Thesis for the Degree of Master of Science

Development of Embedded Optimal Control Platform for Efficient Energy Consumption and Growth in Fish Tank

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Dedicated to my parents and my

family for their love and support.

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This study is wholeheartedly dedicated to my beloved family, who have been a source of inspiration and by continually providing their spiritual, emotional, and financial support.

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List of Abbreviations

IoT: Internet of Things

FLC: Fuzzy Logic Control

ML: Machine Learning

RNN: Recurrent Neural Networks

LSTM: Long Short-Term Memory

WSN: Wireless Sensor Network

FAM: Fuzzy Associative Matrix

Abstract

The fish farming industry has been receiving considerable attention and experiencing tremendous growth in the last decades around the world. Fish farming has the potential to overcome the requirement for the food because the world population is increasing day by day. Fish farm is one of the widely suggested fields for investing money because it supports a year-round production of fresh fish resources around 40% increased production rate in comparison to natural fish hunting. Ensuring healthy fish production involves elaborate monitoring and stable controlling of the fish farm; however, management of the resources inside fish tanks is a challenging task. It requires continuous monitoring and control, so energy consumption and labor cost are the central portions of the expenses. Using new advancement of technologies can support fish production improvement, cost reduction and automation of process.

The Internet of Things (IoT) is one of the fast-growing technological areas which are influencing our daily life. Devices in our digital world are being furnished with various types of new types of technologies including microcontrollers, raspberry pies, sensors, transceivers, actuators, digital connectors, and Internet protocols. These technological advancements can give a wide range of opportunities for the development of interconnection among various devices and their users. The Internet of Things can support new types of services for companies, individuals, businesses, and governments with connecting various application scenarios to gather a number of parameters from the real world and using these data for future decisions and assessments by analyzing this data. The central key aspect of the embedded devices is a lightweight connectivity development for IoT devices and the development of fault tolerance interaction among them. These devices consist of light control actuators, video detector cameras, home automation tools, smart and autonomous vehicles, smart healthcare toolkits, intelligent actuators, and just to name a few. The installation of these smart devices can give various services to users, such as sensors collect the actual environmental information, and based on these gathered real data actuators are used to increase or decrease the environmental parameters via local network or Internet connectivity. Currently, IoT based applications are being widely utilized in

various domains, including healthcare, self-driving transportation, aquaculture, agriculture, industrial and home automation, power management, traffic controlling, aerospace engineering, and numerous other fields.

Machine Learning(ML) allows electronic technologies to learn autonomously from historical data and to utilize this knowledge to make predictions, decisions, and assessments independently. These types of applications are highly compute-intensive. As a result, these applications are conventionally executed on local servers, cloud servers, and personal computers. A new type of powerful embedded processors and advancements in algorithms, now machine learning algorithms can be performed directly on devices in the field Embedded Machine Learning. Embedded Machine Learning based applications can accomplish a number of achievements in the century of Industry 4.0. For instance, IoT sensor devices which measure optical or acoustic discrepancies and inconsistencies, then directly activate quality assurance functionality to the production or system state observation. Moreover, during the activation of cameras and microphones, these devices automatically monitor visual parameters and minimize soundwave errors based on contact, vibration, voltage, speed, temperature, and pressure sensor parameters. Then, these collected parameters also can be used for future improvement of the products. Embedded Machine Learning Algorithms has attracted many researchers to seek solutions for complex real-world problems. The highest percentage of the existing literature is paid attention to develop and run applications on a PC, local, or cloud server. However, these methods are not able to bring expected income to users. In this work, we attempt to take Embedded ML and IoT applications to the autonomous system development with deploying the to the Fish Tank, which is one of the most fast-growing industries.

In this thesis, we propose an embedded optimal control platform based on ML and Optimization algorithms for efficient energy consumption and fish growth in Smart Fish Tank. We have developed the proposed embedded optimal control platform that integrates context-awareness, prediction, optimization, and control functionalities for controlling environmental parameters optimally in Fishtank. We have installed various IoT sensors and actuators to the fish tank and develop the context-awareness unit for the collection of sensing values from the real-fish tank environment. So the indoor environment data used in this work is real data which is collected from the fish tank during the three months. External environmental data collected from the physical fish tank. We have used the RNN-LSTM algorithm for prediction, the mathematical formulation for optimization, and the fuzzy logic controller for actuator control. A novel objective function for optimization is formulated and implemented for compute the optimal environmental parameters according to the predicted and user-desired environmental parameters data. In addition, we implemented the platform by considering various cases, firstly, we implement the platform based on actual fish tank environmental parameters without prediction model. Secondly, we have implemented prediction, optimization and control module using fish tank sensing data. Thirdly, we used outdoor environmental parameters to the prediction module. Fourthly, we consider the actuators control parameters in order to optimize energy consumption. Lastly, we implement the proposed platform by considering the power policy data. Besides, the control of the environmental parameters is tested with and without optimization schemes. Performance evaluation results prove that the optimization module with predicted values is 18% and 28.5 % effective in terms of environmental parameter optimization and energy consumption minimization compared to without optimization scheme. Furthermore, the proposed prediction-optimization based environment control energy consumption is 27%, 23.6%, and 11.8% effective in energy consumption compared with without prediction-without optimization, with prediction-without optimization, without prediction, and with optimization results. Also it spends 918 krw, 753 krw, and 423 krw less money for compared to other schemes.

1. Introduction

1.1 Motivation

Humanity overcomes the enormous challenge for providing food and livelihoods as the population continuously increases, and it is expected that the population will be more than 9 billion until 2050 [1]. The inordinate influences of climate change, natural disasters, and environmental degradation will damage the natural existence of products [2]. World Fisheries and Aquaculture announced that fish production in 2016 reached the highest point compare to other years (171 million tons), 88% of this fish production was used for human consumption. Today, fishery products are one of the highly exported food items around the globe. According to the 2016 statistics, nearly 1/3 portion of world fish resources in international businesses are invested in human consumption or other purposes [2]. Fishers have been hunting 2.5 times more fish products from natural environments, such as sea, ocean, lake [3], this means if fish are caught at a faster rate and quantity, then the remaining fish cannot reproduce, the populations of fish are likely to reduce in a short time. In the last four decades, the quantity of fish has decreased by half compared to 1970 years [4]. The natural balance of oceans is likely to be destroyed due to continuous pressure and uncontrolled usage of oceans' wild resources. According to these existing and further coming problems, individuals, researchers, worldwide organizations, institutions, and societies have to work cooperatively to create practical and optimal ways for the development of alternative scenarios in fish farming. One of the highlighted examples among solutions is the Aquaculture industry, which is the most productive and abundant concept which has been experiencing significant development in the last decades around the world. Aquaculture is the farming (raising, harvesting, and breeding) of fish, shellfish, or aquatic plants in brackish, fresh or saltwater [5]. From 202 currently existing countries and territories 194 countries are active users of the aquaculture industry [6]. The contribution of fish farming to the global production of fish related products and aquaculture combined increased steadily and reached nearly 47 % in 2016, and it was more than 20 percent compared to 2000. Generally, the advantages of fish farming include efficient fishery products, a new type of job opportunities, excellent economic support, fish farms can be installed anywhere; waste materials can be reduced, reused, and recycled via fish farming [7]. However, with fish farming benefits, it has its own challenges, too. These challenges include lack of water source, predators' effects, different fish diseases, difficulties in managing ponds, flooding and to name a few [8]. If we take management of fish farms as an example, SFP(Sustainable Fisheries Partnership Foundation) report describes that nearly 40% of fish tanks and ponds have a terrible management system, and they produce fish products with various viruses [9]. To overcome the issues mentioned above, expert fish farmers need to combine a new type of technological advances with fish farms such as IoT devices, machine learning, and optimization algorithms, which can check, control and predict optimal conditions to the fish farm environment without human interference. The Internet of Things can offer a variety of new services at every stage of our lifestyle. IoT application scenarios can provide overall accuracy, automatization, efficiency, minimizing the total expenses, and optimization of management processes in different real-life problems [10,11,12]. After analyzing previous studies [13,14,15], we have categorized six essential benefits of the IoT based fish farming environment: (1) automated environment control, (2) reducing damages caused by disasters, (3) decreasing labor cost, (4) fish production cost-reducing, (5) improvement quality of fish products, and (6) designing and developing required fish farm environment without limitations. As the number of IoT devices increases, technologies become more mature, the quantity of the data being published also increases. IoT technologies are becoming the most significant sources of new data compared to other technologies, through analyzing and comparing the historical and real-time data IoT applications can provide a more optimal environment to the users.

1.2 Background

Fish farming is a raising, breeding, harvesting the various fish types in fish tanks or ponds with a fully or partly controlled environment for optimum fish production during the year. Figure 1 describes the model of fish farms with essential components. Effective management and control of the fish farm require a perfect understanding and setup of various control processes, including optimal filtering, energy saving, indoor design, oxygen dissolving, bio-security control, scalable design, continuous monitoring, and control.

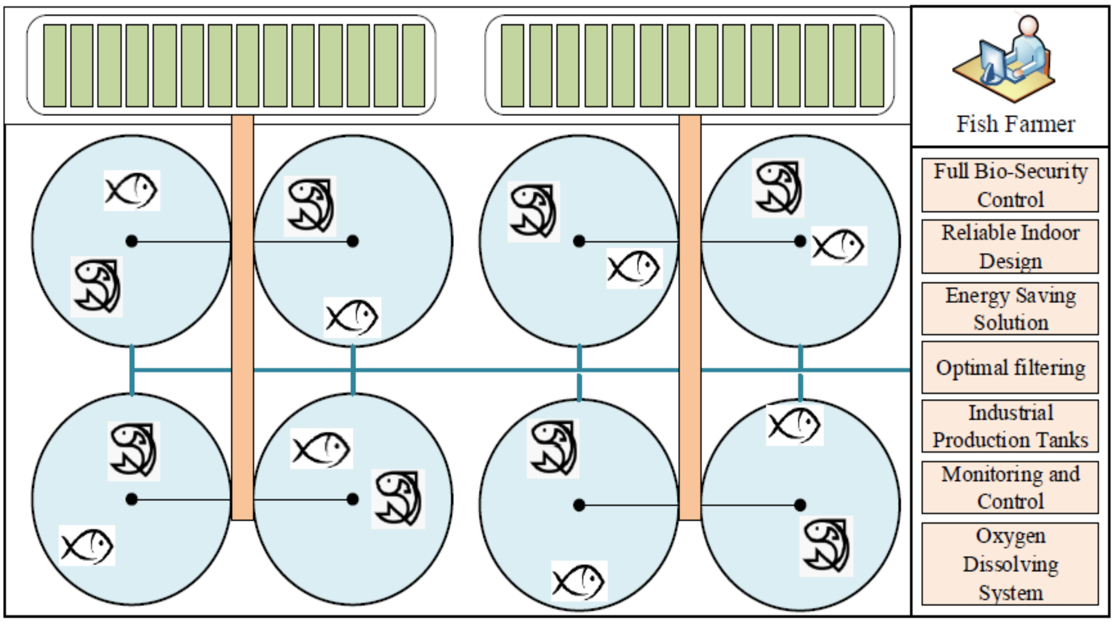


Figure 1: Various essential components of Fish Farming [16].

