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A Decision Support System for Urban Agriculture Using Digital Twin: A Case Study With Aquaponics

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ABSTRACT There are many pressures on the global food system such as urbanization, climate change, and environmental degradation. Urban agriculture is an approach to producing food inside cities where, globally, more than half the worlds population live. It has been shown to have a range of potential benefits, for instance in reducing waste and logistics costs. Increased uptake of urban farming can even relieve pressure on the natural environment by reducing the burden of production required from farmland by creating space for it to recover from accumulated damage as a result of the use of unsustainable farming practices historically. This article describes an approach for a new type of decision support system suitable for urban farming production. We discuss differences between the requirements and the users of decision support in urban agriculture, and those of ordinary agribusiness enterprises. A case study is performed using a novel technology for urban farming: a cyber-physical implementation of aquaponics is enhanced with adaptive capabilities using a digital twin system and machine learning. Aquaponics is a farming technique that utilizes a harmonious nutrient exchange cycle for growing plants and fish together, while conserving water, and possibly without the need for soil or even sunlight. Empirical results are provided that evaluate the use of data driven decision analytics and a digital twin model to plan production from the aquaponic system during a three month trial. Another set of results evaluate a proposed modelling framework for large scale urban agriculture ecosystems. This concept forms the basis of the suggested approach for an urban farming decision support system that coordinates the activities of many independent producers to target collective goals.

INDEX TERMS Decision support, urban agriculture, modelling, simulation, digital twin, Internet of Things, metaheuristics.

I. INTRODUCTION

This paper presents a design for decision support of a novel farming methodology in which many different production units can be synchronized together to respond to consumer demand in a way that minimizes waste. Initial results are also included. Simulation, optimization, and elements of cyber-physical systems are used to optimize farming in a setting that is complex due to interrelated natural, human, economic, social, engineering, and sustainability aspects. Urban agriculture is a wide ranging set of approaches to farming that bring food production directly into cities, and as a result can create benefits of increased food security and sustainability overall [1], [2]. In the result section we evaluate the efficacy of a model based digital twin approach, and a machine learning approach for performing predictive decision analytics to predict production from urban farming (a scalable "aquaponics" installation). We also evaluate the ability of a modelling framework to generate meaningful insights about urban agriculture system design as a step towards a decision support system that uses an online simulation to coordinate many urban farms together in a food system that is enhanced with an Internet of Things infrastructure.

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The environment and users of a decision support system for urban agriculture are different from the situation and users of decision support systems for traditional agriculture. The urban setting and stakeholders interact in a fundamentally more complex way. There are also novel opportunities to design different farming paradigms and different ways of farming. Including different ownership structures where farmers and consumers may not be clearly delineated, and there are different challenges for the logistics of distribution, inventory, and waste. Especially if the potential urban agriculture benefits are to be fulfilled.

The main premise of the proposed decision support system is that using a networked infrastructure, such as promoted in ''smart cities'', and decision analytics and online simulation, it will be possible for diverse independent urban farming installations scattered throughout an urban area to work in a coordinated way so that production from urban farming could be scaled up to compete with the volume and consistency of traditional agribusiness [3]. While maintaining, and optimizing, the social and environmental benefits inherent to urban agriculture [2], [4].

There is a movement in international bodies towards ensuring farming engages whole communities and avoiding top down solutions [5], [6]. With more people living in cities urban agriculture brings humans into proximity with food production and this creates whole range of interesting dynamics where the people living in cities can to a greater or lesser extent support their own food production. Changing the food production and distribution network to have food consumers taking on roles as producers whether for their neighbours and others sharing the urban environment would lead to new types of business and market opportunities, and patterns of engagement and farming. There are parallels in the way the business models of electricity utilities responded to rooftop solar panels [7], and how this changed the way the stakeholders interact when consumers of electricity resell electricity generated. Because farming is a fundamental human activity a range of far reaching tangible and intangible benefits can also be elucidated. Benefits of urban agriculture have been identified in food security, resilience to climate disruption, environmental sustainability, and positive economic and social outcomes [8].

Aquaponics is a particular farming technology that makes use of the symbiotic relationship between plants and fish in a specially constructed system. Water cycles between fish and plants, micro bacteria are used to break down fish waste and these nutrients nourish plants such as vegetables and other crops [9]. A system of tanks, pumps, and filters moves water and nutrients between plants and fish and the whole system can be monitored and controlled based on sensor feedback in a cyber physical system [10]. The only ongoing input is fish food, while water can be conserved and recirculated since by the activity of the micro bacteria the nutrients don't reach dangerous concentrations for the fish and also the water remains oxygenated. An aquaponic installation may be viewed as a type of artificially controlled ecosystem [11]. Research looking specifically at aquaponics in various locations and contexts but especially in low and middle income countries is often focused on food security [12]. It has been used in extreme food security situations, for example the United Nations Food and Agriculture Organization (UNFAO) spearheaded a successful project promoting aquaponics in the Gaza strip, an arid and dense urban area in protracted crisis.[1] Food security is an issue with varying degrees of acuteness in many places and aquaponics has been tested in locations such as China, Singapore, Bangladesh, and Australia [13]–[15].

Aquaponic installations are complex systems. By updating simulation states in real-time with feedback read from sensors the modelling accuracy can be improved to enable better predictions. For example, responding to unforeseen system states such as may arise from equipment failure or other deviations between the model projections and the real farming system. In aquaponics, as well as farming generally, complexity arises from the interaction of natural and human elements [16] and results in the formation of a complex, at times unpredictable, system. Reasons include the heterogeneity of elements such as plants and fish in aquaponics, the presence of processes with non-linear dynamics (for example plant growth, nutrient production rates), the presence of thresholds, and the existence of feedback loops. The system behaves differently depending on threshold levels of concentrations of nutrients and these in turn cause further changes in system dynamics in a feedback loop, see Section IV-B3 for further discussion. Because it is a complex system, we identify simulation as well as data driven analytics, particularly machine learning, in order to allow models of the system behaviour to dynamically adapt, and also to optimize meeting farming system goals such production, waste efficiency, and quality criteria.

New ways of modelling and approaches decision support are required to handle new production methodologies that are possible in urban agriculture. Decision support for traditional agrifood logistics are designed for a highly controlled, hierarchical supply chain and inventory management supply and demand chain [17], however many benefits from urban farming could be attained by taking into account a decentralized system of cooperating stake holders, living in cities, with diverse goals. Besides, novel farming methods such as aquaponics and other techniques for urban farming [18] have different entities, concepts, and design elements compared to established farming where agricultural decision support is usually applied. Co-location of production and consumption, as can occur with urban agriculture, changes logistics and creates fluidity between roles of farmer and consumer. This can lead to new business models as has been observed with energy when consumers resell solar energy and they become ''prosumers'' [7]. Food could be produced locally by individuals living in cities based on local demand and distributed without needing long term storage. This could lead to revolutionary changes in the operation of the food demand chain and has a potential for reducing waste such as

[1] http://www.fao.org/3/a-i5620e.pdf

by matching supply with demand [19]. This would require a decision support system to consider many competing issues such as a possible trade-off between waste minimization and food security for instance. The ability to implement optimization in settings and consider this type of risk management is a focus of the decision support system proposed in this paper, it necessitates a detailed model of the food system from production to consumption.

Situating agricultural activities in cities creates new layers of complexity that are not present in other farm settings. It results in biological, ecological, social, and economic systems interacting together, and the resultant complexity mean that it may be difficult to predict outcomes or to coordinate farms and target specific goals for producing food. However, in order to implement large scale production in cities it is necessary to be able to predict and control production. Other researchers have also observed that "a future food production system in a smart city context calls for a new type of decision support system" [20]. In this paper, we consider decision support required for urban farming at two main different scales. First, at the smallest scale of a single production unit, we develop methods for optimization of production to meet unit targets (in this paper the prototype for individual units are aquaponic installations but the concepts are more generally applicable). At a larger scale, we examine the problem of a decision support system for coordinating a set of farms to realize a wide range of system goals.

At the local unit scale, parameters such as the amount of water pumped, the power of lights, and so on, can be set and updated, at higher scales consumer demand distributions, logistics issues, even traffic, and stock levels can be tracked. The system may have to be reconfigured to target new goals and objectives sent from a coordination module or when unusual events occur such as component failure, unexpected crop or fish behaviour, or holiday demand. In experiments from an actual aquaponic installation, we study the performance of the approach and examine the use of dynamic simulation modelling to predict key system variables related to production and also a model free, data driven, machine learning approach. At the level of coordinating a city wide urban production system we define a framework for consolidating multiple urban type farming units and report initial experiments using data from the city of Shenzhen, China.

