 3.17 as scatter points with a regression line as a reference.

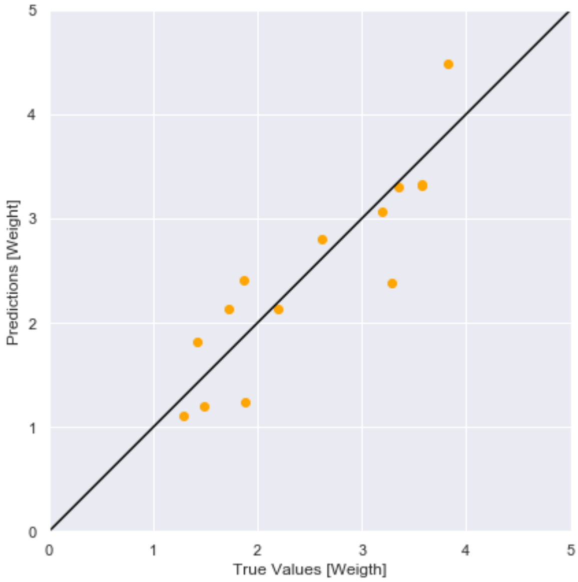

Figure 3.17 Predicted values vs. true values.

3.5. Discussion and future work

Analyzing the dimensions plotted in Figure 3.13, some important differences can be visualized in the latter stage of growth of crops. After reviewing the plant's masks, it is noted that in certain images, the plants went out of the range of the cameras, leading to some dimension miscalculations with this specific dataset. This problem is produced by the proximity of the cameras in the presented experimental setup shown in Figure 3.4. This has been already corrected for further experimentations and expected maximum size of the selected crops should be considered when installing the cameras.

Another interesting point are the occlusions that are noted when plants achieve a big enough size to be in touch with each other. Since one of the purposes of this work is to evaluate the model with occlusions (realistic multi-instance scenario), this point is also validated successfully. However, occlusion may confuse the segmentation process and extra error is added to the growth rate and weight estimations in this case. For the presented study, an extra 10% error approximately is introduced by occlusion when comparing the results of plants 1 and 2 (with occlusion) against plant 3. Nevertheless, due to the size of the NFT channel selected for this study, this error will be considerably reduced when moving to realistic setups where space between plants is increased to accommodate plant size. Anyhow, the effect of occlusion and potential solutions for it will be investigated further to try to minimize its impact on the proposed key performance metrics. With the vision-based framework and the two proposed models in this study to calculate crop performance metrics (growth rate and fresh weight estimation) that are designed to work as an online evaluation tool, the existent lack of tools that promote the implementation of smart applications in aquaponics can be covered.

3.6. Conclusion

Computer vision systems' interest in food grading has been increasing and adopted due to the non-destructive and contactless features of the process. An aquaponic system, on the other hand, is a farming method that combines recirculating aquaculture system for the farming of fishes and soilless hydroponics agriculture, promising to be one of the answers for the food and sustainability crisis. In this study, a solid tool to predict and calculate two key performance metrics in aquaponics is presented and validated in this paper. The growth of plants is estimated within 30 mm of error for both length and width, and fresh weight is estimated within less than 0.5 g of error.

The proposed method proves to be accurate and flexible enough to be used in real scenarios and is not limited to one instance segmentation or manual methods that can be disturbed by potential changing conditions of the environment. The methods presented offer the opportunity to rely on smart algorithms that can be constantly improved using dynamic data and implemented in online systems reducing the feedback time loop. This contribution will help and promote the introduction of new implementations, such as research for complex relationships between optimal parameters, detection of illnesses using computer vision, or adjustable autonomous farms that could lead in a short time to precision farming in aquaponics. Achieving the concept of precision farming in aquaponics will help in the development of the commercial implementations and the widespread of this technology around the globe, impacting the food scarcity and lack of green and sustainable resources in these difficult times.

Chapter 4 Wireless Sensing Module for IoT Aquaponics

In this chapter, a wireless sensing module (WSM) is designed and implemented in an aquaponics grow bed to gather information about six different parameters related to the water quality and air condition. Then, a framework to store the data and interact with the online performance metrics built in Chapter 3 is presented to promote future applications of smart algorithms and prediction tools. The construction and successful deployment of this work will promote the building of solid models to monitor and predict the behavior of aquaponics systems with less human intervention and lead to the adoption of smart technologies for optimal parameters autoregulation and precision farming.

4.1. Literature review

Research efforts have been made towards the development of monitoring systems and posterior visualization of relevant aquaponic parameters, but only a few of them are aiming at modeling each parameter interaction and thinking of future autonomous smart implementations. Nagayo et al. implemented a GSM Arduino-based monitoring and control system capable of sending alert messages to the users when certain measurements reach dangerous levels, such as temperature, relative humidity, light, pH, water level, DO, EC, TDS, and salinity. A graphical user interface (GUI) was then designed to display the information and the generated data could be extracted from the system using NI LabView [49]. Odema et al. created an IoT-based aquaponics system that allows remote monitoring and control of the sensed parameters such as EC, temperature, humidity, pH, and DO. The authors used a Modbus TCP standard protocol to pull measurement data from the sensing nodes of a supervisory computer [22]. Vernandhes et al. used an Arduino connected to a web server through an Ethernet Shield. A GUI was then created for real-time monitoring and control, enabling users to remotely switch on or off the exhaust, pumps, and mist makers [53]. Wang et al. utilized an Arduino and a WRTnod with a sensor acquisition module. The module contained different sensors to provide real-time data on temperature, humidity, light, water level, and DO in an aquaponic system. The data was sent wirelessly to the control and management system, which stored the data, processed it, and sent it to the server. Finally, the user could analyze the data and make data-driven decisions to control each aquaponic component [43].

Even though these contributions have been useful and contribute to the enhancement of aquaponics, remote monitoring, and control of system parameters are not enough anymore. The construction of smart decision-support models capable of predicting and correlating parameters will exponentially increase the adoption of aquaponics, by reducing costs and increase the overall flexibility. To build algorithms and predictive models for aquaponic systems, the availability and robustness of the acquired data are key to obtain accurate representations of the system itself. Since its inception and to become a database for prediction and control tools, data needs to be well-structured and defined.

In the following sections the development of a wireless module that promote Aquaponics IoT will be approached, the module development, working framework, experimentations, and results are presented next.

4.2. Module development and experimentation

A wireless sensing module (WSM) is fabricated to sense six different parameters: pH, electroconductivity (EC), water temperature, air humidity, air temperature, and light intensity using an Arduino as the controller. This module sends the data wirelessly to a database locally stored in the main controller (Raspberry Pi). The main controller and the Arduino can communicate through an access point using a Wi-Fi module installed in the Arduino controller. The main controller is running a parallel process capable of estimating the growth rate and predict the fresh weight of the crops from pictures of the current state of the grow bed using two different cameras [91] and store these performance metrics along the sensed values received. In addition to that, the database is uploading to the server all the pictures obtained from the aquaponic environment. Figure 4.1 shows the process just introduced. The components for the construction of the module are listed next.

- 1 Arduino UNO USB Microcontroller
- 1 Liquid PH Value Detection Sensor
- 1 Analog Electrical Conductivity Sensor
- 1 DS18B20 Water Temperature Sensor
- 1 DHT22 Air Temperature and Humidity Sensor
- 1 LDR Sensor
- 1 ESP8266 Wireless Sensor
- 1 2- Channel Relay Module

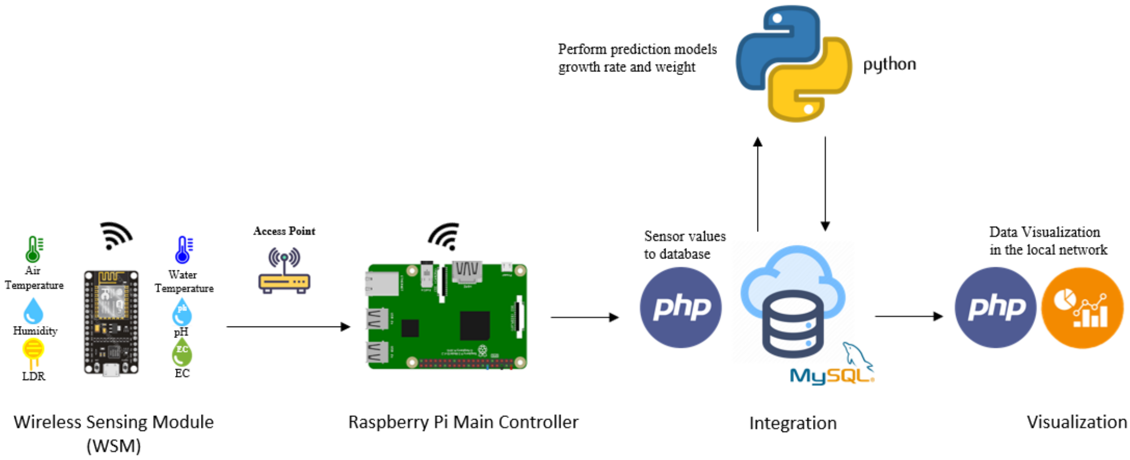

Figure 4.1 Process schematics of WSM construction and working principle

For the construction of the wireless sensing module, first, the six sensors are connected to the Arduino as needed. In some cases, transistors or resistors are required by the sensor manufacturers. Two of the sensors (EC and pH) use individual modules with BNC connectors. These two sensors need specific calibrations with different solutions and mathematical relations. For this type of sensors and to avoid noisy readings by aliasing, a 2-channel relay is then installed to power the sensors at different times and execute the readings asynchronously. The Wi-Fi module is installed in the Arduino using the serial ports. Figure 4.2 shows the main connections required for the WSM using the components just listed.