These essential processes provide various advantages for fish farmers, such as effective fish tank design and construction, selection of suitable fish species for healthy fish production, water quality management, and real-time quality control. In this study, we aim to develop an embedded control framework to the fish tanks using ML and Optimization algorithms with controlling water quality parameters namely, water temperature, conductivity, pH and level using various sensors, and actuators. We have deployed Machine Learning, Optimization, and Control algorithms to the IoT device to control the fish tank actuators with low cost and high profit.

1.3 Challenges

Here, we briefly describe the typical issues and challenges faced for healthy fish production that requires continuous attention and care. There are given a list of some challenges identified during the study:

- Over usage of chemicals: Viral resistance to antibiotics is attributed to the over usage of chemicals in our food, including fish and fish products.
- Source of virus/disease transfer: If the fish tank environment is not well-managed, then it produces unhealthy products that are combined with various chemical viruses and illnesses.

- Ecological system pollution and destruction: Chemicals used fish tank facilities often have a negative influence on surrounding areas and can potentially pollute nearby underground water pathways.
- Fish feeding: Less feeding or overfeeding fish can cause an adverse effect on fish growth and water quality.
- Water quality: Water quality is one of the vital components of the maximization the healthy fish production. Poorly controlled water quality brings various illnesses and problems for fish growth.
- Water usage: Too much freshwater is often needed to fish tanks and cages each year. Water purification and processing are used to reduce the need for freshwater by purifying water for aquaculture.
- Energy consumption: Energy consumption and labor cost in fish farms account for more than 50% of the cost of fish farm production, so minor improvement in performance can lead to significant cost reduction.

After analyzing the above-mentioned problems, advanced technologies such as IoT, Machine Learning, Optimization and Control algorithms can support automation of environment control, cost minimization in fish production, water quality improvement for healthy fish growth, and decreasing labor cost and human interaction as well as, the collected data using IoT sensors can be used for making future decisions and improvements.

1.4 Scope of the Study

We have proposed an Embedded Machine Learning based solution IoT Fishtank environment optimal control platform using TensorFlow Lite for efficient energy consumption and fish growth. IoT devices are installed successfully to the real fish tank environment and collected data is used for prediction and optimization algorithms. We have developed a complex embedded solution to the fish farm from the initial installation and gradually work towards the system development. It is expected that the developed system in this study will help to increase the effectiveness and productivity of fish tank with controlling in embedded IoT devices.

The research methodology adopted for this study has three main phases is described in Figure 2:

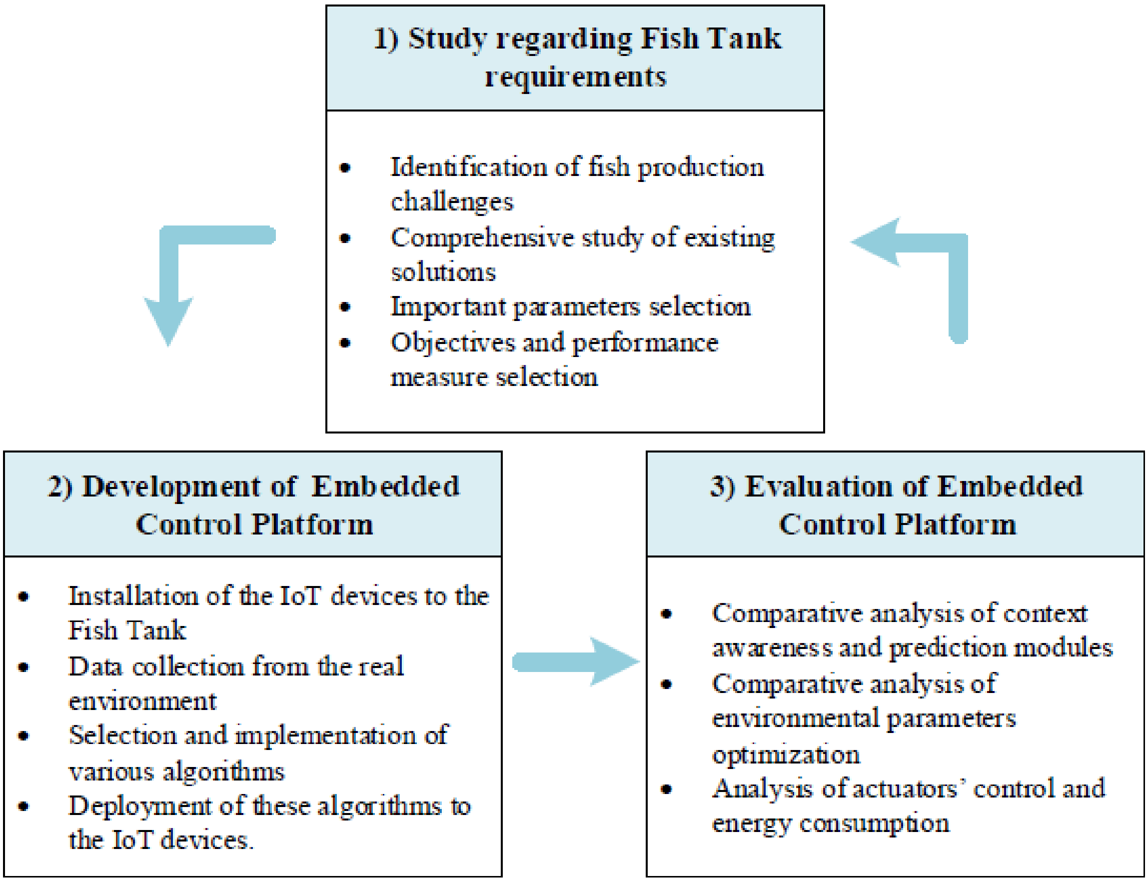


Figure 2: Development phases of the Proposed Embedded Control Platform for Fish Tank.

- Study regarding Fish Tank requirements:
  - Identification of fish production challenges
  - A comprehensive study of existing solutions
  - Important parameters selection
  - Objectives and performance measure selection
- Development of Embedded Control Platform:
  - Installation of the IoT devices to the Fish Tank
  - Data collection from the real environment

— Selection and implementation of various algorithms

— Deployment of these algorithms to the IoT devices.

- Deployment of these algorithms to the IoT devices:

  — Performing the platform evaluation based on real sensing values

  — Comparative analysis of context awareness and prediction modules

  — Comparative analysis of environmental parameters optimization

  — Analysis of actuators' control and energy consumption.

In this study, we aim to implement embedded ML technologies based optimal control embedded platform for efficient energy consumption in Smart Fish Tank. The main goal of this work is directly performing optimal smart fish tank environment control processes on the IoT devices with minimum energy consumption and maximizing environmental comfort.

The development of the proposed system includes the following five main phases:

— Firstly, installation of the sensors and actuators to the fish tank, and a real-time context awareness model from the environment;

— Secondly, the training the RNN- LSTM based prediction model using internal and external environmental parameters to predict temperature, pH, conductivity, and water level. As well as, converting this trained model to the TensorFlow Lite;

— Thirdly, the formulation of the optimization algorithm to calculate the most desirable environmental parameters for fish growth with efficient energy consumption;

— Fourthly, the development of the Fuzzy Logic control, which computes up activation level and activation duration to IoT actuators using predicted and optimal values.

— Lastly and most importantly, the deployment of the overall platform to the Embedded Device.

The rest of the thesis is structured as follows. Chapter 2 presents the related works for the proposed topic. A discussion of the related studies is divided into three subsections. Namely, IoT based Fish Farm environmental monitoring, embedded machine learning solutions for smart environments, and IoT based control solutions for fish farming. Chapter 3 outlines the design of the proposed embedded optimal control platform with a detailed discussion of the system components. In Chapter 4, the experimental and implementation environment is discussed briefly. Experimental results and performance analysis of the proposed system are represented in detail in Chapter 5. Experimental results and result analysis are categorized into four subsections: context awareness module analysis, experimental results of the RNN-LSTM prediction module, analysis of Optimization module results, and analysis of fuzzy logic control results. Finally, Chapter 6 presents the conclusion of the thesis with future work plans.