A digital twin is a virtual representation of a real system that is, in general, implemented using simulation. We apply the paradigm of a Dynamic Data Driven Application System (DDDAS) [21], [22] to support the close coupling that is required between a real system and the virtual representation. In a DDDAS, sensor data and the simulation model are closely coupled in a real-time feedback loop to reflect the environment as it evolves in real time [23]. Currently there is limited research looking at applying digital twin for modelling biological processes or systems in which man made and natural systems interact such as farming. The majority of applications of the digital twin concept are in manufacturing. Earlier versions of some of this work was introduced in earlier conference publications, see [4], [24] and [25], with the latter receiving the Best Paper Award in AsiaSim 2019.[2]

The contributions of this article are summarized as follows:

- *Design for Distributed Urban Agriculture Planning and Decision Support System:* Urban agriculture calls for a new type of decision support system that supports many independent users and stakeholders who are autonomous and may be in competition.
- *IoT Aquaponics Unit:* A cyber-physical aquaponic farming system prototype.
- *Analytics for Predicting Aquaponic Production:* Machine learning is applied to predict system variables that relate to production rates in an aquaponic installation using sensor data.
- *Digital Twin of an Aquaponic Unit:* We provide an implementation of a digital twin of the aquaponic unit. We compare the performance of a digital twin model to predict production variables with the machine learning approach. It is also required to update the model by ingesting new data to re-calibrate the model with the real system, this is facilitated by the cyber-physical design.

The rest of the paper is structured as follows: section II describes background and related work; section 3 describes a planning and decision support system for coordinating multiple farms and planning agriculture initiatives at the city level; section 4 describes the cyber-physical aquaponic system that was developed; section 5 provides results and empirical analysis; and section 6 concludes the paper.

II. BACKGROUND

This section reviews the urban farming practice itself using aquaponic installations with degrees of intelligent control from simple rules to analytics, further, we discuss differences, and gaps, in requirements for decision support in urban agriculture versus "traditional" large scale agribusiness.

A. DECISION SUPPORT SYSTEMS AND URBAN AGRICULTURE

The food system that supports modern societies requires not just farming but also extensive logistics (packaging, distribution, storage, refrigeration, and so forth) before retail. In urban farming some aspects of logistics are simplified, such as reducing the need for moving food over long distances, and others more complex because the metropolitan setting creates additional constraints and participants.

Objectives of agricultural systems to optimize include subsets of the following: production volume, quality, farming profitability [17], [26], food safety [27], reducing food miles, and others. When considering urban agriculture there are some goals that are not relevant in traditional agricultural production (also goals that take on added importance for urban farming). These goals are related to sustainability, food security, the economics of interacting farmers and other city dwellers, and many diverse social and

[2] http://ssagsg.org/AsiaSim2019/

environmental considerations. An example of a social goal only relevant for urban farming is to increase life quality metrics of people living in cities by their being involved in farming with intrinsic benefit gained from the activity [8], employment and other considerations are also relevant.

Urban agriculture includes many different farming techniques. Examples from the literature include vertical farming [2], roof-top farming, controlled environment agriculture, vacant lots and guerilla gardening [1]. Most take place at a smaller scale than agriculture enterprises which have, at least in most parts of the world, been consolidated and integrated to become even larger during recent decades [28]. Economies of scale, efficiencies, and market control in agribusiness supply chains result from larger farms and unified ownership has some business benefits [29].

Coordinating multiple urban producing farms, of different types and at different scales, each with differing degrees of independence for the benefit of different stakeholders is another approach. Using technology to improve efficiency instead of hierarchy, this kind of distributed approach may also be a viable way for feeding large populations with urban farming. Instead of massive centrally managed farms multiple small and large urban farming projects may be coupled while allowing for different degrees of autonomy and ownership. Coordinating production from these urban farms to target unified goals taking into account local demand, constraints, and objectives, is the rationale for *a new type of decision support system* that could improve the feasibility of urban agriculture as a means to support many people. That is by feeding more people by increasing the production from urban food systems and still keeping (or even enhancing) benefits such as reducing waste, shrinking the environmental footprint required for food production, providing resilient food security through local availability, reducing food miles [30], and community engagement and participation.

In recent decades, farmers have been quick to apply innovations such as remote sensing technology, IoT integration, and decision analytics, historically, farming has been at the forefront of human innovation, and among modern industries agriculture has often continued to lead in the adoption of technology [3]. Precision agriculture [31] involves using sensors and IoT systems to more ‘‘precisely’’ control farming activities, the control loop is the key element in these systems. Remote sensors of many types monitor variables such as soil moisture, crop development stages, weather, and more, this data can be used to perform tasks and also adjust levers that farmers know influence production goals [32], [33]. Cloud based applications can facilitate more advanced ways of using of data in precision agriculture and power computationally intensive processes such as optimization [34], cloud systems also assist with integrating farm production with upstream parts of the supply chain.

Knowledge co-production is a way of generating knowledge in which technical experts and society produce new knowledge and technologies together. Rather than groups with specific expertise, technocrats, deciding what is important for non-experts an iterative and cooperative exchange takes place [35]. Agriculture innovation that affects the way society runs is more likely to be successful when it takes into account local constraints and stakeholders as opposed to imposing technology externally [6]. This is considered in the proposed decision support system. Agent based simulation is applied in planning, refining, and monitoring the operation of an urban agriculture system and it enables planners to pose high level stylistic type questions [16] to evaluate different policy ideas using what if analysis to assess wide ranging impacts. If applied appropriately, such as by local governments, this could facilitate engagement with an expanded set of different users of the decision support system. In urban agriculture, such an approach is even more important because many stakeholders with conflicting objectives interact closely in cities.

This brings us to another related body of research not usually associated with decision support systems for profit making enterprises but rather focused on social sciences and environmental studies. This literature looks at modelling land use and the human environment interaction more broadly to understand environmental, social, and economic contexts. For example changes in the environment and land use as it evolves over time due to farming and natural environment dynamics and is influenced by policies of different kinds. This requires modelling not just one organization or enterprise but many independent entities. Agent Based Modelling has been successfully used in this type of research [36], [37].

Models have been developed of human-environment interactions in rural settings that predict the impact of social and economic factors such as household income on shifts in land use as well as taking into account a wide variety of other endogenous and exogenous factors [38]. Textured models of land use change that with multiple spatial and temporal scales are of benefit in producing accurate predictions using models that take into account complex dynamics [39]. There is limited research that is focused on urban farms not rural settings. Modelling the urban environment with farming requires that many additional systems are considered such as population, infrastructure, even traffic. An urban agrifood system also has a fundamentally different supply chain structure with less emphasis on storage, flatter hierarchies, and closer coupling, see Figure 1. Smart cities provide a platform for the sensors and network infrastructure that is required to implement the integration of the additional systems for modelling that are needed for the proposed decision support system for urban farming, including coordination of independent entities and online model updates [40].

The paradigm of Dynamic Data Driven Application Systems (DDDAS) formalizes the methodology. DDDAS have been used in other domains as a powerful tool to connect virtual representations of systems with their physical counterparts in real time [41]–[43]. Global optimization techniques, for example evolutionary algorithms and other meta-heuristics, can be applied to optimize over complex system models such as agent models [44]. Highly detailed

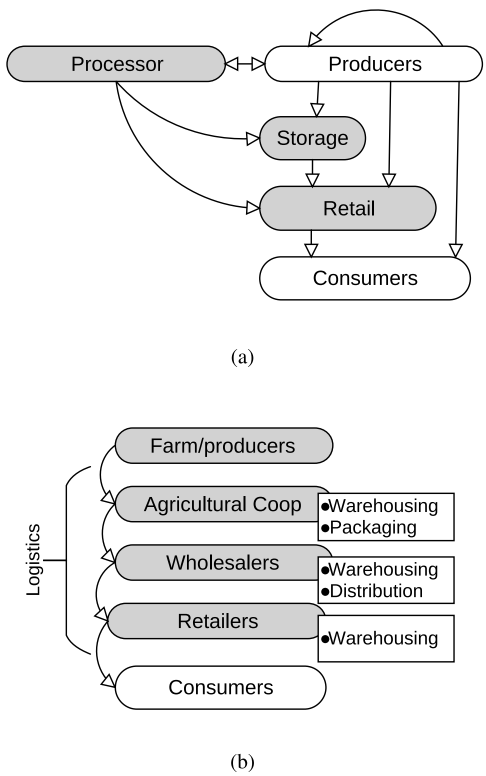


FIGURE 1. **Logistics in (a) urban, and (b), traditional agriculture supply chains.**

agent based models can enable recommendations to take into account the complex interplay of nature, human activity, and technology to predict emergent system behaviour [36] in a highly flexible way difficult to do with other approaches. For example it is possible to simulate dependencies between logistics, sustainability, and food quality to model dynamics that emerge from changing rules that govern interactions between various interacting entities [45]; and to predict the effect of agricultural policy decisions of social and economic variables [37]. In sections III and V-A we describe an agent modelling framework for urban agriculture that builds on this research.

In the next subsection we review existing cyber-physical applications in aquaponics. This is to focus on the particular instance of urban farming that is testing in this paper. In the later sections evaluate enhancement of cyber-physical aquaponics using digital twins.