Second, the sensors are physically placed in the grow beds of the aquaponic system, namely on the hydroponic component. Further work will include the placement of different sensors in the fish tanks and biofilters of the Aquaponics environment. To place these sensors some fixtures and bases were 3D printed to be attached to the NFT channel as shown in Figure 4.3.

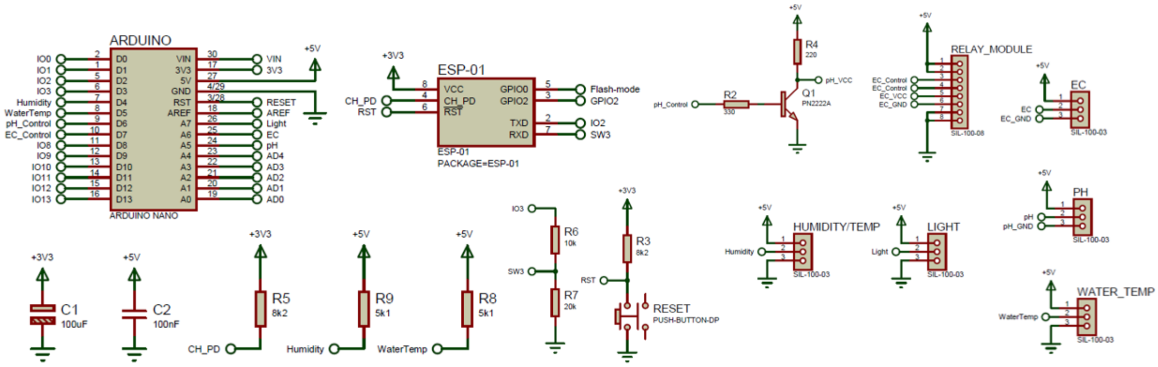

Figure 4.2 Connection Schematics

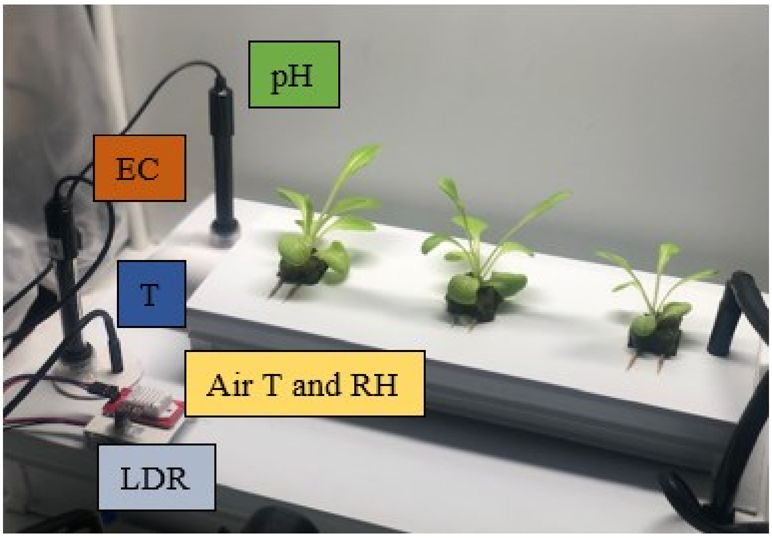

Figure 4.3 WSM experimental setup.

4.3. Results

The WSM is designed to extract data in real-time and serve as a feeding process for smart algorithms as a well-studied, balanced, and designed database. Herein the importance of the module to communicate wirelessly, supporting the commercial scaling deployment with the ability to link several modules installed at different locations and send the data to a main controller, following the distributed control systems (DCS) in automation [92].

The WSM is tested for a 14-day lapse in an experimental setup with an NFT channel as the hydroponics component of the process. There, Little Gem Romaine Lettuce is the crop selected for this study. The database is constructed following the process described and showed in Figure 4.1 and the setup to grow the crops and the explanation of the components is detailed in a previous work [91].

To start the process, the Arduino controller in the WSM starts to retrieve the values from the sensors and send them as unique values through the Wi-Fi antenna to the main controller every five minutes. This main controller is responsible of execute the parallel actions that refer to the evaluation of the growth rate and fresh weight estimation. Once these sensed values are received, the main controller formatted and insert them in a MySQL database at the local level using PHP. Next, the database is uploaded to the server and displayed through PHP. Figure 4.4 shows an image from the database displayed in the server. The database can be accessed through an IP address and is formatted to display a unique ID and a timestamp value to identify the correspondence with external processes. Each of the sensing measurements are displayed with the correct labels in columns such as light, temperature, air humidity, water temperature, water pH and water EC. Figure 4.5, on the other hand shows the values recorded for 3 days during the experimentation part displayed in continuous measurement plots.

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ID	Timestamp	Light (lux)	Temperature (°C)	Air Humidity (%)	Water Temperature (°C)	Water pH	Water EC (uS/cm)
4138	2020-03-30 12:25:12	478.98	23.20	96.70	25.13	6.91	2496.18
4137	2020-03-30 12:20:06	484.85	23.10	92.00	24.88	6.95	2336.65
4136	2020-03-30 12:15:00	496.58	23.00	83.50	24.88	6.93	2399.21
4135	2020-03-30 12:09:54	484.85	23.10	77.50	24.94	6.94	2455.52
4134	2020-03-30 12:04:48	515.15	23.40	92.00	24.94	6.92	2424.24
4134	2020-03-30 12:04:48	515.15	23.40	92.00	24.94	6.92	2424.24

Figure 4.4 Example of database entries

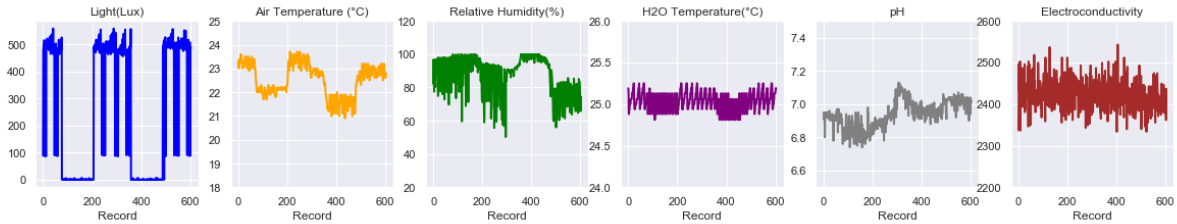

Figure 4.5 Example of time series of database records

At this point, the database is fully accessible and can be used for a variety of basic implementations such as remote monitoring or trending visualization. The next step in the process and which makes this setup more valuable is the linking in real-time of the sensed values database with the outputs from the parallel process that estimates the growth rate and the fresh weight of the crops. The main processor then, link the tables based in the time where the records were measured and establish the final database with sensed values (light, air temperature, air humidity, water temperature, water pH and EC) and the parameters extracted from the images of the plants that are shown in Figure 4.6. This final database is then a complete scenario of the status of the system and will be used in future work to deploy and predict parameter relationships and optimal levels.

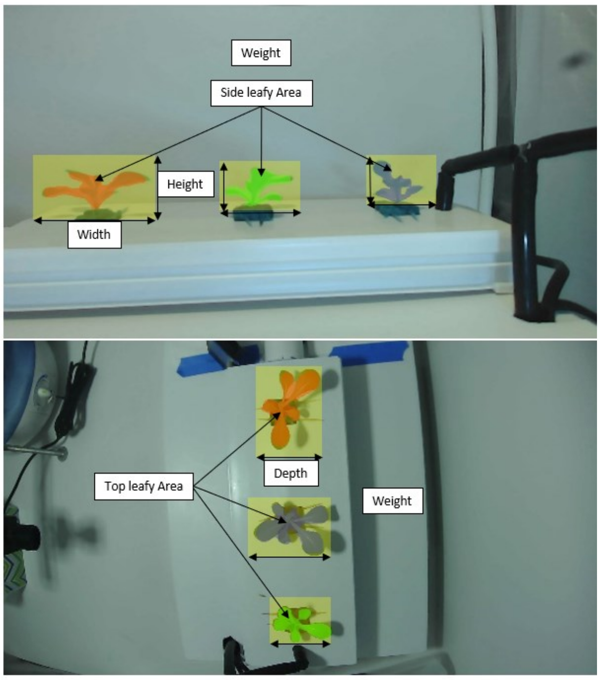

Figure 4.6 Extracted parameters

4.4. Conclusion

At this point, due to the available resources and the limitations from internal regulations about animal experimentations the sensors were just located in the hydroponic component. Future work will include sensors in the aquaculture tank such as dissolved oxygen, ammonia, nitrites and nitrates, salinity, dissolved solids among others.