2. Related Work

Discussion of the related studies is divided into three subsections, namely IoT based Fish Farm environmental monitoring, embedded machine learning solutions for smart environments, and optimization-based solutions. Simbeye et al. suggested a Wireless Sensor Network (WSN) based water condition control mechanism for aquaculture. This system measures various water quality values, including dissolved oxygen, water quantity, and water level as a real-time data [17]. Another WSN-based water condition control system is outlined by Chen et al. [18]. Luo et al. implemented and deployed for a real-time water parameter change detection concept [19]. The authors utilized GPRS and ZigBee based communication protocol for the connectivity among sensors, control actuators, and the central management unit. In that project, data acquisition and low-latency are provided with improving the reliability of communication. Zhang et al. proposed that the financial efficiencies of the IoT devices utilization to the fish farms they proved that deployement of IoT devices to the fish tank environment minimizes the expenses and maximizes the income significantly [20]. Idachaba et al. suggested a pond management system which comprises various sensors to detect the changes in water quality of the pond that can be controlled from any distance through CCTV (closed-circuit television) technology [21]. Wang et al. suggested GPRS and ZigBee communication protocols based online water condition measurement concept for monitoring the chemical parameters' condition in water [22]. This study described a distributed quality monitor framework to monitor various aquaculture parameters from any water-related field using variety of intelligent sensors [23]. Wireless Sensor Networks based water recycling system monitoring concept based on ZigBee connectivity are proposed in this study [2424]. Cario et al. designed and implemented an acoustic network that can detect fish farm underwater environmental values effectively [25]. For the assessment of the effectiveness of the fish growth, we need to collect, analyze, and pre-process the water EC, temperature, pH level, water level, dissolved oxygen, and turbidity data continuously. LoRa technology can provide faraway transmission of real-time data with less energy consumption [26]. Another LoRa based study with faraway connectivity capability were utilized to build a LAN network for data transmission about the current condition of the fish and food quality [27]. Lee et al. introduced machine learning integration to the embedded sensor technologies for Internet of Things applications [28]. Intelligent IoTSP- Machine Learning, Artificial Intelligence Tensorflow algorithms implementation to the embedded NVIDIA Jetson chips concept was suggested in this study [29]. Min et al. outlined an ML-based digital twin mechanism for optimizing the production in the petrochemical factories [30]. Robinson et al. proposed a signal language recognition system through a convolutional neural network embedded using Raspberry PI 3 [31]. Deep learning enabling approaches on IoT devices was discussed in this study [32]. Material recognition methodology was suggested using deep learning solutions in embedded software [33]. Venuto et al. presented a P300 Brain activity-based embedded system remotely driving mechanical device [34]. Zeroual et al. introduced the Tensorflow lite framework based on deep authentication methodology for mobile cloud computing [35]. Hasan et al. developed IoT and Tensorflow based smart parking models for the detection of free parking spaces [36].

2.1 IoT based Fish Farm Environmental Monitoring and Control

Over the last decades, IoT based applications have been applied to the number of studies as surveyed in [37,38]. The IoT based applications in the field of aquaculture are used to increase the fish production, quality and to decrease costs. These applications are helping fish farmers to make clear and better decisions [39,40]. South Korean largest telecommunications operator South Korean Telecom introduced an IoT-based fish farm management concept in North Jeolla Province [41]. Their proposed system increases the fish farm management process by connecting wireless embedded devices and it helps to enable farmers for monitoring their fish tanks remotely through their smartphones in real-time. Fish pond sensors continuously check the water temperature, oxygen, and pH, for detecting any minor changes in the water. SK Telecom's open IoT platform controls the data flow through IoT Gateway and then analyzes the data, and the current environment results of the fish tank are sent automatically in real-time. One of the widely used IoT based applications in the aquaculture field is Indian Eruvaka technology [42]. Their platform provides continuous monitoring of the water temperature and oxygen condition, and the user can check the fish farm environment and fish feeding processes through the mobile application. This system helps to maximize profit by minimizing the monitoring cost. Shareef et al. [43] presented the real-time aquaculture environment monitoring framework based on IoT, with developing sensor node, actuator node, station, and decision making units. In that study, the measurement of the chemical parameters of the fish farm water was collected to the database, and the notifications were sent to the user to analyze the current condition of the fish farm. Based on decision-making rules actuator nodes activated to improve the water quality. Minghu et al.[44] proposed an aquaculture multi-parameter monitoring system that included accurate data collection, real-time data analyzing, process control and notification services. Their proposed system structure was based on the master-slave concept of the network, fish tanks' temperature, salinity and dissolved oxygen sensors as a slave collected data from the environment, and the collected sensing parameters were sent to the Master unit. PLF (Precision Livestock Farming) concept was presented [45] to continuously monitor and control the fish farm operational process using IoT based real-time video streaming. In that study, they utilized four types of IoT devices, namely, surface camera, stereo video, sonar and acoustic telemetry for analyzing the fish observation in commercial cages. Based on gathered data they controlled the fish feeding process and regularly maintained the fish growth rate with avoiding feed wastage. Ekaterina et al. [4646] suggested an automatic fish detection and tracking system by installing low-quality video sensors to the fish farm. In this study, Kalman filter and Viola-jones methods were used to estimate fish parameters, they emphasized that controlling and understanding the natural fish migration could provide optimal fish feeding process, fish growth management and improve the quality of products. Wireless sensors based aquaculture monitoring system was introduced in this study. Their proposed system is described in Figure 3, as can be seen, sensors monitor pH, oxygen, water level, and temperature values of the fish tank via the various IoT sensors, and the ZigBee protocol is used to forward the collected sensing data to the server. Moreover, they developed the rule-based control module to activate or deactivate the water pump actuator based on sensing values. The rule-based control module included IF-THEN rules for activating the actuators. If the current water level is below than user assigned threshold, then the water pump is activated to increase the water level until the user preferred level. If the sensor detects the overflow from the tank then automatically activates the overflow system in order to decrease the water level.

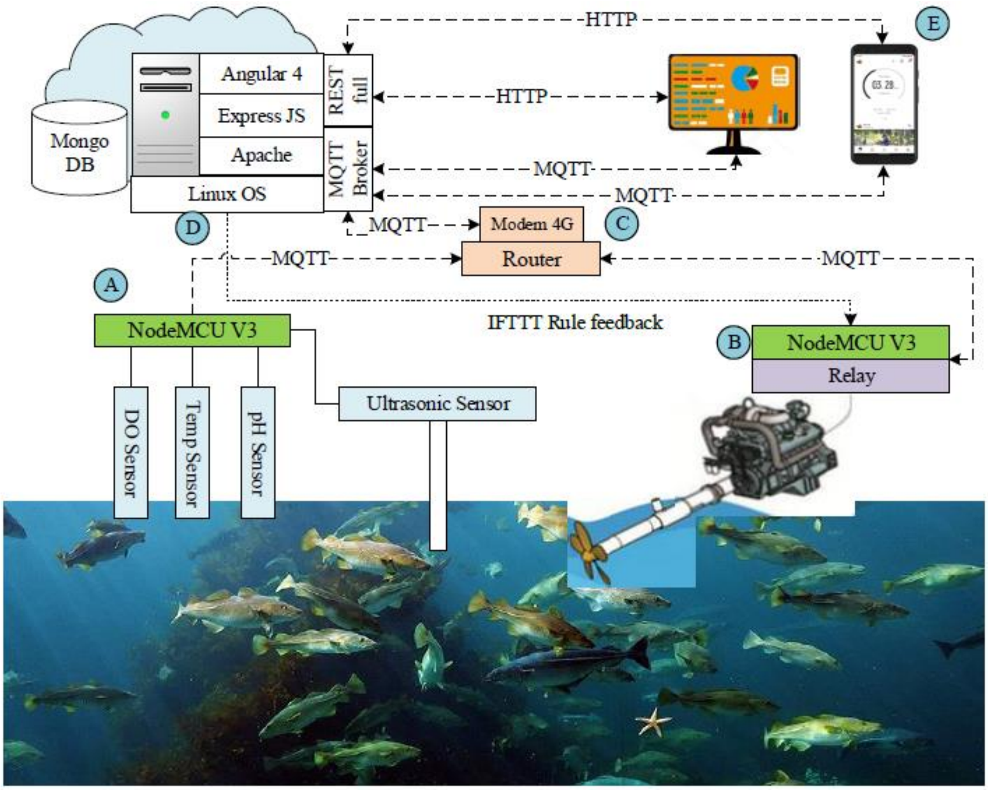


Figure 3: IFTTT model for smart aquaculture using cloud and IoT[47].

Partical Swarm Optimization based Decision Support System (DSS) is proposed in this study [48]. The main aim of this study is the maximizing the production strategies for increasing the profit by considering various processes of the fish farm.

Kodali [49] developed a smart greenhouse irrigation system with an attached water storage tank. That proposed system included humidity, temperature sensors, and a fogger actuator. Required water obtained from any sources such as rainwater harvesting, canal tube, firstly stored in the water tank. Ultrasonic embedded sensors installed to the fish tank, which monitors water level continuously and send notifications to the user as soon as the water level decreased from the requirement. The microprocessor was used for the activation or deactivation of a water pump according to the water level. Their proposed approach decreased water consumption by 70-80%.

Prieyen et al. [50] introduced an IoT based smart water tank system control using an android application. Their proposed system included three central units, namely, sensing unit, control unit, and motor unit. They developed a simple rule to their system for controlling the motor if the current water level was below minimum level motor was activated until the water level reached the maximum level. In contrast, if the actual water quantity was the same as the maximum quantity, the motor was deactivated. ESP8266 and an ultrasonic sensor were utilized as microcontrollers and sensors, respectively.

Narrow Band Internet of Things technology is proposed to remote water level meauserement system for industrial water storage tanks were suggested by [51]. The authors used two different sensors for sending alarm (Magnetic switch sensor) and checking water level (Floating sensor arrangement) for their proposed approach. Magnetic switch sensors installed with buoyant objects to the bottom and the top parts of the water tank. According to the water level, buoyant objects moved and magnetic switch influenced on the alarm and water level (in peak point or basement) were sent to the system. Alarm and LED actuators activated automatically at the same time when the current water level was below or above the desired ranges. The study [52] presents LabVIEW and Arduino based on a non-contact water level control system for water storage tanks. Ultrasonic sensors monitor the water quantity, according to the actual water level LabVIEW application forwards the data to the Arduino device, then the water pump is ctivated or deactivated automatically through the Arduino. The current water level data of the tank is visualized on the graphical user interface, which is provided by LabVIEW.

Shankar et al. suggested an intelligent water level control model for regulating water consumption for tanks [53]. Their proposed system overcomes water wastage in water tanks based on an IoT and mobile application; more precisely, this system detects overwatering of the tank water tank and, based on overflow conditions the alarm is sent to the farmer. As the current water level increases and crosses from the user desired threshold, then the system automatically gives the notification to the user. According to alarms and notifications, the user can activate or deactivate the water pump through the mobile application.

Fisher and Moore [54] developed a continuous optimization solution for water control valves based on pump pressure in different set-points. This system helps to minimize the pump energy consumption by keeping open one control valve nearly all times. Their control method is simple and does not require more hardware than a conventional control method. Each air handling scheme monitors chilled water to provide the discharge setpoint of the air temperature. The pump's speed is controlled by the variable frequency drive in differential pressure. There was a 44% reduction in power consumption in the utilization of the new differential pressure reset program.

Raju at al. designed and implemented a Raspberry Pi-based embedded environmental parameter collection system for aquaculture [55]. This system continuously checked the water condition using IoT devices and gathered information are analyzed on a cloud. The cloud server supports auto-generated alert/notification functionality. If any environmental value becomes out of threshold, then notification is sent to the user. However, their suggested concept does not include any optimization or control functionalities.