B. ENHANCED AQUAPONIC SYSTEM

An aquaponic installation is a controlled environment in which fish and plants are farmed together in a way that enhances both production of fish and crops. The fish waste products give nutrition to the plants, while plants, and micro bacteria, purify the water in which the fish live. Natural or artificial grow lights may be used. The main components are a tank for fish and a grow bed for plants which are connected by pipes and pumps. Section IV describes the details of the implementation that is used in this paper. In this section we review the state of the art in technological enhancement of aquaponic installations with "cyber physical" concepts and methods. That is engineered systems that are built with, and depend upon, the integration of computation and physical components [46].

Recent work reports implementation of aquaponic systems that use sensors for monitoring parameters such as water quality (measured by PH or turbidity) in the tanks, and then make adjustments to optimize the operational behaviour. For instance a small scale implementation with a goal to grow high quality "local" organic produce is reported in [47]. Sensor readings can be directly used to adjust system settings using simple rules in a similar way to precision agriculture control loops. Control and optimization are both important elements in precision agriculture, the majority of case studies in the literature are not using data driven methods and optimization to optimize the whole system behaviour, instead these types of systems manage by setting key parameters with if-then type rules that use readings from one or more sensors [48]. Similarly, we observe this is the case in literature specifically on aquaponic installations. The cyber-physical aquaponics systems that we review here implement rule based analytics models to control system variables/components/activities directly from sensor observations. Examples are to add fish food with a timer, to alter the water levels in the fish or grow tanks directly from sensors of water level, to recirculate between fish tank and grow bed, to turn on/off the grow light with a timer, to adjust the PH level by adding a base if a PH sensor records a deviation near a preset acidity threshold, and so on.

Low cost integrated monitoring and control is possible using micro processing devices to coordinate networked components, process sensor data feeds, and apply rules. For instance, in [49] a Rasberry Pi microprocessor monitors PH, temperature and dissolved oxygen levels. In [50] they focus on monitoring water PH and adjusting it to influence plant and fish growth rates. A mobile application to monitor temperature and humidity is described in [51], on the basis of sensor readings a fan, water pump and mist maker are remotely activated/controlled. Other similar systems use Intel Edison or Ardino microprocessors [52].

To our knowledge, the cyber physical aquaponic systems discussed in the literature at present do not attempt optimization of the whole system, rather sub-systems are controlled by local optimization processes or decision rules based on prior assumptions [50], [51], [53]. This may be because of the limited processing capacity of small micro processors to support more computationally intensive modelling, machine learning, and global optimization procedures [54].

III. PLANNING AND OPERATIONAL COORDINATION OF AN URBAN FARM SYSTEM

An important element of the proposed approach is the use of streaming data from sensors, and external simulations, being used to update and possibly refine the models used in system state representations and for generating projections.

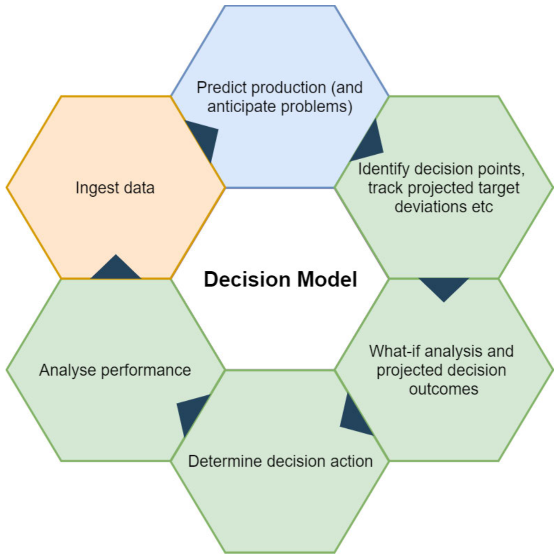


FIGURE 2. Iterative decision process.

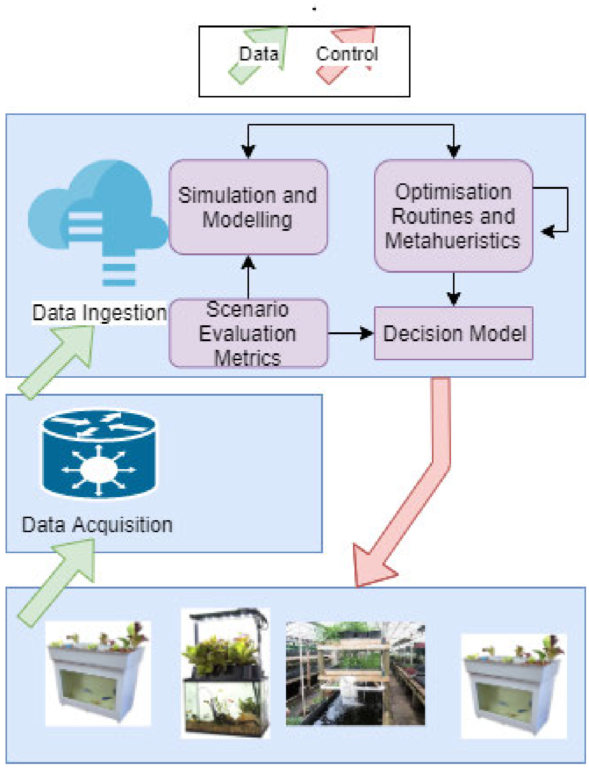


FIGURE 3. System wide optimization through application layer. Multiple farming units are able to be coordinated and optimized from a shared control process.

Simulation outputs can also guide data collection. These techniques enable advanced data-driven simulation capabilities that can provide more accurate analysis and prediction through dynamic augmentation of models with data inputs. Steps in the decision process module are specified in an iterative process where data is ingested into the system, extrapolated, and used to anticipate the behaviour and track adherence to a dynamic production plan. It is iterative because as new data is read the performance is analyzed again and the process repeats. Figure 2 summarizes this cycle.

A. DECISION SUPPORT SYSTEM OVERVIEW

A decision support system for urban agriculture needs to take into account the urban environment. An agent based model of urban agriculture is developed to handle the complexity of nature and human interactions with logistics, operations, and other relevant urban systems. An agent model for urban agriculture has different requirements from agent models for agriculture that are described in the literature for traditional farming. The potential to reduce the distance needed to transport food by the co-location of production and consumption creates opportunities that are not a focus of the food supply chain in conventional agribusiness, see figure 1. As an example there is a possibility to reduce food waste by recycling food waste as fertilizer but this should take into account social and environmental dimensions such as spatial distribution of farms and housing in a city environment. This section describes the design of a proposed agent based model for urban agriculture.

The decision support system has two main use cases. The first problem is urban food system planning and design for strategic planning decisions. Such as selecting farming technologies to be promoted by policy and the way farms are spread across a city, the purpose is to design a food system that can increase the effectiveness of an urban food system before it is implemented or if changes are proposed. The second use case is operational management. This case is supported by using real time data from sensors to perform adaptive control and tactical management. The decision support system would connect different stakeholders and allow them to coordinate activities via a gateway. These users would include farm installations, retailers, distributors and consumers.

Figure 3 shows the concept of using a dynamic data driven application system in which an agent based model of the city is continually updated with real data from sensors. There are several stages of processing from the level of individual farms, to data acquisition which merges data across the different farms, to a cloud based global modelling and optimization unit. Based on the optimization process, feedback such as to adjust production in different ways would be implemented. The main elements considered include categories of farm production, food storage and distribution, consumer demand, and nutrition. Production creates a "push" dynamic where food is produced and passed on to retailers, and consumer demand results in a "pull" dynamic where specific types of produce may be "requested". There is a requirement for consumers and producers to blend roles and have numerous small scale producers joining in production activities. Geographic Information Systems (GIS) and demographic characteristics of the urban environment are included as further data sources to construct the model.