The main contribution of this method proposed is the ability to link online measurements (regular monitoring systems) to real time performance metrics. In this case, the values from the sensors (which reflects the current state of the systems) are linked to the performance of the plants in terms of growing rate and fresh weight, opening the possibilities to perform further analysis about correlations between optimal parameters. Here, the feedback loop time can be reduced and the control systems in place can be adjusted with live data to improve the output of the process. Further work can include the calibration of sensors to work with less error due signal disturbance [77].

Also, the high flexibility of this system offers the opportunity to adopt it at a commercial scale since it is not limited to standalone execution and it communicates with a central controller that processes the data and can receive information from multiple locations.

Chapter 5 A digital twin framework for grow beds in aquaponics systems

This chapter proposes a digital twinning process of the grow bed (hydroponics component) of an aquaponic system. The main objective of the presented research is to create a virtual platform in which aquaponic practitioners can visualize the results obtained through sensors and smart systems in real-time. For example, an interface is proposed to showcase the individual growth rate and fresh weight of crops estimated using an online tool based on image processing and deep learning segmentation described in Chapter 2. Also, system parameters such as pH, electroconductivity, water temperature, relative humidity, environment temperature, and light intensity are recorded and linked to the performance metrics. From there, a database is created to serve as a base for the implementation of smart algorithms that relate performance metrics versus parameters to achieve optimal parameters. Finally, an exploratory analysis of the information is presented as an intuitive approach of the behavior of system.

5.1. Literature review

Recently, valuable contributions have been made for mobile/computer devices to monitor parameters [39], [93]–[97], remote applications to monitor and control outputs [22], [98]–[102], wireless networks and sensors [103] and smart implementations [104], [105]. However, to integrate all the considered inputs and smart systems, a complex model is needed that enables users to intuitively make use of the available systems. On top of that, a simulated scenario for aquaponics will benefit a deeper understanding of the correlations between parameters, thus, leading to optimization and increased control over the system. In the author opinion, developing a digital twin would support this research effort.

Digital twins (DTs) are commonly composed of three components: physical entity, virtual representation and the communication channels between them [106]. DTs are typically adopted to improve the performance of physical entities by leveraging computational power and techniques and using a virtual counterpart [107]. The origin of DTs is attributed to Michael Grieves and the work developed with John Vickers of

NASA in 2003 [108]. The initial conception intended to provide the foundations for product life-cycle management for situations where the possibility of gathering data was scarce, manually performed, and/or limited by the available resources [109], with the potential risk of, eventually, putting the concept in standby. The rise and interest in digital twins nowadays is mainly attributed to the advances in the technologies around the Industry 4.0 era, such as internet-of-things (IoT), big data, real-time sensors, and big data management and processing techniques [110].

A representation of the basic principles behind a digital twin is displayed in Figure 5.1. Jones et al. did a highly valuable work characterizing the digital twin concept through a literature review, facing the reality where the ideas around digital twin were diverse and did not converge mainly due the disorganized rapid growing of the applications, limiting the nourishment of the area and the maturation of the concept [111]. As of today, a better and clearer understanding about the components of a DT and their interrelationships are considered, and the expected impact of future research will be higher and in a broad range of industrial applications. The adoption of a digital twin is a valuable tool for the optimization of the process and labor reduction because it promotes the implementation of models for prediction, optimization, and the use of monitoring interfaces. However, a single contribution that researched to implement the concept of digital twins in aquaponic systems can be found in the literature authored by Ahmed et al. [112]. Here, a model was constructed to simulate the behavior of the system under current monitored conditions (air temperature and humidity, light intensity, pH, electroconductivity, water level, water flow, and water temperature). The authors modeled some system characteristics such as the fish feed rate, the total dissolved solids in water, fish weight gain, the water pH and nitrates, and plant growth. The author reported good estimations in most of the predicted models, except for the nitrates and plants growth. The main drawback of their proposed system lies in the lack of feedback from the real system in terms of plants growth and rate. This result is expected since the changing conditions of the environment and the 'somehow' changing-adapting behaviors of the living organisms alter their growth conditions continuously.

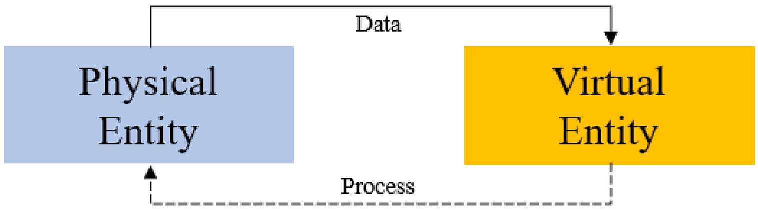

Figure 5.1 Digital Twin Schematic

This chapter proposes a digital twinning process of the grow bed (hydroponics component) of an aquaponic system as introduced before, during the next sections the work will be explained in detail.

5.2. Research methodology

The digital twin framework for aquaponics and the process developed in this paper is based on available literature, which takes on consideration theory and review publications on digital twins [109], [111], [113], manufacturing processes [114]–[116], and farming implementations [117], [118]. Expanding the concept and developing a framework for our case of study is work of the authors of this chapter. In the following subsections the general concepts of a digital twin implementation and its use to develop an aquaponics framework are explained.

The analysis in this chapter is based in a comprehensive systematic review of the literature about digital twins. The objective of this research is to propose a framework of digital twinning that can be generally applied to aquaponic systems. For this purpose, qualitative methods are used, in this case, systematic approach and experimentation. The systematic analysis is based on a qualitative analysis of selected journals and

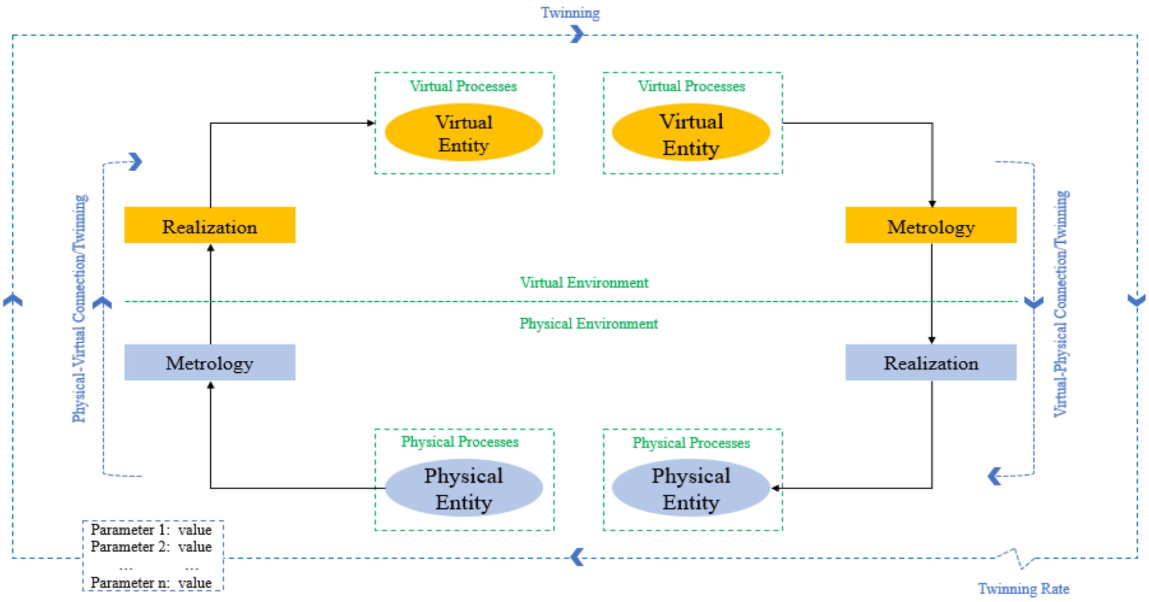

Figure 5.2 Components understanding schematics, after [111]

conferences that infers the framework proposed. The experimentation design and setup are done using the CropKing® NFT Desktop System. In this sense, the plants are grown for 15 days and the vegetable selected was Little Gem Romaine Lettuce. Specific details about the experimentation procedure are defined in section 5.3.2.

This research methodology is organized as follows: first, the generic framework of a digital twin is introduced in section 5.2.1 based on the systematic review; next, section 5.2.2 report on the proposed framework for aquaponics; then, section 5.3 encompasses the case of study, experimental setup, and components used for this research; and, lastly, the results obtained as proof of concept are presented and discussed.