2.2 Embedded Machine Learning Algorithms for Smart Solutions.

Machine Learning(ML) allows electronic technologies to learn autonomously from historical data and to utilize this knowledge make predictions, decisions and assessments independently. These type of applications are highly compute-intensive, as a results these applications are conventionally executed on local servers, cloud servers and personal computers. A new type of powerful embedded processors and advancements on algorithms, now machine learning algorithms can be performed directly on devices in the field Embedded Machine Learning. Embedded Machine Learning based applications can accomplish a number of achievements in the century of Industry 4.0. For instance, IoT sensor devices which measures optical or acoustic discrepancies and inconsistencies, then directly activate quality assurance functionality to the production or system state observation. Moreover, during the activation of cameras and microphones, these devices automatically monitor visual parameter and minimize soundwave errors based on contact, vibration, voltage, speed, temperature and pressure sensor

parameters. Then, according to the collected parameters, the manufacturer can make future improvements of the products.

The Internet of Things (IoT) is the leading reason of the evolution of embedded ML algorithms and IoT systems, as the amount of the collected data is also soaring with the dramatic growing number of sensors utilized. The Internet technology and data transmission techniques are developing fast, suchs

currently 5G network communications have already widely utilized in many industries. However, sensor data transmission to the cloud servers is not always beneficial or feasible.

There are a number of reasons why we need to pay attention to the deployment of Embedded Machine Learning techniques:

- Network cost – data transmission to cloud servers or local servers requires continuous overloading the networks. As a consequence the price of the traffic increases.
- Coverage – In some locations, such as tunnels, basements, caves, due to insufficient coverage, the network communication is difficult.
- Latency – Excessive Round Trip Time for sensing data forwarding and receiving control commands to actuators. Real-time systems and applications are needed a quick response with low latency.
- Privacy – Data espionage becomes more difficult because of the frequent requirement to protect external requests to video and audio files from industry systems.
- Data Sovereignty – System administrators and operators require to have overall management over the data.
- Safety – Various risks for the manipulation of data and devices.
- Energy Consumption - Data receivers and data transmitters consume a relatively high energy.

- Extra Devices - Sensor and actuators are needed to accommodate with external data transmitter antennas and suitable cables.

After analyzing the problems mentioned above, we propose optimal control embedded platform using TensorFlow Lite for efficient energy consumption and Fish Growth in Fish Tank. We train RNN-LSTM based prediction module using TensorFlow, and we convert this trained model to the TensorFlow Lite format. RNN-LSTM model forecasts future temperature, water, pH level, and conductivity values to the fish tank, then this model deployed to the IoT microcontroller. As the new sensing values come to the already trained embedded machine learning model, the embedded ML predicts future environmental parameters to environment locally. Moreover, we also deploy optimization and fuzzy logic algorithms to the IoT microcontroller which can provide control functionalities to the proposed system. Prediction algorithms provide technologies to learn from historical data and assist accurate decisions for uncertain future to boost expected income or avoid potential risks. Basically, historical information is utilized to create a mathematical model for targeting essential trends. That created mathematical model is then used with actual data to predict what will occur next, or to recommend steps to reach optimal outcomes. In engineering fields historical data for using in the prediction algorithms usually comes out from sensors, connected systems, and instruments in the world. In business systems' historical data at companies may include sales data, transaction results, marketing information and customer comments. That collected information can be inputted to the predictive algorithms to increase the capability of the existing systems, then these systems will be able to decrease operational expenses, predict energy requirements, anticipate equipment collapses. For instance, IoT sensor nodes measure vibrational values of vehicle parts and give alerts or notifications before vehicle fails on the road. Companies also deploy prediction algorithms to make more error-free forecasts, such as forecasting the electricity demand on the power grids. These predictions provide more effective resource planning, such as scheduling of different electricity plants.

Machine Learning algorithms are utilized to find relations in data and to create models which forecast future outcomes. Several Machine Learning algorithms are available, including neural networks, linear and non-linear regression, support vector machines, decision trees, and many other algorithms. Prediction algorithms are widely used in industries, such as healthcare, finance, pharmaceuticals, aerospace, automotive, and manufacture, in order to find out the future expected parameters based on various historical parameters.

There are given some examples which are using prediction algorithms in industries and their use in various fields [56]:

- Automotive – creating new advanced achievements in autonomous vehicles. Companies are developing driver assistance tools and new type of autonomous vehicles use prediction algorithms to analyze sensing data from connected vehicles and to set up driver assistance techniques.
- Energy Production – forecasting the energy requirement and electricity price. Predictive analytics based applications are used to monitor historical trends, weather, and seasonality to provide accurate future decisions.
- Medical Devices – utilizing pattern-detection algorithms to detect various illnesses, such as cancer. A cancer measurement device checks and analyzes the breathing process and sounds of patients, then gives feedback via a desktop or mobile application to detect the illness.
- Agriculture – optimization of irrigation and detection of pesticides and herbicides of crops. Agricultural sensors measure the actual condition of the water, soil, crop condition and used as an input parameter for the prediction algorithms to forecast expected water, soil and illness condition for the crop.
- Industrial Automation and Machinery – Prediction of machine failures. If we take a plastic and can production company as an example, they save 50 000 Euros in a month using a condition measurement and forecasting the maintenance of the application which reduces waste and minimize downtime.
- Aerospace Engineering – Observing aircraft engine robustness. To increase aircrafts activation duration with reducing operational expenses, manufacturers developed a real-time apps to

predict the performance of fuel and oil consumption, liftoff, control failure detection, mechanical conditions.

Predictive analytics is the process of utilizing historical information to make forecasts using the existing information. These processes require data or statistics, data analysis and ML model to build a prediction model to forecast future parameters.

Figure 4 presents the general prediction algorithms workflow. Techniques that are described in the prediction workflow are needed to utilize to build accurate prediction applications. As can be seen from the diagram, there are four main phases:

- *Data import* from different places, including databases, spreadsheets, and archives. In this study, we apply the real sensing data which are gathered from indoor fish tank. Used sensors are temperature, water level, pH level, and conductivity level sensors. Also, we also have outdoor environmental temperature, humidity, and solar radiation parameters which are con

- *Data preprocessing* by removing outliers and combining various data sources. We have identified and removed missing data, data spikes, and abnormal data points. Then we combine the collected data into a single CSV file; more precisely, tables in a CSV file are indoor temperature, pH, water level, conductivity, outdoor temperature, outdoor humidity, outdoor solar radiation, and time series values.

- *Development of the accurate prediction model* using the aggregated data using AI, ML, statistics or curve fitting tools. Fish farm environmental parameters forecasting is a complex process due to various external and internal factors, so we select Recurrent Neural Network's LSTM model to create and train the prediction model. We iterate the fish farm dataset with various approaches. After successful completion of the training, we test the trained model against new data to calculate the performance accuracy.

- *Model integration to the production environment.* Once we train an accurate prediction model for forecasting temperature, water level, pH level, and conductivity levels, we deploy it to the real fish farm environment IoT device using TensorFlow Lite, and connect it to the desktop application to analyze the future environmental parameters.

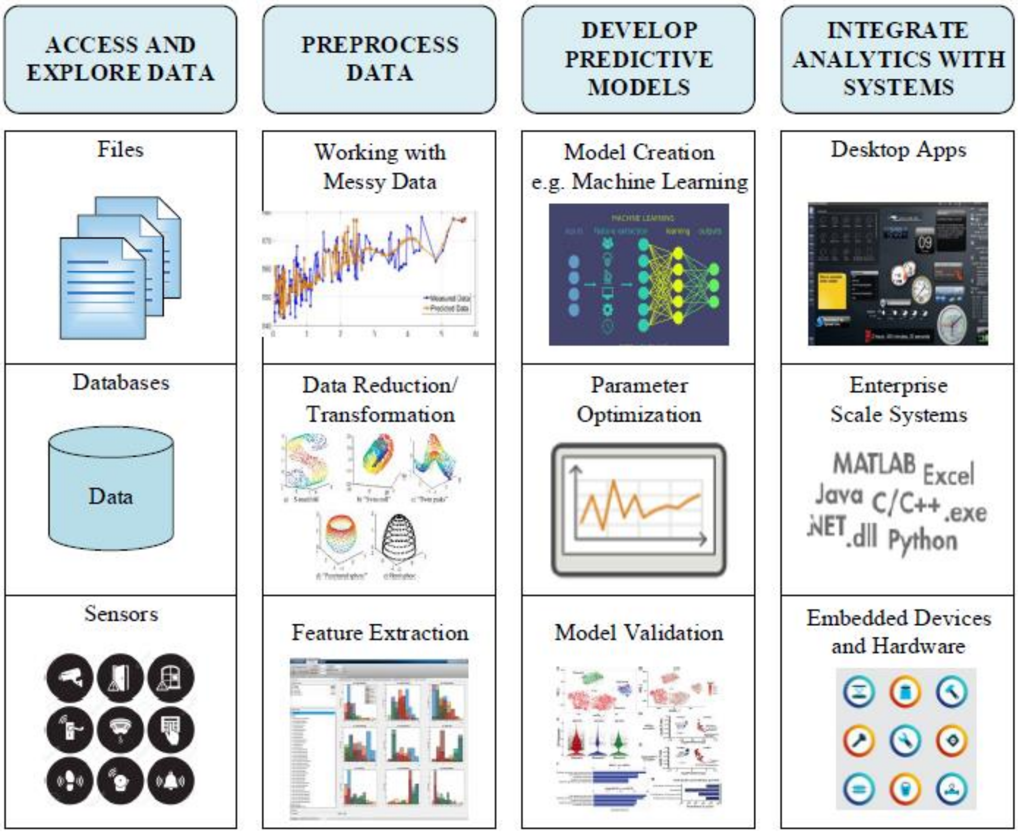


Figure 4: The workflow diagram of prediction algorithms [56]**.**

We now describe previous studies related to the prediction-optimization frameworks and their problems of interests. Amjady et al. presented a wind power prediction framework based on the prediction-optimization concept. In their proposed system, the hybrid neural network was deployed to forecast wind power, and the prediction module was combined with an enhanced PSO algorithm in order to increase wind energy prediction strategy, feature analysis capabilities, and forecasting engine [57]. The global optimization-based energy prediction concept was described in [58]. In that study, predicted temperature and humidity values were taken as input parameters to the ANN-based training module to investigate predicted energy requirements. The global optimization method was utilized to evaluate the effectiveness of the number of neurons to increase network layers for the accuracy, which influenced prediction and identification. Tulabandhula et al. presented a loss function minimization module for an unlabeled dataset with combining the prediction error and the operational cost optimization [59]. Ullah et al. suggested a water pump control module with efficient energy consumption for the smart fish farm which included prediction, optimization and control functionalities [60]. In their system, the current fish tank water level is monitored continuously using the water level sensor. Kalman filter-based prediction module predicts future conditions using historical data. Predicted values are used to compute an optimal condition to the fish farm based on user requirements and optimal resources environmental utilization. Finally, the rule-based control module provides an operational duration and pumping level to the water pump.