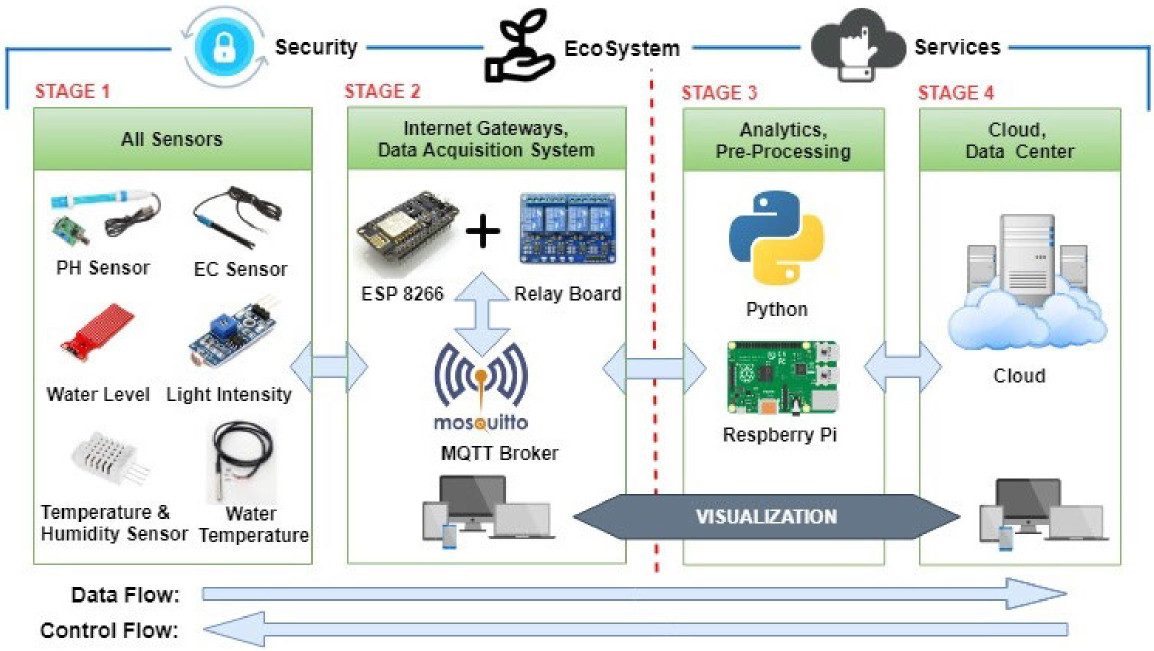


FIGURE 4. Architecture and components used in the food production system. Control and co-ordination takes place at the farming units through an initial pre-processing stage. Additional processing is on applications running on a PC or in a cloud data center. This allows more advanced analytics and modelling processes to be supported.

Figure 4 shows the system architecture required to implement the system from the level of individual farms, data acquisition, and up via a preprocessing step to enable further coordination in the cloud layer where global optimization and advanced predictive analytics and modelling capabilities can be implemented. The steps from sensors to preprocessing are discussed with reference to specific components to make the description more tangible in the description of the prototype of an aquaponic farm installation (section IV). In the next subsection we provide further details of the modelling framework on which the global optimization can be based, this would run in the cloud and data center layer.

B. MODELLING FRAMEWORK

We demonstrate a test of the modelling in a scenario that makes use of data from Shenzhen, China, see figure 5. Data is from a variety of sources including GIS information for the urban landscape and demographic records. To evaluate the tool for planning decisions, a number of stylistic questions are tested by using ''what-if'' analysis to measure the response of the model. Potential urban agriculture policies that were considered included restrictions on *l*ocations of retailers, farms, the farm *s*cale (''is it better to have many microfarms by numerous individuals versus a few large central farms''); the proportions of different *food types* that are a focus of demand, how to increase the proportion of urban food types consumed versus traditional agriculture food types. The model considers the amount of calories per person, shelf life and waste generated (by using an expiry date for storage and limiting the stockpile inventory levels). Also by setting different patterns for *consumer home locations* via a shape file and city census data it the model makes it possible to consider heterogeneous *consumer profiles* of sex, socioeconomic status, food preferences, shopping strategies, and store type preferences all with different profiles of calorie requirements and income etc. We also looked at *retailer* locations and profiles with different stock management plans, sourcing from urban or ''traditional'' farms and relationships between urban farms. Finally, we evaluate *farm* locations and farm profiles including inventory stock management, production parameters and crop types.

Agent types include producers, consumers, and manufacturers. Passive objects represented include: urban farms, farming-units, and food/produce. Figure 6 summarizes the framework illustrating connections resulting from decision hierarchies and product flow.

Each consumer agent is assigned a location, an inventory, and a profile with variables including calorie need. Socioeconomic variables (gender, age, income level) influence shopping and food preferences. Dependency between socioeconomic attributes and shopping habits has been found to be important in other research [55]. Retailer agents have coordinates for a location in the city, a stock level, a sales strategy, and a sourcing plan. Farm producers are termed manufacturers in the figure and they make a decision for starting an urban farm which may evolve from simulation dynamics and economic utility or be configured. Investment plans for decision making to start farms includes location

FIGURE 5. **Depiction of the model for the Shenzhen scenario. The top panel shows the geographical area, the second superimposes road and transport network, the third shows agents moving on the road network (blue for consumers and green for farms).**

preferences and a production target that relates to farm scale. Urban farm-units have a production plan that specifies what crops they grow and the rate of production and maximum inventory. Production rates are determined with vegetation models that specify crop growth [56]. In the model, the concept of food stock is generalized for inventory of entities that may be consumers, retailers, or farms. In the simulation tests included in this paper consumers initiate their shopping expeditions when stock is depleted to a threshold. Further discussion of the modelling framework is in an earlier conference paper [24].

IV. DIGITAL TWIN FOR AQUAPONICS

In aquaponics nutrients are first introduced through fish food. Fish waste then nourishes the plants in a process also supported by microbial activity. The cleaned water is recirculated back to the fish tanks completing the cycle. Aquaponics has been used in urban farming and it allows intensive farming while being efficient with use of space and water. In this section we describe a digital twin powered aquaponic prototype which fits into the network and processing infrastructure described in section III. The system includes physical, sensing, computational, and natural components, see figure 7. Optimization and prediction modules include a model based digital twin virtual approach, and also data driven models based on machine learning.

As shown in figure 7, a cycle of pipes and pumps connect the grow bed where crops are situated with a water tank that houses fish. Water circulates between these two main locations via a filtration system that extracts solid waste. Other fish waste products such as ammonia are dissolved in the water, to extract it for plant food the system makes use of living bacteria that convert the ammonia to nitrates through the process of ''nitrification''. Ammonia concentration is also poisonous for both fish and plants and it has to be broken down so the healthy function of the bacteria is essential for the successful operation of the system. In summary, nutrient rich water from the fish tank passes to a grow bed for plants, after plants use the nutrients in water it is purified and can be safely sent back to the fish tank. The system can work with artificial or natural light. In the prototype, LED lights were used which provide greater control over the growing environment and allow photosynthesis to occur without sunlight. Other components include an aerator used to increase oxygen levels in the aquatic system for fish and also the bacteria that perform nitrification.

Sensors are situated in the fish tank and the grow bed to monitor water and room temperature, humidity, fish feeding events, and PH levels. We provide details of the specific hardware and software that was used in the following subsections.

A. CYBER-PHYSICAL MODULES

The cyber physical system extends the aquaponic system described in the previous subsection with sensors, a gateway for sensor data stream acquisition, an integrated computational processing unit, and a cloud processing capability. Sensors collect data on humidity, water temperature, PH, light intensity and Total Dissolved Salts (TDS). The data acquisition system digitizes the sensor readings and forwards it to a micro processor via WiFi. Aggregate data is initially subjected to preprocessing and initial analysis involving if-then rules. The formatted and error checked data is forwarded to the cloud for storage and more intensive processing and modelling. Information such as coordination of multiple installations, sharing training data, and any other meta-level coordination processes are also done using the cloud processing. A backup solar power supply and UPS makes the installation more autonomous and robust.

1) SENSORS

a: DHT22:

A low cost highly effective and reliable sensor to measure humidity and room temperature. Temperature is important because plant growth is directly dependent on ambient temperature. DHT22 worked on 3-5V and send digital reading to ESP8266 using a middle data pin. Readings are valid in the range of −40C to 80C. We have used Adafruit libraries (https://www.adafruit.com) that are compatible in ESP IDE.

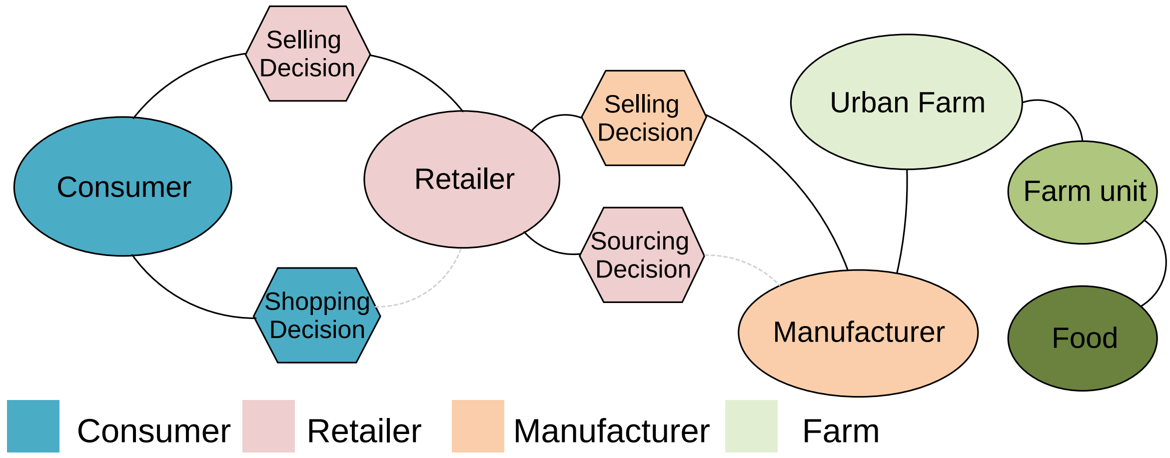


FIGURE 6. Overview of the framework. In the model "manufacturers" decide to farm depending on perceived utility.