5.2.1. Digital twin framework

The generic methodology for the construction of a digital twin framework and its application is based in Figure 5.2, which displays the schematics of the relationship between the digital twin components [111]. A twinning process is based on the virtual to physical and physical to virtual relationships in which identical scenarios are presented in both environments. The main concepts and processes needed for a digital twin are presented below.

The concept of physical and virtual entity refers to a specific real object, product, machine, or process and its virtual counterpart. Expanding the concept, the word environment is introduced for both cases (i.e. physical environment and virtual environment) that refers to the whole system and the internal relationships; not just limited to the level interactions (physical to virtual and virtual to physical).

The parameters are another key component of a digital twin system and it refers to the type of data and information of the processes that is passed between the physical and virtual environments. Fidelity and state are two attributes that describe the characteristics of the selected parameters. Fidelity describes the value and accuracy of each parameter while State describes its current condition.

The other two important components are the physical-to-virtual connection and the virtual-to-physical connection. In these connections lie the main differentiators of digital twins compared to other virtualization processes, i.e. simulation models. Physical-to-virtual connection is the communication and virtualization process: how the state of the physical entity or environment is transferred to the virtual parameters such as interfaces, graphs, databases, and so forth. There are two phases in this connection type, the metrology and realization. Metrology refers to the method in which the parameters are captured (i.e. sensors) and sent to the virtual component, and realization refers to the virtualization approach used to update and execute accordingly regarding the parameter inputs. The continuous mode in how this connection is established is what makes this process an online interaction. The virtual-to-physical connection represents the flow of information that goes from the virtual side to the physical part. This information or analysis output enables the functionality in the physical system to adjust or change its processes, for example, to improve its performance. This connection is identical to its physical-to-virtual counterpart, with similar actions (metrology and realization) as aforementioned. In Jones' opinion, this is the valuable paradigm of digital twins since it defines the bidirectional relationship between the virtual and the physical twins. However, the official definition of the digital twin by the CIRP encyclopedia of production engineering does not include this interaction as mandatory, which is also addressed by the same authors [119].

Physical and virtual processes are the specific activities performed on each of the levels, i.e. simulations, modelling, prediction, and optimization of virtual processes or manufacturing tasks, along with the control and design of physical processes. Finally, the twinning rate defines how the frequency at which the virtual and physical environments are synchronized, which leads to consider digital twins as a real-time virtualization. In the next subsection, the generic framework just presented is implemented for aquaponic systems. Based in the concepts just introduced, these general components are defined in an aquaponic framework.

5.2.2. Aquaponics digital twin framework

Aquaponics itself is a complex farming method due the symbiotic relationships between its components (aquaculture and hydroponics) when compared to the components alone. Developing a digital twin framework addresses the need to have a better understanding of these relationships and how they can be improved. Following the framework aforementioned, the digital twin for aquaponic systems is discussed below and summarized in Table 5.1. Here can be seen the how the components (e.g. connections, parameters, metrology etc.) in the generic DT framework are related to the aquaponics environment and the named hardware, connections, procedures and physical entities in aquaponics are listed.

In an aquaponics system, the physical entity refers to the machine or process where the main output of the whole system happens. Fish tanks, where the fish are farmed, and grow beds are the principal entities in the physical side. Virtual entity are those representations of the physical ones. As such, 3D modeling software is often used to build this objects, machines, or processes in the virtual environment. The physical and virtual environments involve all the individual physical components and the virtual processes associated to them. For example, the physical environment includes the bio filters, pumps, feeders, aerators, humidifiers, sensors, etc. besides the physical entities previously mentioned. Then, the virtual environment includes the interface, buttons, notifications, graphs, tables, and so forth that establish a virtual dashboard or interface that represents the physical environment.

Table 5.1 Generic components in Aquaponics Digital Twin framework

Component	Generic Framework Definition	Aquaponics Framework
Physical entity	Specific real object, product, machine, or process physically present.	Fish tank and Grow bed
Virtual entity	Replica of the existing physical entity into the virtual world	3D models or representations of the fish tank and grow beds.
Physical environment	All the physical entities and the relationships between them	Physical entities plus pumps, lights, humidifiers, water treatments, sensors, etc.
Virtual environment	Virtual entities and the tools to display them such as graphs, buttons, interfaces, models, etc.	Interfaces, graphs, tables, buttons, Andon, notifications, etc.
Parameters	Parameters that define the behaviour of the physical system and help the virtual environment to perform the mimicking	Include but not limited to pH, electroconductivity, RH, ammonia, nitrites, nitrates, light intensity, etc.
State	State of the parameters, can be defined in terms of values, levels, stage, etc. Fidelity and state are inherent adjectives of the state.	Commonly values of the parameters and growing stage of fished and plants
Physical-to-virtual connection	How the data is transferred from the physical to the virtual environment	IoT technologies such wireless modules, SQL, programming languages and others.
Virtual-to-physical connection	How the data is transferred from the virtual to the physical environment	Depends in the type of physical and virtual controller, i.e. RsLinx for ABB controller, for Siemens.
Metrology	Measuring the state of the parameters in either of the physical or virtual environments.	Sensors, cameras, etc. for PVc. Evaluation tools, mathematical models and other for VPc.
Realization	The actions that the correspondent environment take to adjust/change based on the metrology input.	Database constructions, building of graphs, notifications, etc. in the PVc. Hardware control, change in levels in the VPc.
Physical processes	Process executed in the physical environment.	Seedling, harvesting, feeding, water treatments, etc.
Virtual processes	Processes executed in the virtual environment.	Smart prediction models, data tracking and recording, levels adjustments, etc.
Twinning rate	Rate at which the interaction between environments is performed.	Commonly ‘real-time’, in noncritical processes defined lapse times such as 5 min, 30 min.

Parameters are an important component in any digital twinning process and extremely relevant to virtualize and simulate an aquaponic system. Several parameters are defined in aquaponics: pH, water and air temperatures, water level, dissolved oxygen, electro-conductivity, total dissolved solids, salinity, total ammonia-nitrogen, nitrites, nitrates, flow, relative humidity, light intensity, among others. In some cases, more complex depending parameters obtained from the physical side can be included as parameters, for example, fish age, plant's growth, or remaining available resources. Those parameters monitor the performance of the system in a more comprehensive fashion.

Physical-to-virtual and virtual-to-physical connections are mostly generic in digital Twin and depend more on the controllers and interfaces adopted rather than the aquaponics application itself. On the one hand, generic tools used in the physical-to-virtual connection can vary from industrial protocols and applications developed by hardware and software companies to open source developments. For example, SQL, MySQL, or PHP are highly used for the transfer and storage of the data acquired, to build procedures, and control internal processes. Additionally, several IoT technologies are now available to build robust connections, e.g. wireless modules [39]. On the other hand the virtual-to-physical connection is mostly limited by the specific components chosen in the physical and virtual side, although in a few occasions, connections may be built using open source communication protocols at the risk of having cybersecurity issues.

Additionally, the dependence of communication protocols and physical devices increases when considering the incompatibility of physical devices and certain software or communication protocols. For example, taking the commercial controllers from the ABB Company (Allen Bradley PLC's), the communication system will solely rely on RsLinx, which is the communication protocol from the company that allow their PLC to send and receive information and be controlled remotely. The initial selection of the physical system brand determines the protocols and software that will be used to generate the digital twin.

Part of it can be avoided if the use of micro-controllers is implemented to control the physical environment. The development of the connection tools is easier since they are mostly open source and are available for the use with Raspberry Pi, Arduino, and other open-source controllers. Herein, the software or programming language that is used to build the interface is the main factor for the resources available, in which each case is different.

Finally, aquaponics metrology is often constructed through a series of sensors for the parameters, cameras, mathematical, and smart models installed in the grow beds and fish tanks. Realization refers to the reactive effect of the metrology part and makes use of the controller used and the metrology applied, while the twinning rate defines the heartbeat of the system. To display sensor results, asynchronous updating of its values occurs every second , however, if more complex processes are developed, such as prediction tools or optimal parameters adjustments, elapsed times around 5 minutes is a good option [22] . As aquaponic systems are slow dynamical processes, changes occur in the long term, enabling long synchronization of the digital twin and easing the introduction of complex and tedious tasks.

5.3. Aquaponics digital twin

5.3.1. Case of study

A case of study is developed to prove the concept of digital twin in aquaponics. The scope of the experimentation is limited to applying the concept in the hydroponics (grow beds) component of the aquaponics environment. For our case of study, Figure

5.3 illustrates the specific aquaponic components using the framework provided in the previous section.

Physical entity refers to the grow beds and the virtual entity to the built model that mimics it. The physical environment are all the components listed in the subsection 3.2 and the virtual environment are the virtual entity, information displayed, and the graphical user interface (GUI). The parameters are the sensor measurements. The values of the components are considered the state of the parameters.