2.3 Optimization algorithms and their use cases

Growing demands are putting increasing pressure on experts and system designers to seek efficient and economical ways of resource utilization. Optimization methods are commonly used to meet complex user requirements with given constraints [61].

This is the sequence of steps that computer programs usually use to find the best solution to a problem. The optimization algorithm aims to maximize or minimize an existing solution by systematically selecting the input parameters from the assigned set and calculating the values of the functions. Optimization consists of finding the "most useful" values of certain objective functions, including various kinds of objective functions and various kinds of domains, depending on a specific area. However, the optimization does not always mean the selection of the best solution to problems. It is often included in the "Difficult problems" category because the nature of the problem can make this impossible. However, there are no polynomial-time algorithms for optimization problems that are NP-complex. In other words, in the worst case, the algorithm used may require an exponential calculation time to be optimal, which leads to a calculation time that is too long for practical reasons. The optimization algorithm can be used in any field which requires mathematical calculations, such as engineering, business, medicine, and so on. They can find the most optimal designing tradeoffs, control parameters, and data pattern analysis [62].

In recent years, many studies have paid attention to use approximate methods such as artificial neural networks or heuristic solutions, instead of using conventional optimization algorithms, for instance, Lagrangian relaxation, linear or quadratic programming or Nelder–mead simplex method. Heuristic algorithms are considered a straightforward methodology that supports satisfactorily. However, they are not as optimal as expected [63].

One of the most widely used solutions for solving complex optimization problems is dividing this optimization problem into various parts or a variety of steps, then step by step solving each portion of the problem and then combine all of the solutions in order to create complex problem solver for a complex problem. The methodology mentioned above plays an essential rule among researchers, and it is one of the widely used techniques. However, this type of solution is not accounted for in the theoretical explanations. In algorithms, computer science, mathematics, engineering researches, mathematical optimization is finding the optimal parameters among a number of existing alternatives. Basically, optimization algorithms aim is that increasing or decreasing the actual function parameters continuously by selecting input parameters from the mentioned set and estimate function parameters. Basically, the optimization algorithms are utilized to find the fittest ways of solution among all possible solutions. An optimization issue can be divided into two sections depending on whether the variables are continuous or discrete [64].

All optimization problems are driven by the known or unknown objective function, which is usually a mathematical expression that somehow relates the problem parameters in a way that can accurately assess and quantify the utility of selected candidate solutions. Any combination of problem parameters can be considered a candidate solution, and evaluation of objective function for the same combination can help us decide whether or not to consider them as a final solution [65].

Every problem is an optimization problem and it may have its own specific requirement, different from other problems. Therefore, there can be no single solution for solving all kinds of optimization problems. At one end, recent developments in processor manufacturing technology enabled us to have enormous computation power while on the other hand, user requirements, problem nature and complexity is also on the rise. As a result, many different optimization algorithms are developed. Figure 5 presents a typical classification of famous optimization algorithms. Energy management and control systems are computer-based applications utilized by people who have special knowledge about power-related fields to analyze, manage, and maximize the overall performance of the system. Therefore, inside the fish farm closed environment, we can manage, control, and optimize the usage of electrical energy using energy management and control.

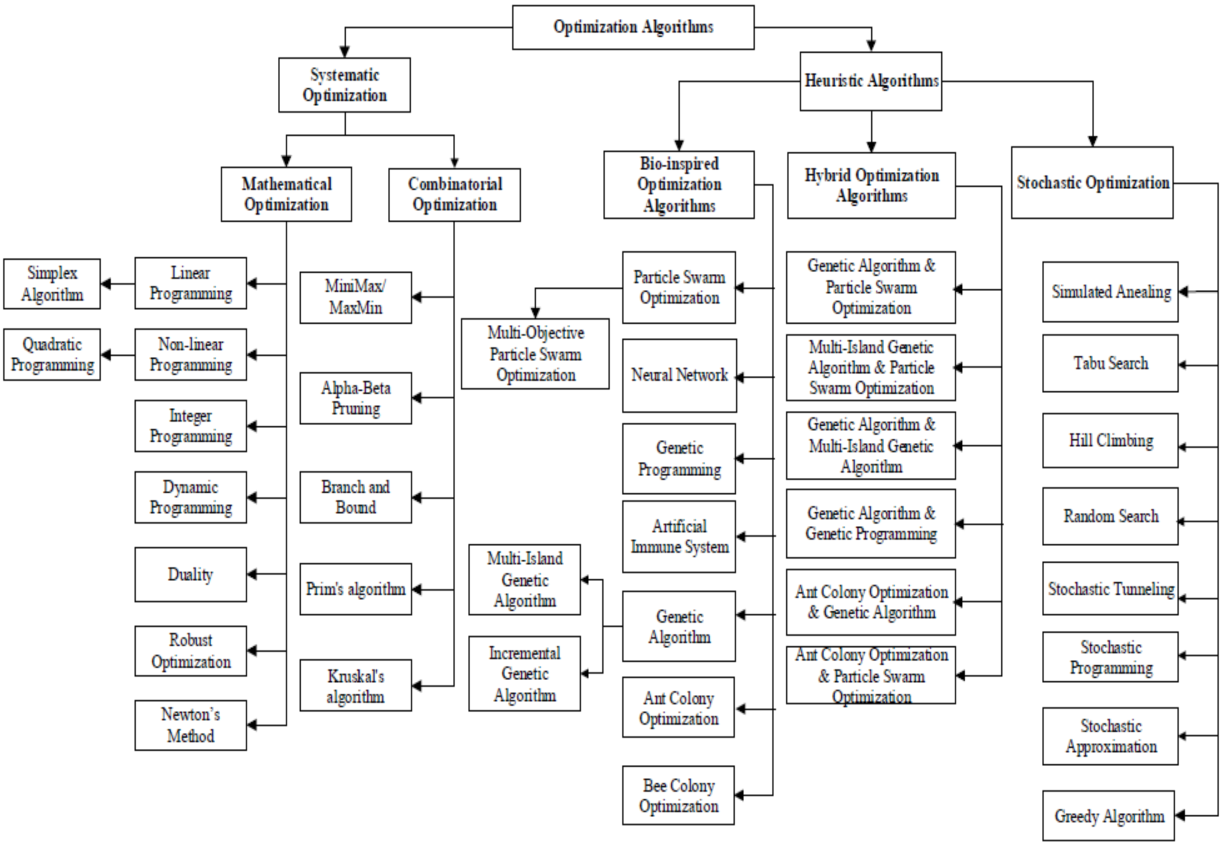


Figure 5: Typical classification of primitive optimization algorithms[66].

Morsly at al. studied this problem and has presented a binary particle swarm optimization (BPSO) based solution for optimal placement of cameras in the field [67]. Binary PSO is a variation of standard PSO for dealing with binary variables; here they consider camera placement in the grid is a binary variable i.e. its value will be one if a camera is placed in the grid cell, otherwise 0. Secondly, camera calibration is also very important in surveillance application for improved quality of captured videos and images.

Zheng et al. introduced a novel method using two vanishing points and a single vanishing line for minimum calibration condition in [68]. They formulated the camera calibration problem as a least-squares optimization problem to address the limitation of existing methods to find the appropriate focal length for the camera along with principal point and rotation angles. Cooperative surveillance is also an interesting field where more than one cameras or micro aerial vehicles (MAVs) are deployed to monitor same area of interest (AoI). In cooperative surveillance, the same region is observed from different angles and thus capturing more information about the scene or mission. However, its very challenging to dynamically deploy and control multiple MAVs such that they shall maintain safe distance and have collision-free flight over AoI while keeping in view device limitation and environmental constraints.

Saska et al. proposed a PSO based solution to solve this high dimensional optimization problem in [69]. For surveillance of traffic on particular road segment, unmanned aerial vehicle (UAV) can be deployed. Liu et al. modeled UAV route planning as multi-objective optimization problem in [70]. They tried to achieve this task with the minimum number of UAVs while ensuring minimum cruise distance among the UAVs using an adopted evolutionary algorithm NSGA based on Pareto optimality technique. Too many surveillance cameras generate an enormous amount of video data resulting in storage, transmission and analysis challenges. Exploiting the strong correlation between successive frames in video streams sharing the same background, Tain et al. proposed a novel encoding scheme using block-level background modelling (BBM) algorithm for video compression by identifying static background in frames for long term reference [71]. For increasing the accuracy of the proposed encoding scheme, they developed an optimization algorithm using the rate-distortion concept for the surveillance source (SRDO) algorithm. Through experimental analysis, they have reported that BBM and SRDO can effectively increase compression performance and be used as a critical component of many video-based applications for smart cities. A review paper about the various optimization techniques is outlined in [72] for power consumption scheduling for smart homes. Evaluation is performed in monetary terms so that relative utility of each scheme can be the highlight and quantified. As the energy scheduling problem is a linear optimization problem, therefore LP algorithm outperform all other schemes. Other optimization techniques also provide comparative solutions and are expected to perform well for more complex optimization problem where LP will fail. They observed that in online configuration, PSO wroks well, however, in extended offline scenarios, PSO can achieve a significant reduction in cost. Lorestani et.al. has developed an invasive weed optimization (IWO) algorithm for energy management controller (EMC) in order to optimize energy scheduling of associated resources to generate enhanced lookup tables [73]. They determine the power generation schedule for connected resources over hourly intervals. During the optimization process, constraints regarding operational limitations of power generating resources are considered along with varying electricity tariffs. To study the impact on operational cost of SHEMS, several scenarios are investigated. Zhang at al. has developed a framework for home energy management to support demand response program for domestic users in [74]. The proposed framework i.e. home energy management system (HEMS) allows the combination of domestic geothermal power resources in the future smart grid along with plug-in electric vehicles. Their proposed optimization scheme for scheduling flexible home appliances takes into account various factors such as predicted outdoor temperature, renewable resources output power, users preferences and electricity price. Through simulations, they verify the effectiveness of the proposed scheme and have reported 47.76% reduction in energy cost. Braun et al. [75] introduced the optimum controlling settings for water supplement systems without using storage; this system was based on optimization and system-based controlling. Chilled water loop supplement and the return temperature difference was also thought to influence on the pump power and chiller loading. Their proposed ChW system was developed, and three variables were chosen for the optimization case. Optimization is 3.3% effective compared to the baseline in annual cost saving.