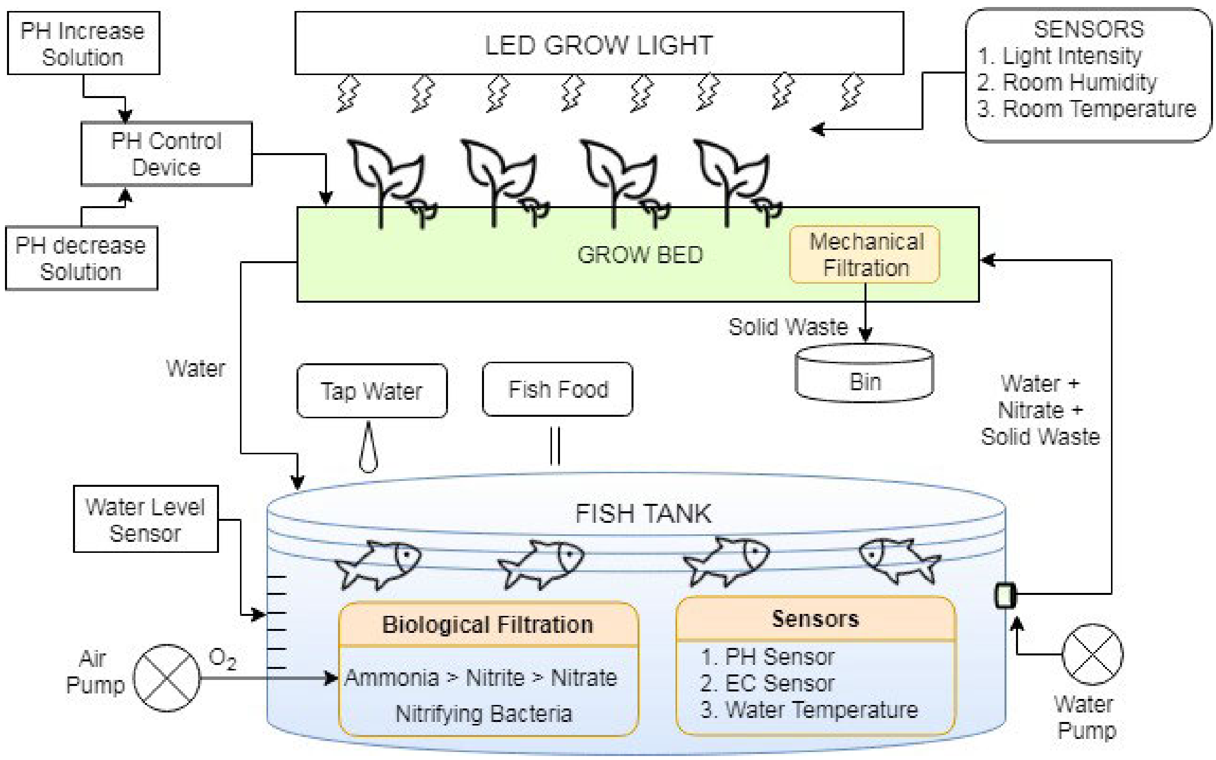


FIGURE 7. Design of the aquaponic system.

b: DS18B20:
Water temperature is measured with a DS18B20 sensor. This device operates on a 9 to 12bit representation. Operational readings are in ranges from -55C to $+125$C. Data is transmitted to the ESP8266 and if valid are sent through the MQTT broker over WiFi.

c: LDR SHIELD:
LDR is a relatively cheap and effective alternative for a LUX meter. Accuracy is $+/-1.5\%$ of readings. The sensor was calibrated with an existing professional LUX meter. It measures the intensity of light, if the light is lower than 50 lumens the grow lights are activated directly from the micro processor using an if-then rule.

d: WATER FLOW SENSOR:
Water flows between fish tank and grow tank are tracked to provide direct feedback to control the operation of the water pump.

e: TDS/EC SENSOR:

Measures total dissolved salts in the water which is proportional to the amount of fish feed introduced to the fish tank. In the system we directly adjust the feed rate to target a TDS value via if-then rules to maintain it in a range.

f: PH SENSOR:

A PH probe is used to measure the PH. This probe needs calibration in a buffer solution. The buffer solution is a pre-calibrated diluted solution of specific PH value. This calibration process is repeated as the sensor cannot maintain its accuracy. PH sensor readings are thus collected on daily basis only.

2) INTERNET GATEWAYS AND DATA ACQUISITION

a: ESP8266:

An ESP8266/Node-NCU is used for transferring sensor data in digital format over a WIFI network to MQTT broker. This microchip can easily handle the workload of the rule based processing in the aquaponics system. It has 1MB memory, but the code to control these processes only uses 33% of this memory. ML models and other control can be pushed onto this memory once models are trained but it cannot be used to train the models itself.

b: 4 CHANNEL RELAY BOARD:

A 4 channel mechanical coil relay board controls Air and water pumps, as well as growth lights in the smart aquaponics system. This relay board has a 10A max load and can operate directly from digital signals of ESP8266. Load is connected on NC pin. When the digital pin is high the load is off. We have used this reversed logic to conserve energy and increase the life of the mechanical relay components.

c: MQTT BROKER:

A secure MQTT Broker(http://mqtt.org/) gathers topics sent by ESP8266. It is also able to send back messages for control actuation. The MQTT broker is situated on the local IP on the Raspberry Pi.

3) MICRO PROCESSING UNIT

a: NODE-RED ON RASPBERRY PI:

A Raspberry Pi device provides processing at the smart aquaponics unit. The device collects all data from ESP8266 via the broker. NODE-RED computes descriptive analytics results and provides control signals to the system. We have used the Pi model 3B+ which is a more stable version from previous Pi modes B and A. It consumes less than 6 watts of power.

b: THINGSPEAK/MANGODB/MYPHP:

Thingspeak (https://thingspeak.com/) is used for description and visualization, it also provides a back storage of recent readings and events. At the unit level, further local data persistency and storage is through MangoDB and myphp.

4) OTHER PHYSICAL COMPONENTS

a: WATER PUMP:

The water Pump uses 13 watts and can attain a rate of 15 liters per minute to circulate the water from the fish tank to the grow-bed tank.

b: AIR PUMP:

A 5 watt 3.5L/min air pump was found to be sufficient for the 62 litre tank capacity. Because it is crucial for fish survival, a backup 3 watt air pump (2.5L/min) is set to switch on if the main air pump fails.

c: GROW LIGHT:

Grow lights as well ambient sunlight provide energy for photosynthesis. Two 12 Watt white led panel lights and one 30 Watt grow light were used, they were set to 45%red, 35%Blue, 30% infrared.

d: FISH FEEDER:

An automatic feeder is set to dispense food depending on the TDS level. This is an important control in our system because the TDS has to be maintained within limits. Fish are sensitive to over eating and can die or become ill but too little feed results in sub-optimal growth.

B. ANALYTICS MODULES

IoT devices provide real time streaming data and basic processing for describing the current state of the aquaponic farming units. This information is then able to be used in more complex services that forecast future states and system outputs. Information can also be shared throughout the urban agri-food system as described in section III for instance to share training data. Quantities that are predicted include production of food (plants and fish weight), and several variables that are important for the successful operation: nitrate concentration and ammonia production which are required to be maintained within certain limits for safe optimal performance. The digital twin of the aquaponic unit is updated with observations of the current state and future predictions of variables so one can predict complete future system states based on a current trajectory. This functionality of predicting future states is not possible in traditional cyber-physical systems, nor is the data driven prediction that is obtained from machine learning.

1) DATA PRE-PROCESSING AND DESCRIPTION ANALYTICS

On data ingestion information is processed and stored for visualization and manual control. We used the Arduino IDE to upload programs to the smart ESP8266. Adafruit libraries were also added to provide additional features [57]. Data processing and presentation is by Node Red[3] on Rasberry Pi. MQTT Broker[4] gathers topics sent by ESP8266 and forwards

[3]https://nodered.org/docs/hardware/raspberrypi

[4]http://mqtt.org/

control and actuation messages. A secure MQTT broker is situated on the local Rasberry Pi IP.

Thingspeak[5] provides a graphical interface for information presentation. Node-red on pi, node-red is able to subscribe to topics from broker and provide immediate visualization in realtime as the installation operates. This is the limit of the cyber physical system. Further prediction features and advanced analytics are implemented in external processors such as in the cloud.