The physical-virtual connection is achieved using a wireless sensing module, php, MySQL and the connection from visual studio to the database in the network. Here, the metrology is the action of sensing the parameters and the realization in the physical system corresponds to the database construction with the process of gathering and analyzed the raw data. The virtual-physical connection is executed using the IoT Core module and Visual Studio to control the outputs in the main controller. The metrology stage in this connection mode refers to the growth rate and fresh weight estimation

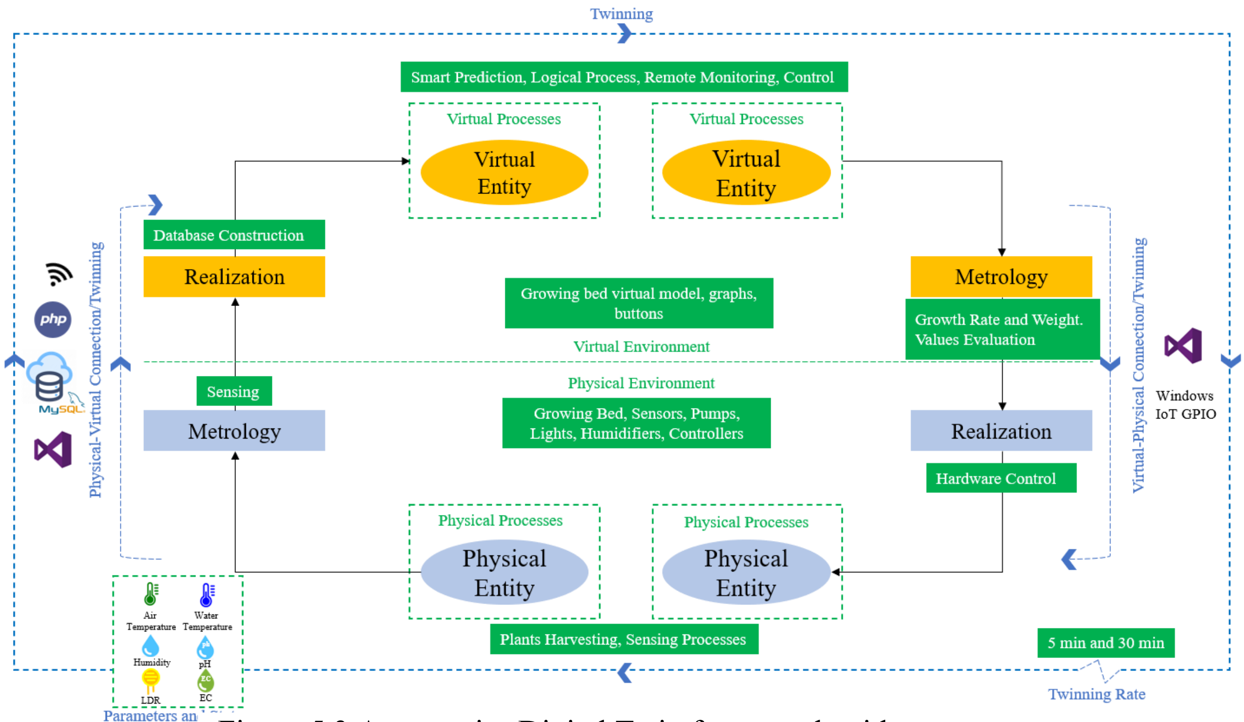

Figure 5.3 Aquaponics Digital Twin framework with components

using the prediction models and the logical process to evaluate the sensed values against the optimal levels. The realization on the other hand in this case is the action to turn on or off the outputs depending on the conditions. Physical processes are specifically the growing of the plants and the process involved (water flow, humidity, light) and the sensing of the parameters. Virtual processes correspond to the execution of the prediction process, the logical classification of the levels, and the remote monitoring and control of the system. Lastly, the twinning rate is determined by the one second for the displaying of the sensors values, five-minute interval between the database records and thirty-minutes time-lapse between predictions.

The project development will be explained following an explanatory process. First, the experimental setup will be described along the components installed and experimental principles such as frequency and working logic. Secondly, the process to calculate the growing rate and fresh weight estimation will be shortly explained. Third, the process used to construct the database will be introduced. Fourth, the twinning interface and the tools to build it will be presented. Fifth, the feedback loop from the virtual to the physical environment will be introduced, and the performed actions will be explained in detail.

5.3.2. Experimental Setup

A NFT hydroponic grow bed setup is designed and constructed for the experimentation part. The frame of the device was assembled using MDF (medium density fiber) board. This holds the NFT channel (grow bed) with a water pump and a heater, two cameras (one at the side and other one at the top of the grow bed), artificial growing lights, a camera ring light (to provide consistent light to the cameras), and a humidifier. As for the sensors introduced in the system, pH, electroconductivity, water temperature, air humidity, air temperature, and luminosity are used. For the main controller, a Raspberry Pi is selected, while an Arduino Nano is employed as the sensing unit.

To the Raspberry Pi, two cameras are connected and work with scheduled scripts that take pictures every 30 minutes from 6:00 am to 6:00 pm. The growing lights, the camera ring and the humidifier are connected to the 4-channel relay module which is triggered by outputs from the main controller. For the sensor modules, all of them are installed in an Arduino Nano with the corresponding configurations. The pH and electro conductivity sensors are connected to a 2-channel relay module to avoid measuring problems. Also, an ESP8266 Wi-Fi Sensor is installed in the Arduino, allowing the data to be transmitted wirelessly to the main controller (Raspberry Pi) and to the twining interface for real time sensor values display.

5.3.3. Growth rate and fresh weight estimation

The estimation of the grow rate and fresh weight of the leafy crops is done through a smart implementation using a predictive model for the localization and multi-instance segmentation of the plants. The model was constructed using the MASK-RCNN framework proposed by He et al. and the online repository by Waleed Abdulla[90]. The images acquired by the experimental setup are first conditioned to avoid radial and tangential distortion [88] and then the images are segmented using MASK-RCNN. From the prediction model, a script routine is created using Python to extract the parameters of interest which are listed in Table 3.1.

With these parameters the overall height, width and depth are calculated to derive the growing rate of the plants. A linear regression model is then created to describe the fresh weight of the plants, which is validated using experimental results. The fresh weight model is presented in Equation 3.18 with the values of linear regression coefficients in Table 3.6.

The whole model validation and explanation can be found in Chapter 3.

5.3.4. Database construction

Building the database is a key step towards the construction of this digital twin model and future uses of the model in knowledge discovery in databases (KDD) techniques. Regarding the digital twinning process, the mechanisms to send and receive information, the fidelity and accuracy of the information, and the twining rate are defined in this step. As per the experimental setup, six sensors are used to monitor the current state of the system: pH, electro conductivity, water temperature, relative humidity, air temperature, and light intensity. To ensure the future deployment of the system at larger scale, the sensing module is designed as an external device to the main controller, therefore an Arduino Nano is implemented for this task. The limitation about connectivity of the Arduino Nano is overcome using an ESP8266 wireless sensor that allows the controller to send data wirelessly to the main controller, a Raspberry Pi.

The IoT sensing module processes the values from the different sensors and sends the information through a digital access point to the Raspberry Pi every five minutes. The main controller formats and inserts the values in a MySQL database at the local level using PHP. During this process, a host computer executes a parallel process using the growth rate and fresh weight models and sends the obtained results to the main database every 30 minutes, synchronously with the other records. Figure 5.4 shows the model of the relational database designed with the tables and relationships used. In this figure can be seen the columns of each of the tables (i.e. sensors_records, masked_results, acc_masked_records and variables) and how they are related to each other.

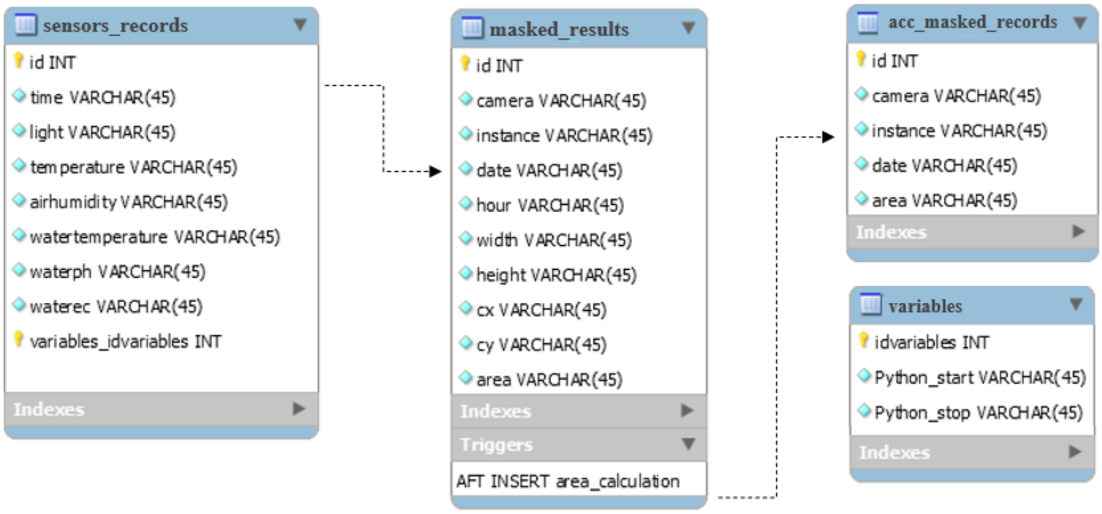

Figure 5.4 Model of the relational database implemented

In summary, a database that describes the current state of the system is available and can be accessed through an IP address from any point in the network. As such, this allows the communication between any devices in the network anytime. Further details are also described in a previous work [120]. Figure 5.5 displays the IoT sensing module interaction process.