Zhuhong Zhang [76] developed a multi-objective optimization algorithm for dynamics environments that aims to control the greenhouse environment. His proposed concept aims to build dynamic multi-objective optimization solutions to clarify and combine to environmental monitoring and improving. For greenhouse control, they created a decision rule for controlling based on MOIA

(Multi-Objective Immune Algorithm). The author deeply considered the algorithm side of the system; however, this work does not consider IoT devices and their role in the greenhouse.

2.4 Limitations of Existing Solution

Most of the studies in the literature are focused on a single key component or two components from environment monitoring, prediction, optimization and control. In addition, all of the existing systems can be used on a personal computer, local or cloud servers. To the best of knowledge, there is no related approaches presenting an integrated solution based on the three related key components in Embedded Hardware. The highest percentage of the existing solutions are paid attention to a selected AI algorithm which is once trained and then used. However, our proposed system can provide real-time environment monitoring, prediction, optimization and control directly on the IoT device. This attempt to take IoT based ML applications to the next level.

With the deployment of ML control applications to the embedded hardware, various advantages can be achieved including network cost, coverage, latency, privacy, data sovereignty, safety, energy consumption and decreasing the extra device usage.

3. Embedded Optimal Control Platform in Fish Tank

3.1 Conceptual Design of Embedded Optimal Control Platform

The proposed optimal embedded platform includes IoT and Machine Learning based real-time environmental monitoring and optimal management process for the smart fish farm. Figure 6 presents the layered view of the proposed system, which comprises the environment of interest, embedded hardware, and embedded software environment.

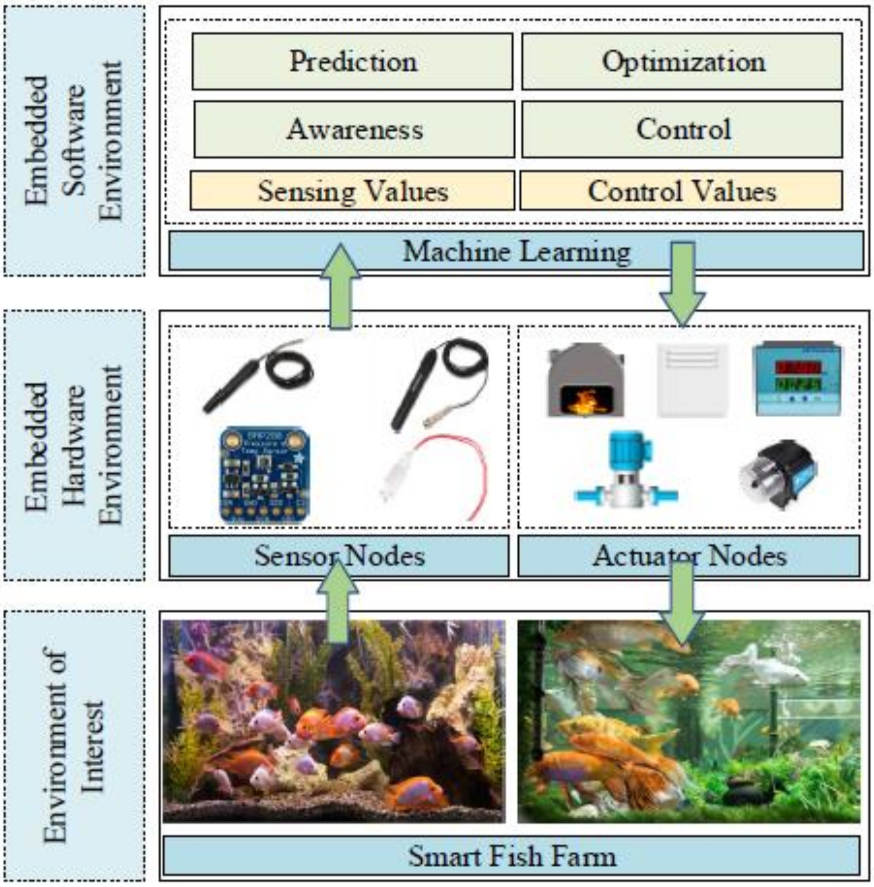


Figure 6: Layered view of the proposed embedded control platform in Fish Tank.

An embedded hardware environment includes the installed sensors and actuators to the fish tank. Four types of sensors (temperature, water level, pH, and conductivity) and five kinds of actuators (heater, cooler, pH controller, water pump and fish feeder) were proposed in this work. Sensors measure the data from the fish farm environmental parameters, whereas actuators are used to control these resources automatically.

Embedded software environment includes the trained and deployed model to the IoT device. This trained model provides context awareness, optimization and control algorithms which can calculate predicted, optimal and required control values for the environment using real-time sensing data. Fish tank actuators obtain control values from the top layer, and desired resources are provided to the environment.

We have implemented and deployed an integrated system that comprises four main modules, namely, 1) context awareness 2) prediction 3) optimization, and 4) control. The conceptual design of the proposed system is presented in Figure 7. The implementation of the proposed system includes four main stages.

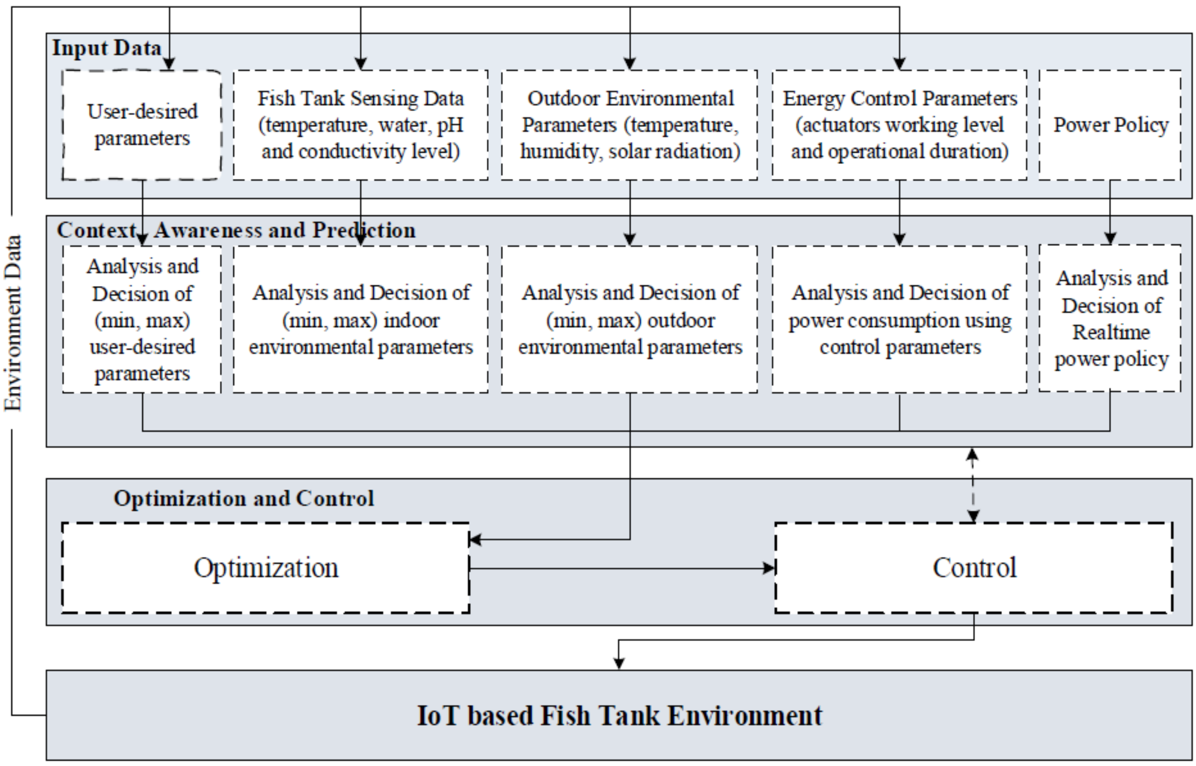


Figure 7: Conceptual design of the proposed embedded control platform in Fish Tank.

In the first stage, we develop the context-awareness module, which gathers information about the user-desired, indoor and outdoor environmental parameters, energy control parameters, and power policy values, then provides the analysis and decision about each parameter for the future decision. In the second stage, we develop the prediction module for predicting the fish tank environmental parameters and the required energy using the real data. In stage 3, we develop an optimization scheme for the calculation of the optimal fish tank environmental parameters using the predicted and user-desired environmental parameters. Also, the learning module is also used to increase the performance of the optimization scheme. In the last stage, we design and implement a control algorithm to control the fish tank actuators automatically.

Detailed conceptual design of the optimal control embedded platform for the fish tank efficient energy consumption is described in Figure 8. We have the environment of interest, the smart fish tank, which requires the IoT based automatic control for providing the healthy productive condition for the fish based on the fish farmer/user desired parameters with effective natural resource usage. The input data for the system includes the user-desired parameters, fish tank indoor environmental values such as, temperature, water level, pH and conductivity values which are collected using sensors, outdoor temperature, humidity, and solar radiation values, control parameters and power policy.