2) PREDICTION ANALYTICS

Prediction modelling allows for extrapolation of certain quantities of interest, either in themselves or for a further step in modelling future system states. A selection of machine learning algorithms were implemented and tests are performed using data from a 3 month period. Methods include Linear Regression (LR), Support Vector Regression [58] (SVR), CART Decision trees [59] (DT), in addition the ensemble method XGBoost with decision trees [60]. XGBoost, extreme gradient boosting, is a technique which has outperformed in many applications, support vector machines is a well established approach, and standard decision trees are interpretable and fast to learn. The machine learning training processes are executed on an external PC processor (or in the cloud/data center). Scikit-learn was used in the implementation of the ML modules [61].

TABLE 1. Features used.

Quantity	Description
Features	
Water Temperature	Fish tank temperature readings
Ambient Temperature	Room temperature readings
Water PH	Fish tank PH
Fish feed	Amount of feed provided most recently
TD	Total dissolved salts
△ PH	Change in PH over recent periods
△ Water Temp	Change in Water Temperature in recent periods
△ Room Temp	Change in Room Temperature in recent periods
△ Fish Weight	Recent change in fish weight
△ Plant Height	Recent change in plant height
Targets	
Fish growth rate	Daily rate of fish mass increase in grams
Plant growth rate	Weekly rate of plant height increase in inches

Two main models are used to predict the daily fish growth rate, and the weekly plant growth rate (in experiments it was found the daily growth rate for plants was not significant and didn't yield useful prediction models). The features and targets are summarised in table 1. In addition to direct readings, the change (△) in some quantities are also used in prediction, note that different lags can be used to generate more features such as long and short term change trends.

[5] https://thingspeak.com/

3) DIGITAL TWIN

The virtual representation of the system is created with a simulation. The simulation variables are re-calibrated as new sensor readings are found. The model in particular is computationally intensive and cannot be run on the Raspberry Pi processor. The simulation works as a series of modules and these include fish feed, TDS, fish weight gain, PH, Nitrates and plant growth. The feed rate depends on feed conversion ratio, fish weight and number of fish. For the type of fish in the system we set the FCR to 0.6, this means that if fish eats one kg of feed, it will convert 60% of it in its body weight. Figure 8 illustrates the interactions of the system modules. The transitions are determined by multiple environment factors, including pH, light strength and temperatures, which also influence the growth rate of the plants and fish. These are set according to the following equations.

Aquaculture output is related to the fish feed, feed conservation ration, and the number of fish [62]:

$$F_r = F_{cr} w_f N_f, \tag{1}$$

where F_r is fish feed rate, F_{cr} is feed conservation ratio, w_f is fish weight gain and N_f is the number of fish in the system per meter cubic. Fish weight gain depends on fish initial weight, water temperature, the fish growth co-efficient is as prescribed by Goddek [62]:

$$W_f(t)_i = [W_0^{1-\beta_f} + (1-\beta_f)\alpha_f e^{\gamma_f T_w} \Delta t]^{\frac{1}{1-\beta_f}} \tag{2}$$

where W_f (g) is the fish weight at a specific time increasing, W_0 (g) is the initial fish weight, T_w is the water temperature (°C), and α_f, β_f and γ_f are species-specific growth-coefficients (In Goddek's paper, $\alpha_f = 0.0277$, $\beta_f = 0.4071$ and $\gamma_f = 0.0697$ is provided for Nile Tilapia) which is calculated based on experimental observation, and i denotes for accumulation of W_f in time (i.e. changing biomass with each simulation step).

Since the value of α_f, β_f and γ_f need to be calculated based on experiment, it would be inaccurate to take the coefficients from original paper and to the simulation. Scipy python package is used for fitting the curve with these coefficients using Use non-linear least squares method.

TDS of water depends on fish feed, EC (electrical conductivity) and their co-relation factor which is different for each fish species:

$$TDS = F.EC.KE \tag{3}$$

Water PH depends on hydronium $HO_3{}^+$, nitrates and water temperature.

$$pH = HO_3{}^+ \cdot NO_3^- \cdot T_w \tag{4}$$

Nitrates which is essential for plants and not toxic for fish. It is modeled by the following equation:

$$Nitrates(ppm) = Ammonia(NH_3) \cdot NC, \tag{5}$$

where NC is a nitrification coefficient.

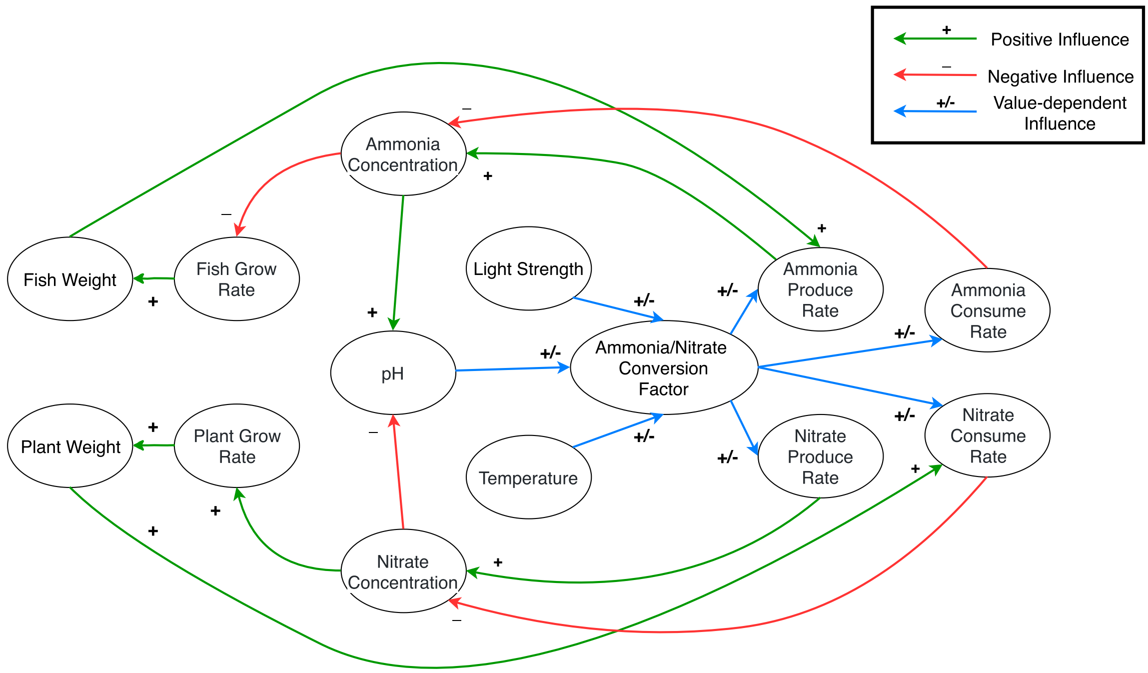


FIGURE 8. Causal loop diagram illustrating relationship between model variables and feedback loops - adapted from [25].

The current assumption is to keep water temperature constant. The plant growth model contains factors of CO_2, nutrients, sunlight and oxygen dissolved in water. We apply a model presented by Akyol [63] extended with factors for BOD and nitrates.

$$X_{new} = (i, It + 1) + y + \beta + BOD\ mg/L \quad (6)$$

Water is re-circulated again and again in our system with water loss because of evaporation and solid waste removal. We model total water loss as described by Wetzel [64]

$$g_h = \Theta A(y_s - y), \quad (7)$$

where, g_h: amount of evaporated water per hour (kg/h), $\theta = (25+19\,v)$ evaporation coefficient (kg/m^2h), v: velocity of air above the water surface $(3m/s)$, A: water surface area $(1m^2)$, S: Dissolved solid quantity removed from system (kg/h), y_s: maximum humidity ratio of saturated air (0.51), and y is humidity ratio air (0.43 kg water in 1kg dry air).

V. EXPERIMENTAL RESULTS

In the following subsections results and analysis are performed of the elements described in the previous sections.

- The planning decision support system is evaluated with a prototype that uses data from Shenzhen. The experiments presented involve applying the model to investigate stylized questions that relate to policies for deploying urban farming in the complex city.
- Evaluation of machine learning to predict system variables in the aquaponic prototype over a 3 month period.

TABLE 2. Inputs to the planning model.

Category	Details
Urban landscape	Shapefile (openmaps)
Policy	Restrictions on farm locations
Food types	Source urban or traditional agricultural calories; production method (see farm types); economic value; shelf life.
Consumer type	Proportions of different types based on demographic data of age and sex, socioeconomic variables; consumption rate for food; calorie requirement; preference model.
Retail locations	shapefile
Retailer types	Stock management plan; source plan; urban farm links (csv)
Urban farm locations	Either dispersed uniform randomly throughout city or concentrated in clusters
Urban farm types	Stock and inventory capacity; energy requirements; capacity; production plan; produce types.

- Evaluation of the digital twins efficacy in prediction system variables in the same 3 month period.

A. PLANNING USING THE MODELLING FRAMEWORK

Data relating to Shenzhen that was used in creating the test are summarized in table 2. Four scenarios were tested to examine certain questions that a planner may have about urban farm locations and retail locations if they wanted to design an urban agricultural food production system. The planner can control locations for farms and different parameters of production and consumption. Four scenarios were tested.