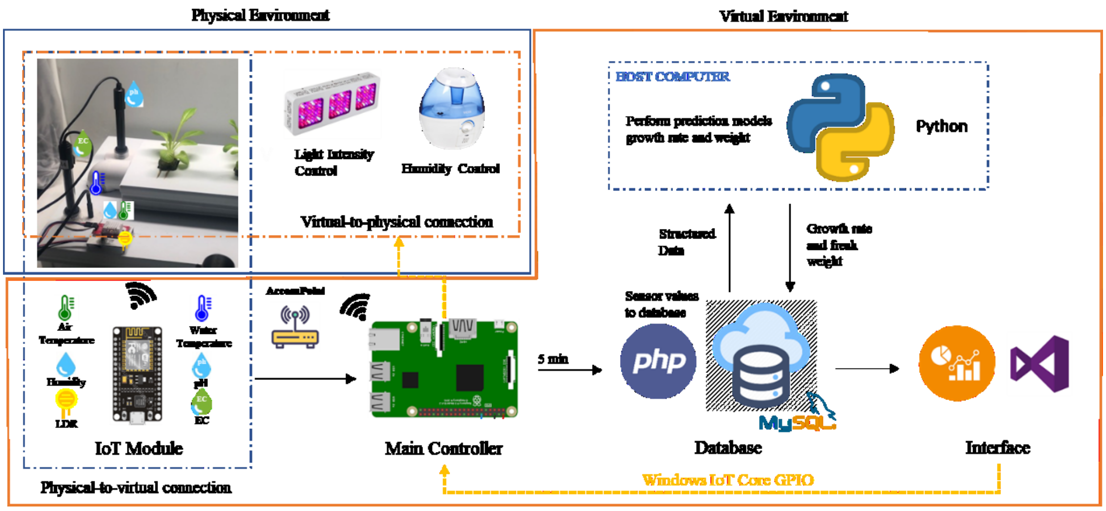

Figure 5.5 Wireless Sensing Module process for database construction

5.3.5. Twinning interface

One of the main benefits of digital twins is its ability to close the gap between the user and the digital process. This can be achieved by giving them a clear understanding about the state of the digital process and the internal activities performed [62]. Introducing a visualization tool in the digital twin process removes the idea of a 'digital black box', giving them total control and supervision of the system at the physical and virtual levels. The twinning interface concept describes the virtual graphical display of the system.

The graphical interface is designed using Visual Studio and it is directly connected to the database to retrieve the information it needs for displaying. Also, a direct connection to the IoT sensing module is done via serial communication, allowing to retrieve real-time sensed values every second. Six different windows are designed to offer the user organized and appropriate requested information, as shown in Figure 5.6, the different windows are 'Home', 'Sensors Tracking', 'Database', 'Imaging', 'Predictions' and 'About'.

In the 'Home' window Figure 5.6(a), a replica of the physical entity (NFT channel) is designed and acts as the main component of this interface. Interactive and resizable reproductions of the plants are modeled and the current size of the crops in the physical side at real time are mimicked in the virtual environment. Information about the growth rate and weight of each of the plant is displayed. For the plant's growth, a decision model is built to categorize the actual size of the plant and assign a stage from 1 to 12. This categorization is made calculating the growth area along the 15 days from previous runs, averaging them and dividing evenly throughout the 12 stages, thus every stage corresponds to an area interval (i.e. stage 1: 0 cm2 to 1 cm2). Based on this level, the scalable digital model that represents the plant current growth status is displayed to the user.

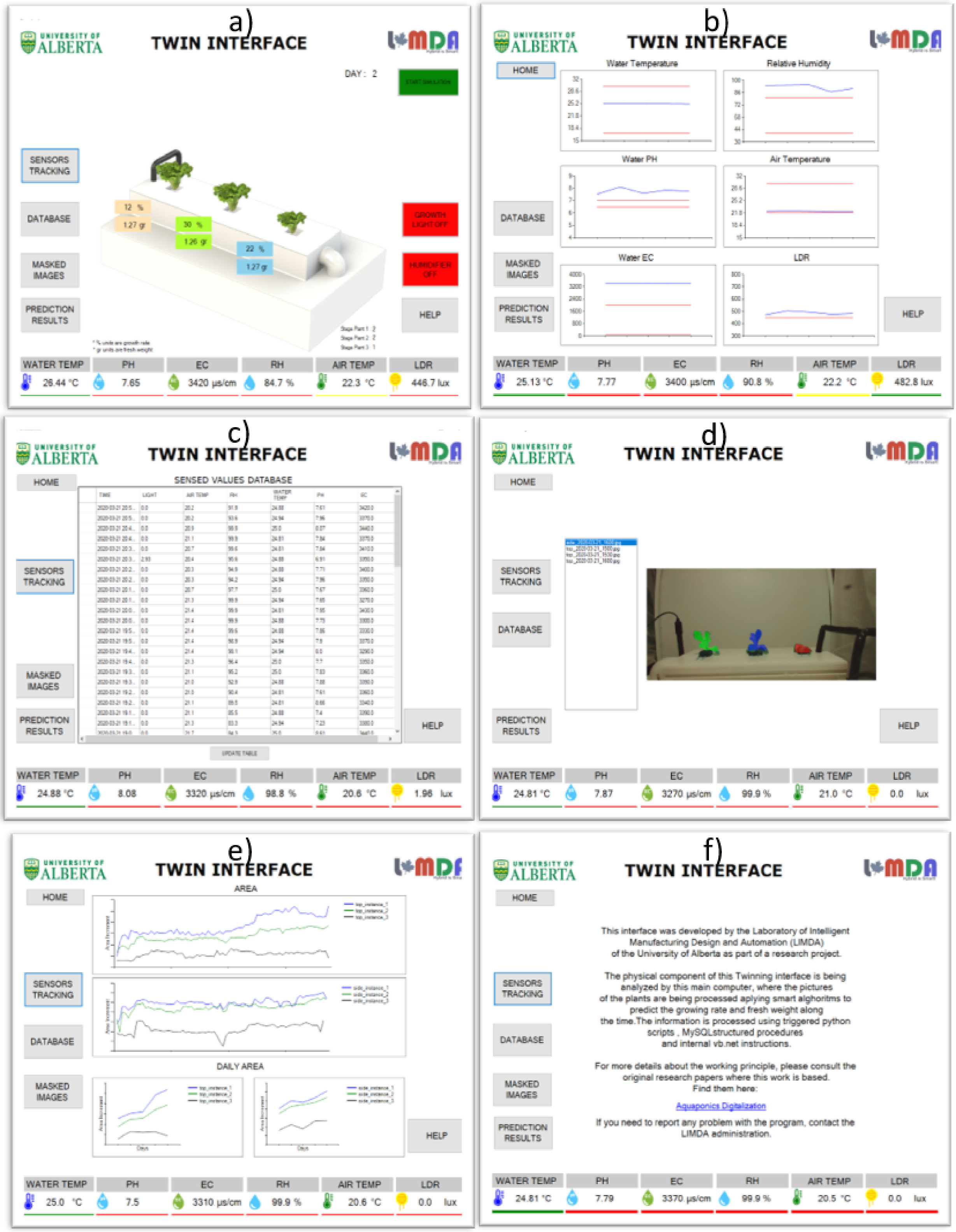

Figure 5.6 Digital twin interface: a) 'Home' window; b) 'Sensors Tracking' window; c) 'Database' window; d) 'Imaging' window; e) 'Predictions' window; f) 'About' window.

Window Figure 5.6(b) is named ‘Sensors Tracking’, where tracking graphs for each sensor are displayed with the historical values of the sensors and is updated every 5 minutes synchronously with the ‘sensors-records’ table. Figure 5.6 (c), the ‘Database’ window is where the all the entries of the ‘sensors-records’ are displayed.

Window Figure 5.6 (d), ‘Imaging’ gives the user the opportunity to visualize the segmentation output of the masked leafy vegetables, as seen in Figure 4, and to identify potential problems in the image processing results. As explained before, top and side pictures are taken of the plants every 30 minutes, with the purpose of extracting information about the state of the plants (Table 3.1). Once a new set of pictures is available, a Python script is executed to run a prediction model to identify the plants location and extract the features of each of them using instance segmentation. At this point the digital interface connects to a specific folder and retrieves the masked images to show them into the window ‘Masked images’ to the user. The features from the plants are saved into a MySQL table named ‘masked-results’. A structured procedure is designed into MySQL to be triggered by the insertion of a new value in this ‘masked-results’ table, therefore, it constantly calculates the average of the areas, height, width and depth features grouping by view, instance and date. This data is saved in a new table named ‘accumulative-masked-records’.