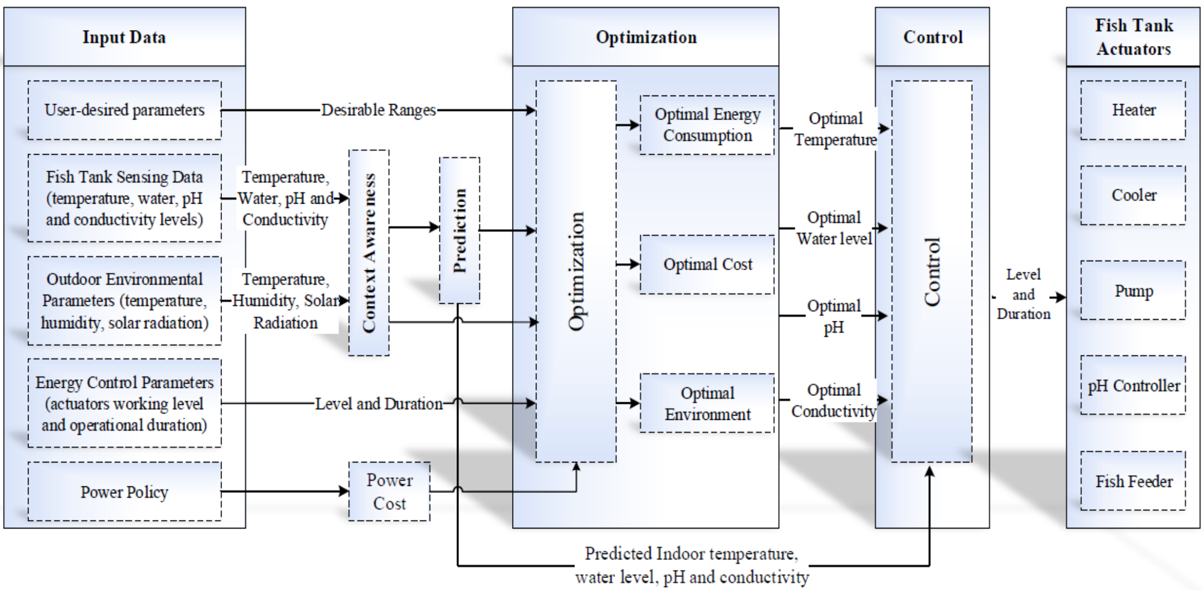


Figure 8: Detailed Conceptual design of the proposed embedded control platform in Fish Tank.

Figure 9 describes the proposed system architecture for the development of optimal control embedded platform using TensorFlow lite for the efficient energy consumption and fish growth in the fish tank. The proposed system comprises three environments, namely, fish farm environment, embedded hardware environment, and embedded software environment.

Embedded hardware environment comprises various IoT devices, sensing and actuator nodes, input/output ports, serial communication ports, power supply, and other essential tools to check and control the various fish farm environmental parameters. Sensing nodes are used to check the environmental parameters in real-time, whereas actuator nodes control these environmental parameters with increasing or decreasing the natural resources according to the user requirement.

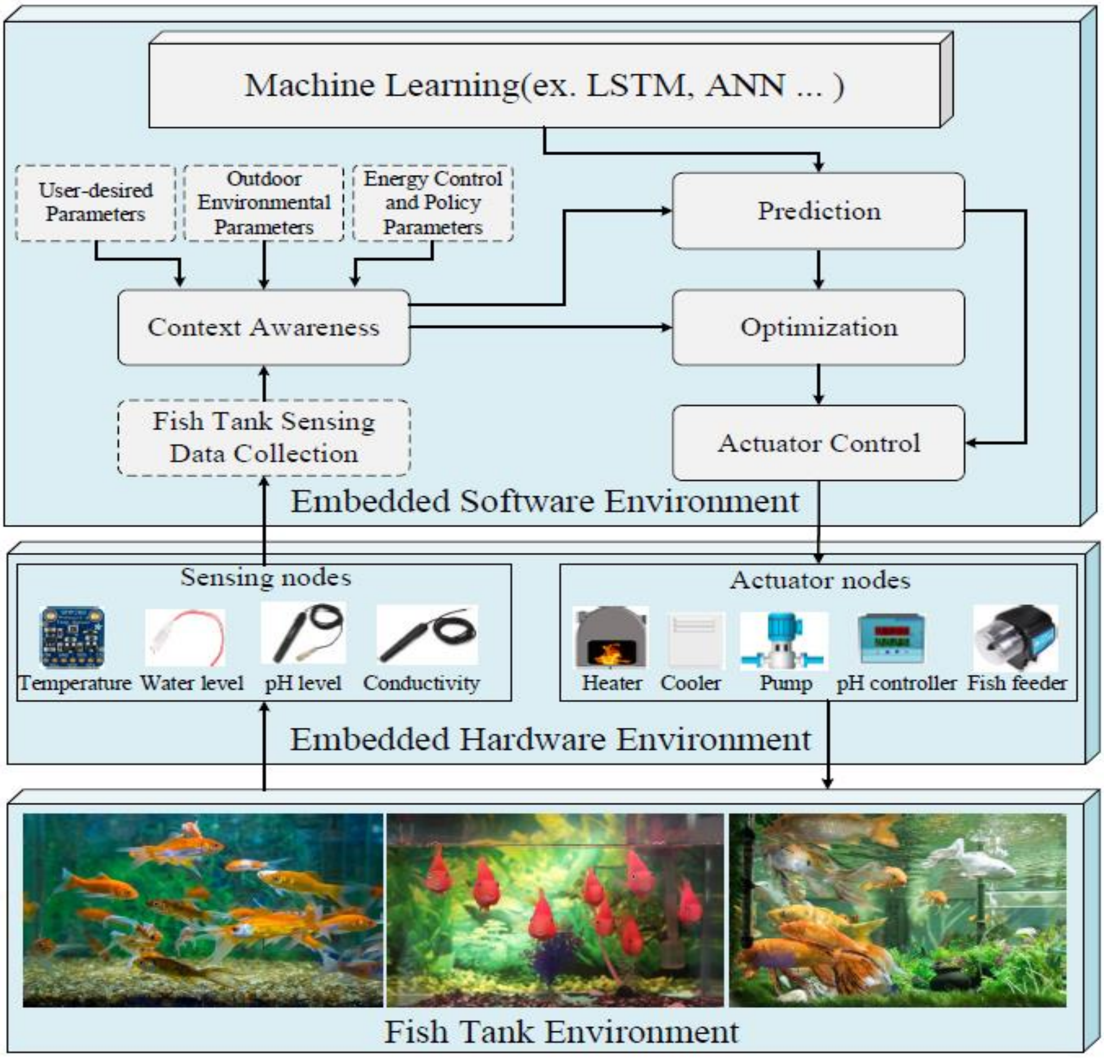


Figure 9: Proposed system architecture for the development of embedded control platform.

The embedded software environment is computer software that is deployed to devices or machines for performing all functionalities on devices without executing these applications in highly compute-intensive processes on PCs, local, and cloud servers. With deploying machine learning (RNN-LSTM), optimization control algorithms (Fuzzy logic) as an embedded software, a number of advantages can be achieved in terms of network cost, latency, privacy, data sovereignty, and power consumption.

IoT sensor nodes are used to measure the indoor environmental parameters from the fish farm environment. Using the historical data, we trained the model to predict, optimize, and compute the optimal control parameters to the fish farm parameters. Then a trained model is deployed to the embedded hardware environment as an embedded software using TensorFlow Lite. As new sensing values come to the embedded software, the software calculates the required future optimal control values with considering cost minimization, and optimal usage of the resources.

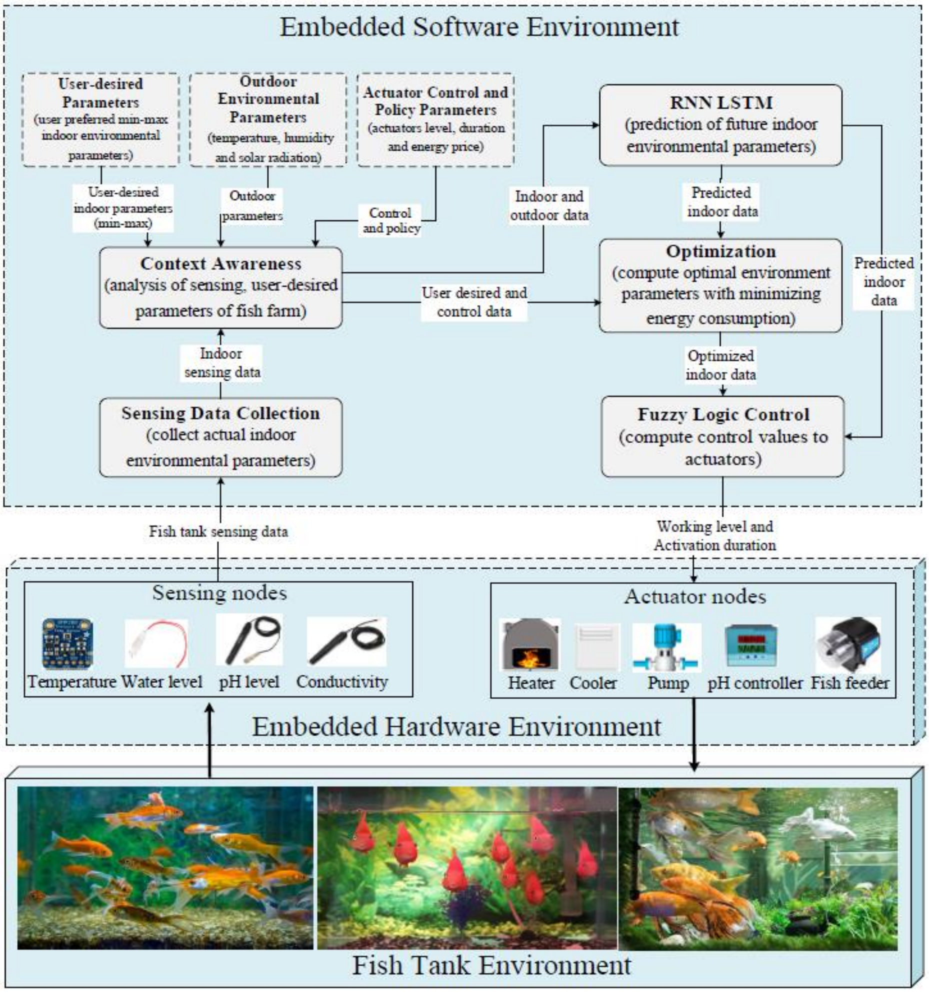


Figure 10: Detailed proposed system architecture for the development of an embedded control platform.