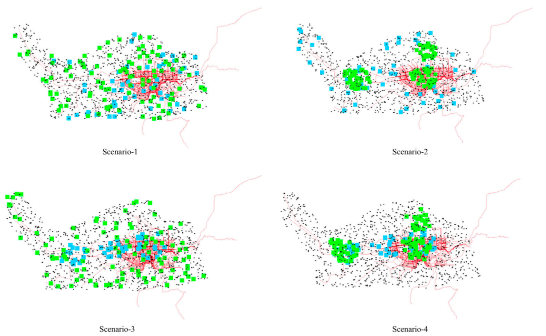


FIGURE 9. Test scenarios 1 - 4 which apply spatial restrictions on farm locations. Green markers show farms and blue markers retail locations.

- Scenario 1 distributes farms and retail locations evenly throughout the urban region,
- scenario 2 restricts operation of farms to certain locations,
- scenario 3 is the same as scenario with the exception that farms can only interact with retailers within a radius of 5km,
- scenario 4 restricts both retail and farm location (see figure 9.

It was assumed that the supply of traditional produce was unlimited, and that the supply of urban produce was specified by the farm production model. It assumed further that a variable of particular interest is the proportion of food sourced from the urban food system rather than the preexisting traditional food system.

Performance metrics relevant to the planning objectives are calculated to represent *consumer satisfaction*: defined as the Euclidean distance between consumer preferences for products and the available products at locations; and the shopping trip distance and time (should be minimized); The *urban agricultural consumption to all consumption ratio*: that is the proportion of food consumed that was grown with urban agriculture. Both are key issues that have been discussed in the literature as influential in determining the success of urban agriculture initiatives [8].

In figure 10, the values of these metrics are shown in the four scenarios. The highest consumer satisfaction was where retailers for urban farms are widely dispersed in the city, but lowest when it was necessary for consumers to travel to purchase food. However, there is a trade off and the lowest urban food consumption occurred where the urban farms were concentrated in certain locations and urban produce was hence not as widely available (this was marginally improved by linking specific shops to farms. The results suggest, given the various assumptions and data used in the model or course, that to increase the percentage of consumption from urban farms, and consumer satisfaction, farms should have higher capacity and be widely distributed in the city with few constraints on movement of farm product between locations. This builds initial confidence in the proposed model representation as it is able to be used to pose and then provide answers to stylized questions [16] that the planner of an urban agriculture system may have.

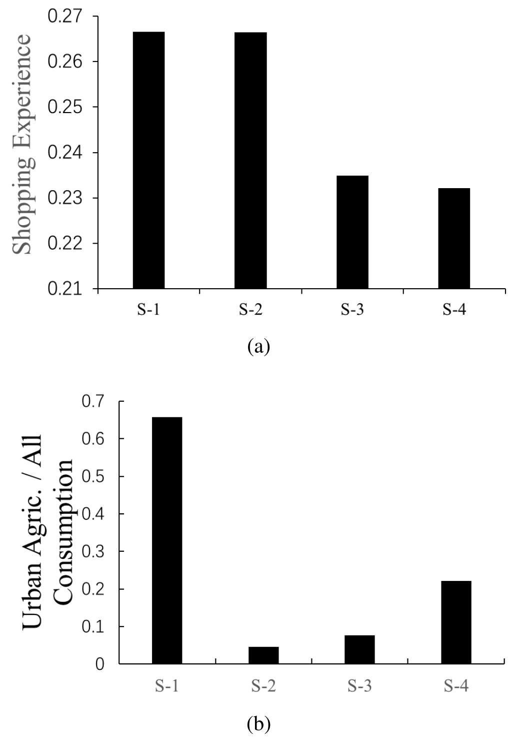


FIGURE 10. Based on the four scenarios metrics were evaluated to estimate: (a) shopping experience performance metric; and (b) the proportion of consumption from urban farms.

B. AQUAPONIC SYSTEM INSTALLATION AND TEST SCENARIO

The results discussed were obtained from a 3 month trial of running the aquaponic system and recording data observations. Parameters that are monitored in real time include temperature, humidity, quantity of fish food fed and PH of water. Figure reffig:dec shows the descriptive readings from the sensors that can be displayed in real time to users.

Ammonia is converted into nitrates by beneficial bacteria. Water was pumped in to grow bed and returns by gravity. 24/7 continuous water circulation was needed to keep the extra waste out of the system and reduce ammonia to keep fish healthy. Bio filtration happens in a tank by using K1 bio media which are continuously getting aeration. Bio media was used so that beneficial bacteria can grow on them as we are using the floating raft technique to grow plants. In the presence of air, the nitrifying bacteria converts ammonia to nitrates which is good for plants and not very harmful for fish. Figure 12 shows the fish at the start and end of the 3 month trial period.

Regarding plants, white Tuberose Bulbs were planted. It is a hard plant and can survive in harsh environments. During our study no fish or plant died. Average temperature ranges from 24-28 degree Celsius. Humidity varies from 30% to 55% depending on day and night cycles. Nitrate concentrations

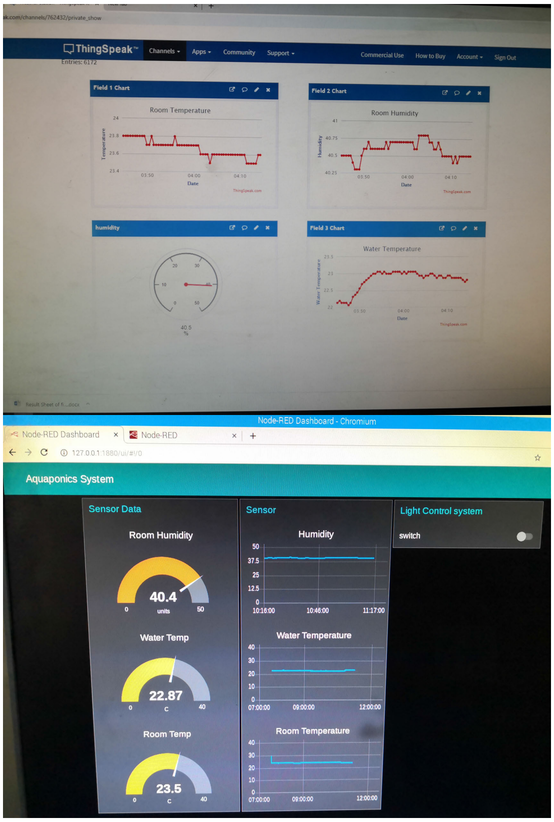


FIGURE 11. Descriptive analytics provided in real time for the aquaponic system control.

FIGURE 12. Fish at the start and the end of the period.

range from 12-46 ppm. Ammonia has been a bit high in our system, in the range of 2-12 ppm. Tank size is 20 gallon or 75 liter glass fish aquarium tank with dimensions 24''L, 12''W, 18''H. Grow bed is a plastic abs material and dimensions are 14'L, 10''W, 6''H. The plants are directly placed in grow beds with the help of gloves and plastic goggles.

C. MACHINE LEARNING PREDICTION

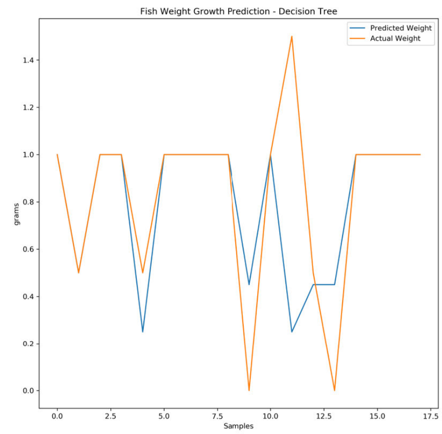
In this subsection, the performance of the machine learning methods described in section IV-B2 for estimating the growth rate of plants and fish are discussed. Table 3 summarizes the performance of the model in predicting the fish growth rate (in grams/day). Similarly, table 4 shows the mean absolute error of the model in predicting the plant growth (in inches/week).

TABLE 3. Predicting fish growth.

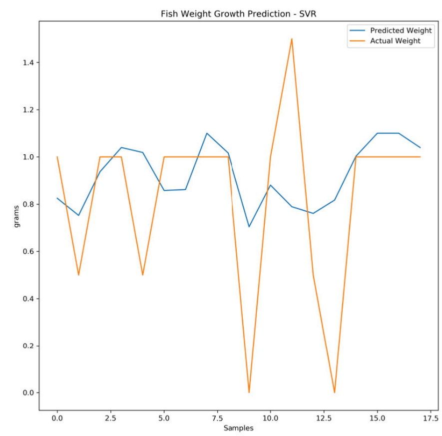
Technique	Train MAE	Test MAE
SVR	$0.13(+/-0.07)$	$0.29(+/-0.47)$
DT	$0.03(+/-0.03)$	$0.29(+/-0.52)$
LR	$0.17(+/-0.10)$	$0.31(+/-0.57)$
XGB	$0.04(+/-0.04)$	$0.36(+/-0.72)$

TABLE 4. Predicting plant growth.