Window Figure 5.6 (e), the ‘Predictions’ window is where the predictive models used show their results. This window displays through graphs at the record level the side and top area of each of the plants and the daily calculations automatically made by the MySQL procedure.

The digital interface by itself calculates the growing rate based in the change in the area of the plant and the fresh weight of the plants using the values in named ‘accumulative-masked-records' and the logistic linear model shown in Equation 3.18 and Table 3.6. Lastly Figure 5.6 (f) displays information about the working principle of the interface.

All the windows share a lower banner that displays the current values of the sensors that are retrieved directly from the sensing module every second. A logical procedure is then developed to showcase the status of the grow bed at that moment. On the other hand, this parameter's values are saved every five minutes directly by the main controller (Raspberry Pi) into a MySQL table in the network called 'sensors-records'. After this evaluation, a three-color code similar to 'traffic lights' displays the current status when compared to predetermined correct ranges. For each parameter, the color chosen is assigned as green if the value is between the acceptable levels, yellow if it ends near the maximum or minimum (15 % from the limits), and red if the value is not conforming, displaying to the user not only the value but also the meaning of the read measurements in terms of performance and adequate grow environment for the plants. A summary of those parameter ranges is presented in Table 5.2 from [121]. Figure 5.7 shows the communication

Table 5.2 Optimal parameters for experimentation

Parameters	Aquaponic
pH	6.5-7.0
Electro-Conductivity	100-2000 µSiemens/cm
Water T	17°C -30°C
Relative Humidity	50 % - 80 %
Air Temperature	22°C -30°C
Light intensity	> 450 lux

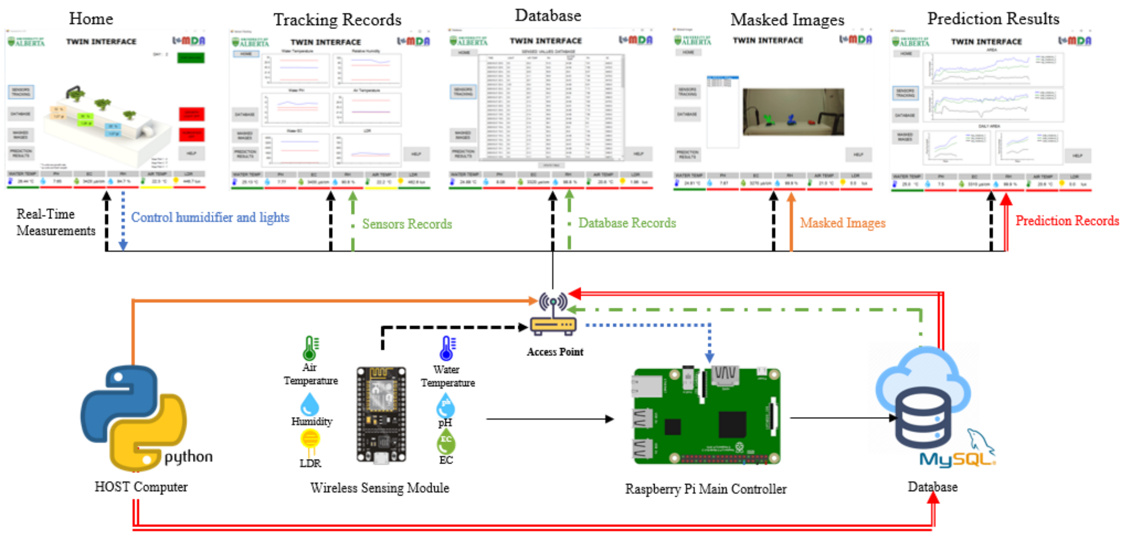

Figure 5.7 Communication of the interface, MySQL and physical component.

5.3.6. Feedback loop

Feedback loop refers to the virtual-physical connection and the way the virtual environment sends an action to be executed in the physical environment. This is possible using the IoT Core connection in Visual Studio. For this case study, simple orders for the feedback loop are designed to prove the concept: the main controller in the physical system is prepared with scripts to turn on and off the system growing lights, humidifiers, and ring lights for the cameras as requested.

After the twinning model retrieves the sensor information and evaluates if the levels in humidity or light intensity are in the correct range of values, it automatically sends a request to the Raspberry Pi to turn on, off, or adjust the specific device to reach adequate values. Also, this action can be performed manually by a set of buttons in the interface. All of the automatic decisions and changes made by the digital twin are logged and notified to the operator of the system via e-mail. Figure 5.8 illustrates this working principle.

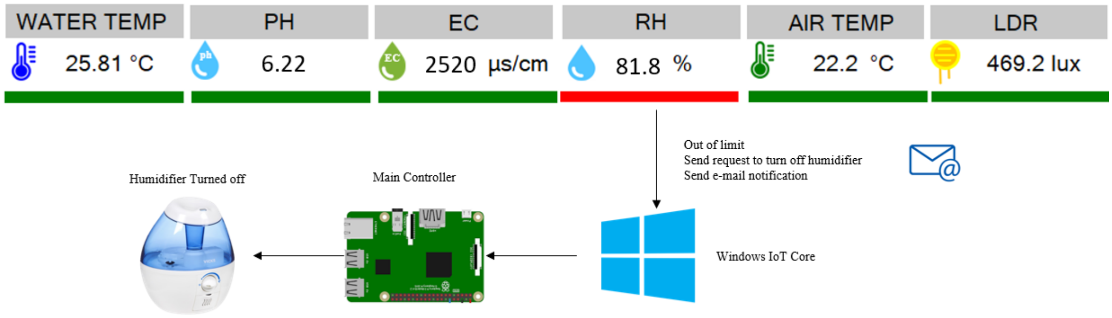

Figure 5.8 Feedback loop process

5.4. Results

5.4.1. Feedback control

Through the continuous analysis and monitoring of the data, it is possible to get a better understanding of the growing behavior of the plants. The presented system proves to be reliable at identifying trends and linking parameters of the environment to two design performance metrics, which is the initial step towards complex implementations. The research community and the aquaponics/hydroponics practitioners will highly benefit from this contribution. Figure 5.9 displays the growing behavior of the three different plants throughout the whole growth process and in a daily basis. From the figure can be note how the pixels area retrieved from the calculations is increasing in each of the instances either in the top view and side view, denoting the ability of the system to successfully monitor the growing behavior through the proposed DT proposed system. Furthermore, the daily calculation gives a better understanding averaging the area increment during the day giving to the operator the ability to easily understand the data. With this implementation, the user is constantly aware of the status of the sensors and, consequently, the plants, and can turn on-off system actuators at will, such as lights and humidifiers. Furthermore, live data can be analyzed almost instantaneously with the use of KDD algorithms that for example allow the system to estimate the growth rate of the plants and predict their weight. As such, a complete understanding of the process can be presented with not only status of the parameters but also the incidence of them in the outputs (performance metrics).