Technique	Train MAE	Test MAE
SVR	$0.29(+/-0.05)$	$0.70(+/-0.28)$
DT	$0.41(+/-0.10)$	$0.75(+/-0.36)$
LR	$0.65(+/-0.12)$	$0.65(+/-0.44)$
XGB	$0.34(+/-0.06)$	$0.69(+/-0.28)$



(a)



(b)

FIGURE 13. Machine learning results.

10-fold cross validation was used to generate model performance in and out of sample (i.e. train and test). The best out of sample prediction performance of the growth rate for fish was attained using support vector regression or decision trees, SVR shows a slightly lower standard deviation of the model predictions. However linear regression also performed fairly similarly. The ensemble technique did not in the particular tests yield an improvement.

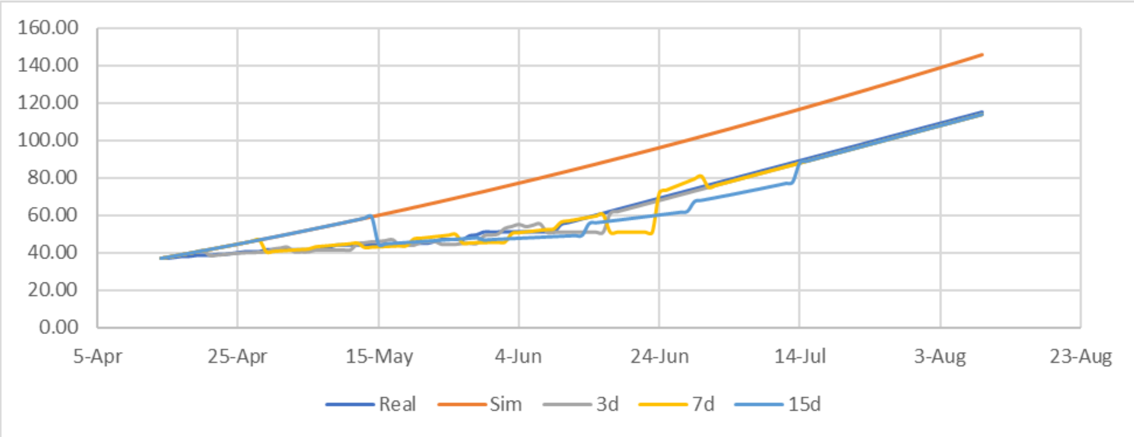


FIGURE 14. Dynamic model for predicting fish production with different time lags. The vertical axis shows predicted fish weight.

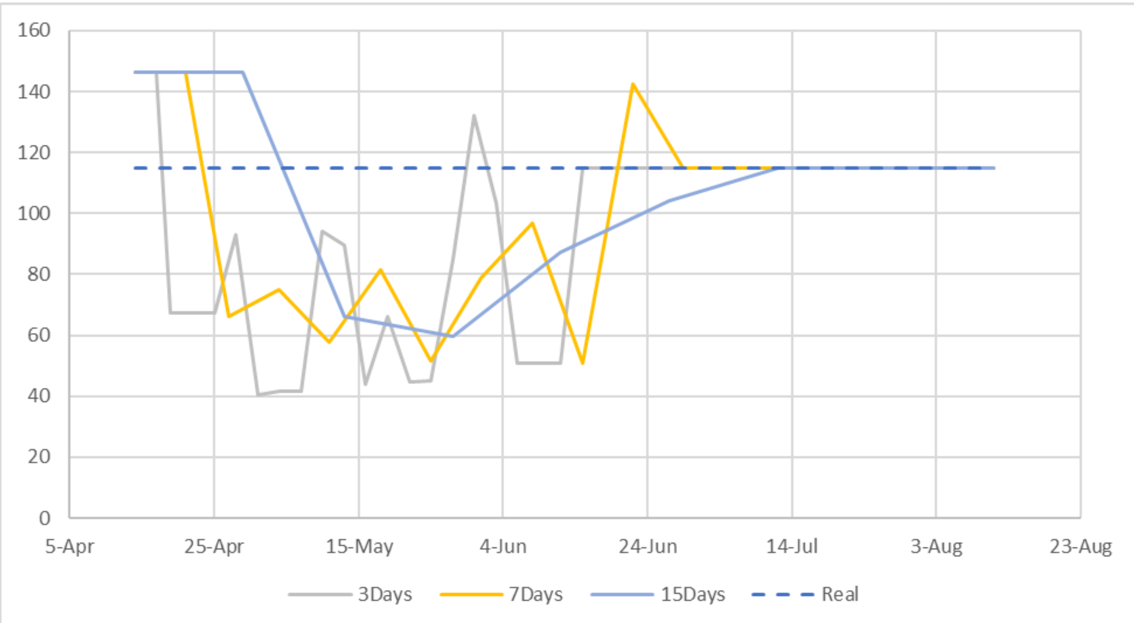


FIGURE 15. Dynamic model for predicting fish production with different time lags. The chart shows changing predicted fish production at the end of the 3 month cycle, the dotted line is the actual production that was obtained.

For predicting plant growth, it was found that weekly values provided better traction for the prediction models to find patterns than daily growth. The best model for predicting plant growth was a simple linear regression. The application of the ML techniques for predicting plant growth suffered from outlier observations which resulted from a dramatic spurt of growth during particular weeks which was not anticipated in majority of other points. Figure 13b, plots actual and predicted values for plant growth with the best approach (linear regression), and 13a shows the values for fish growth predictions with support vector regression.

D. MODEL BASED PREDICTION

The simulation model described in section IV-B3 is used to generate forward projections of system behaviour by extrapolating present conditions read from the sensor network, and by using predicted values to extend the model with predictions of system behaviour for decision making. This section is focused on predicting the fish growth. In the experiments we evaluate the performance of the modelling technique in correctly predicting the production and estimate the sensitivity of predictions to the frequency of data ingestion and model re-calibration events.

Figure 14 charts predicted values versus the actual recorded values of fish weight during the 3 month trial. Using a static model that is not updated with new values overestimated the fish weight gain substantially after the first month, re-calibrating the model more frequently enabled the model to better track the behaviour. It was found that the error increased approximately linearly the greater the look ahead period (values shown in table 5.

TABLE 5. Predicting fish growth with model re-calibrated, accuracy is of looking ahead 3, 7 and 15 days.

Technique	MAE
Static	$21.49(+/-1.70)$
3 steps ahead	$1.59(+/-0.30)$
7 steps ahead	$2.46(+/-0.60)$
15 steps ahead	$4.71(+/-0.72)$

Further evaluation was made in the capability of the approach to estimate final production rates, which would enable adjustments to be undertaken to rectify deviations from plan. Figure 15 shows the predicted final production at the end of the 3 month trial. After an initial overestimation from by all of the models, it was found that the more steady rate of updating every 15 days was less sensitive to minor fluctuations and provided a closer estimate of the final output than more frequent model recalibration at 3 or 7 days.

VI. CONCLUSION

This paper has reviewed recent work in urban agriculture and aquaponics identifying characteristics that warrant a new approach to decision support. The new approach must coordinate a complex human-natural coupled system that comprises of interacting subsystems and involves diverse stakeholders. We developed an approach for a decision support system that uses agent model. This approach is suitable for planning the structure of new urban agriculture systems and defining policies, or making changes to a system over time. The agent model and simulation also forms a basis for a proposed operationally focused system to manage urban agriculture across a city when there may be multiple stakeholders and users. This is a data driven system to coordinate the heterogeneous components and link production with demand adaptively in order to meet system wide objectives. Multiple users could interact with the system via a gateway to evaluate or inform decisions to identify and match food supply and demand in an online way. The details for an implementation of a type of cyber-physical aquaponic unit that fits into this framework and uses decision analytics and digital twin simulation was another main contribution of the paper.

Aquaponics is a promising technique for urban farming. An aquaponic production system is complex, and thus during operation unexpected events and conditions can emerge. It is hard to anticipate future behaviour or production. The approach developed examines predicting future states by using modelling, data driven simulation, and machine learning. We examined performance of these methods in predicting fish growth. A simulation model was recalibrated with new data at different frequencies. It was found that a model based approach is useful compared to machine learning methodologies. Modelling also has an added benefit of working when there is limited representative data available. A data driven approach of re-calibrating and updating the simulation model was found to be feasible. However, although may theoretically be useful for prediction, we find in a 3 month test in the actual aquaponic installation that less frequent updates with real data resulted in slightly more accurate predictions of the final production, and frequent data updates caused fluctuations and instability in predictions. This is encouraging for using a model based approach, and also shows caution is needed in implementing data driven models.

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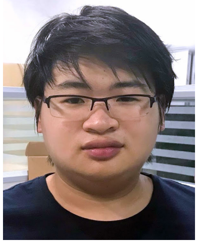

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