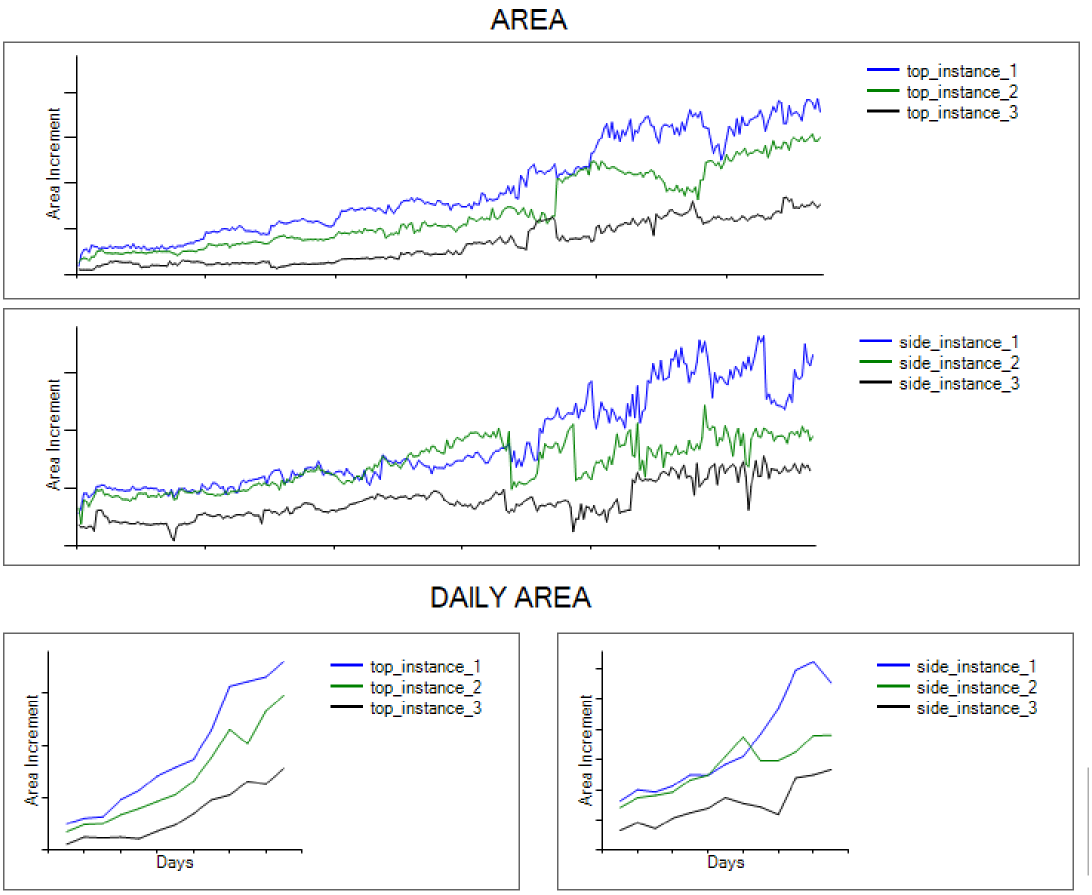

Figure 5.9 Growing process of plants during validation

From the results obtained during the experimentation, it is noted that plant #1 had an overall growth rate of 15 %, with a side growth rate of 14.7 % and a top growth rate of 15.6 %. The average growth rate in the plant #2 is 14.46 %, the side growth rate is 10.25 % and the top growth rate is 18.67%. For plant #3, the average growth rate is 23 %, with a side growth rate of 22.73 % and top growth rate of 23.16 %. As observed, plants growing under the same conditions theoretically, do grow at different rates. One of the limitations of the presented study is that some design and physical aspects of the aquaponics system, such as air flow in the system or distance between plants, are not included. This limits the potential modeling of the growth rate of the plants based on the data obtained using the proposed system. To extend the proposed system to include these factors, among others, will be pursued by the authors in the near future.

Further analysis can be done by comparing, not only the daily growth rates, but the daytime growth rates versus the nightly growth rates. In this study, it is found notoriously that plants growth faster during the morning/afternoon, with an average growth rate of 28 %, while growth is reduced to an average of 16 % during the evening/night. Similarly, analyzing other records from the sensing values during the experimentation, it is interesting to find that the pH values of the water are slightly higher during the morning with an average of 0.15 difference, with average values of 6.9 and 7.05 respectively. The opposite effect can be found about the electroconductivity, where higher values are consistently found during the nights with average of 2500 μSiemens/cm and 2550 μSiemens/cm respectively. Another finding, which is more intuitive, is about the relative humidity behaviour: higher values are found at night, with values around 15%-20% higher in comparison with the morning hours. As such, based on the empirical evidence for the plants studied, different resources' consumption and control strategies might be needed for different hours of the day, while keeping the objective of maximizing the growth of the plant at the end of the day and throughout the whole growth process.

Some limitations about this framework and system will be addressed in future work. A generic digital twin framework is adapted to the aquaponics technology; however, the scope is limited to the resources available: the hydroponics beds. Including the fish tank and corresponding systems, namely bio filters, feeding systems, etc., of the aquaponics system in future developments is necessary to finalize the complete digital twinning of the process. Monitoring the weight of the fish (density in the tanks), assess their health and include the inherent associated parameters, such ammonia transformation and dissolved oxygen, will definitely open more possibilities regarding the control and optimization of the process. Finally, the digital twin aquaponics framework can be validated as a whole in future developments.

5.5. Conclusions

Aquaponics is becoming a popular method as a sustainable solution for indoor food production. Under the background of 'Industrial 4.0', the digital twin technology has been widely used as a tool to realize the interaction and interconnection between physical and virtual spaces. This paper describes the framework and implementation of the digital twin technology for the hydroponic component of an aquaponic system. By integrating IoT technology, databases, control strategies, artificial intelligence, and visualization tools, the virtual model of the physical system can be created, updated to reflect status changes in real-time, and represents a comprehensive reference for aquaponic users.

The presented study showcases the use of the digital twin platform to acquire data in real-time, make use of data-driven algorithms to determine growth rate and fresh weight, and take informed decisions towards a healthy aquaponic environment. Ultimately, it presents a platform towards optimizing crop yield in aquaponic systems. The benefit of this paper for research and practitioners is the provision of an integrated detailed framework for digital twinning, which is to be enriched to determine optimal functionality of aquaponic systems and provide clear performance metrics that support commercialization of the aquaponics technology.

Chapter 6 Conclusion

6.1. General conclusion

Aquaponics has become a trending technology for those that are looking to adopt and develop sustainable and environmentally friendly food production systems. Its capacity to achieve a green transformation of fish aquaculture waste supports the reduction of environmental pollution and it's becoming one of the more promising food production systems for the near future, overcoming the environmental problems and food scarcity the world is facing. Although aquaponics started to become adopted in several countries, the complex relationship between this components (complex management) and the limited available crop and fish species suitable for this technology nowadays makes difficult its adoption at commercial scale which impacts its availability and widespread benefits.

Along this thesis, the main followed idea is to enhance the use of precision farming in aquaponics, to increase the understanding of this technology, and to implement tools that reduce the management complexity of the systems, increase understanding of the process, ease the monitoring of the parameters and predict their optimal relationship.

In Chapter 2, a systematic analysis is presented first to explore the state of the art and future trends of aquaponics systems, with a special focus on sensing parameters, smart, and IoT technologies. The study in this chapter presents the information necessary to simplify the decision-making process regarding the setup of sensors and the adoption of new technologies, presenting a clear scenario of the research trends in this area in aquaponics. This chapter, then, contributes by giving aquaponics experts' technical knowledge about automation, IoT, and smart systems; and automation expert's knowledge regarding the biological processes happening in aquaponic systems. Creating a bridge towards scaled up aquaponics systems will accelerate contributions in the area and enable viability in commercial solutions.

In Chapter 3, following the objectives in the thesis, it is presented the introduction of computer visions systems in aquaponics grow beds as a feasible tool due its non-destructive and contactless features. In this study, a tool to predict and calculate two key performance metrics in aquaponics is presented and validated. The growth of plants is estimated within 30 mm of error for both length and width, and fresh weight is estimated within less than 0.5 g of error. The method proposed proves to be accurate and flexible enough to be used in real scenarios and is not limited to one instance segmentation or manual image processing techniques that can be easily disturbed by the potential changes in the environment where this crops are growth. Through the methods used, the possibility to rely on smart algorithms that can be constantly improved is presented.

In Chapter 4, an introduction of aquaponic system that makes use of wireless technologies and IoT frameworks is reported. The main contribution that is achieved in this chapter is the ability to link online measurements to real-time performance metrics as discussed in the chapter 3, opening the possibilities to perform further analysis about correlations between optimal parameters. Also, the high flexibility of this system offers the opportunity to adopt it at a commercial scale since it is not limited to standalone execution and it communicates with a central controller that processes the data and can receive information from multiple locations.

In Chapter 5, the concept of digital twin (DT), as widely studied in other industries such as manufacturing, maintenance, or design, is introduced to the aquaponics technology to leverage its physical system capabilities with the use of digital tools. The study presented proposes a DT framework for aquaponics that explains each of its components and gives a better understanding about how this process can be used and enriched to determine optimal functionality of aquaponic systems and provide clear performance metrics that support commercialization of the aquaponics technology. Through a case of study, this chapter makes use of data-driven application to determine the growth rate and fresh weight of the plants, by retrieving real-time values of parameters through a digital interface that, then, takes informed decisions towards a healthy aquaponic environment.

6.2. Research contributions

The contributions of this research work were clearly described along each chapter and are summarized as follows:

- Bridge the knowledge areas between biological and automation experts with aquaponics as a common ground, increasing the mutual understanding and promoting interdisciplinary contributions both ways.
- Two well defined performance metrics developments that use new engineering techniques (computer vision, image processing, smart learning algorithms) to monitor and predict crop's behavior.
- Digital twin framework for aquaponics that supports the implementation of digital tools easing the adoption of them by aquaponics practitioners and operators.

6.3. Research limitations

This research is subject to the following limitations:

- Small experimental setup that due its size, brings inherent limitations related to the space, crops to grow, and experimental time.
- Limited budget for the hardware selection such as cameras, sensors and lights that limit the capabilities of the experimentation (resolution, robustness).
- Due to certifications requirements, the aquaculture tanks are not part of the experimentation and it was limited to the hydroponics component of the process.

6.4. Future research

- More experimentation is needed to find reliable results about optimal parameters and the relationship between growth rates and sensed values.
- The introduction of the aquaculture tank will bring the possibility to experiment and train algorithms that involve this component. Work towards the whole system optimization or quality systems in the fish tank will be approached in future studies.
- The fabrication of a fully automated racking system for the hydroponics components is in process.

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