The detailed proposed optimal control embedded platform architecture is represented in Figure 10. We considered temperature, water level, pH, and conductivity level values of the fish tank, among other various fish tank parameters. IoT sensors are used to measure these values from the fish tank and send them to the data collection unit. The context-awareness module provides the analysis and clarifies the required data ranges for better future performance. Based on the collected data, we train a model to predict future environmental parameters with required energy consumption for the fish farm. These parameters are predicted temperature, predicted water level, predicted pH level, and predicted conductivity. The optimization module is used to calculate the optimal environmental parameters based on user preferred and the system constraint settings. FLC is used as a control algorithm for the proposed system to calculate and set the optimal working level and activation duration. In this work, we use a heater, cooler, pump, pH controller, and fish feeder actuators to control the environmental and feeding processes in the fish tank. The FLC module assigns the activation level and working duration for fish farm actuators. Based on these control values, actuators control the temperature, water level, pH, and conductivity level in an optimal condition by minimizing the energy consumption and maximizing the cost. In the coming subsections, we describe algorithms and modules in detail.

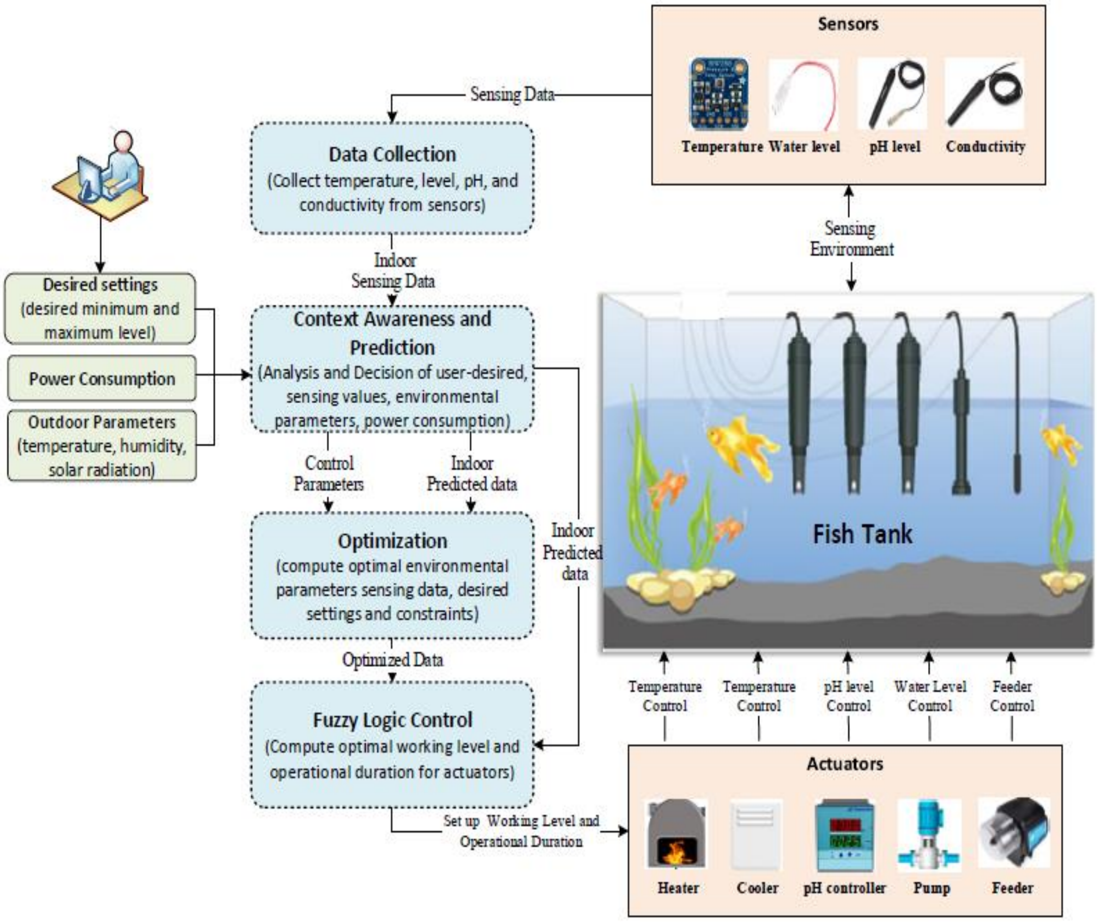


Figure 11: Proposed embedded optimal control platform flowchart diagram.

Proposed embedded predictive optimal control platform flowchart diagram is described in Figure 11. As can be seen from the figure, several processes are combined in this study. Firstly, IoT sensors monitor the fish tank water condition by measuring water quality parameters (e.g., temperature, water level, ph level, and conductivity) to the data collection unit. In the second step, we apply the context awareness and prediction unit to analyze the used desired min max settings, environmental parameters with predicting future indoor parameters for the fish tank. Thirdly, the objective function is used as an optimization algorithm to calculate optimal indoor parameters for the fish growth with efficient energy consumption with considering user desirable parameters, system and control constraints. At the end of the process, fish tank actuators' operational level and activation duration are computed using the FLC. For the calculation of the control values optimized and predicted environmental parameters are used as input values to the FLC module.

Table 1 gives a detail explanation of data with examples. Five types of data are used as input parameters for the proposed system.

Table 1: A brief description of the data used in this work.

Input data	**Description**	**Example**
User-desired parameters	User desired parameters are the most desired values for the environment. A fish farmer knows the most acceptable minimum and maximum temperature, water level, pH level or conductivity levels to the fish growth	20°-25°C ranges for temperature 6.5-8.0 acid ranges for pH level 300–500 μS/cm ranges for cond. 280-320 mm ranges for water
Indoor environmental parameters	Indoor environmental parameters are collected data from the fish tank using temperature, ph level, conductivity and water level sensors with time-series data	18.7166 °C 2/5/2020 11:30 P.M 6 acid 2/5/2020 11:30 P.M 812.60 μS/cm 2//2020 11:30 247 mm 2/5/2020 11:30 P.M
Outdoor environmental parameters	Outdoor temperature, humidity, and solar radiation. This data can increase the performance of the prediction model. Because if the outside is too cold, it will also influence on indoor temperature.	5.08333 °C 2/5/2020 11:30 P.M 93.1% 2/5/2020 11:30 P.M 403.6 nm 2/5/2020 11:30 P.M
Energy Control Parameters	Actuators' control values are their operational level and activation duration. With controlling their working level and operational duration, we can control the power consumption	Water pump: 1 min activation with minimum working level requires 800 watts energy, medium working level 1200 watts energy.
Power Policy	Power policy describes the pricing rate of the energy for the actuators' consumption. The pricing rate in Korea is 78.3 won for the first 200 kWh, 147.3 won for the next 200 kWh, 215.6 won for all over 400 kWh	In this work, to the simplicity of the calculation, we have considered 129 won for 1 kW energy for the calculation of the price

3.2 Embedded Optimization and Control Scheme using Fish Tank Sensing Data

3.2.1 Embedded Optimal Control Scheme in Fish Tank

In this section of the thesis, we present briefly proposed embedded control scheme for the controlling fish tank environmental parameters using actual sensing values and user-desired minimum and maximum parameters. Figure 12 describes the conceptual design of the proposed optimization and control based fish tank control mechanism. Input parameters for the fish tank are user desired minimum and maximum values for temperature, pH, conductivity and water level. Output parameters are heater, cooler, water pump and pH controller's operational level and activation time. Optimization computes the optimal temperature, pH level, conductivity and water level to the fish tank according to the user-desired indoor parameters. Control module calculates the operational level and activation duration to the IoT actuators based on optimal and actual values using IF-THEN rules. For instance, if the actual temperature is less than the user desired minimum, then the heater is activated and increases the temperature level.

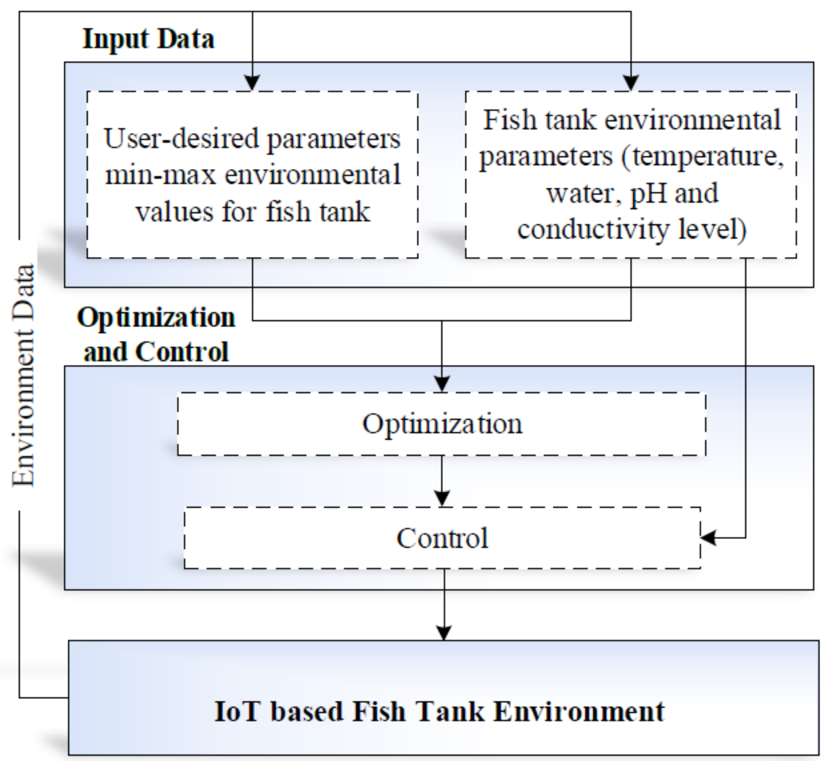


Figure 12: Conceptual design of the optimization and control based proposed system.

The detailed conceptual design of the proposed optimization and control based fish tank environmental control mechanism is described in Figure 13. Input parameters are the user-desired minimum and maximum parameters and actual temperature, water, pH and conductivity levels. Based on these parameters, the optimization module calculates the most optima environmental values to fish production.Input parameters are the user-desired minimum and maximum parameters and actual temperature, water, pH and conductivity levels. Based on these parameters, the optimization module calculates the most optima environmental values to fish production. Then the control module calculates the working level and activation duration to the fish tank actuators using optimal and actual values. It is important to note that this system design is based on optimization and control algorithms and does not include the prediction module. With developing with prediction and without prediction modules, we can evaluate the system and increasing the efficiency of the proposed system.

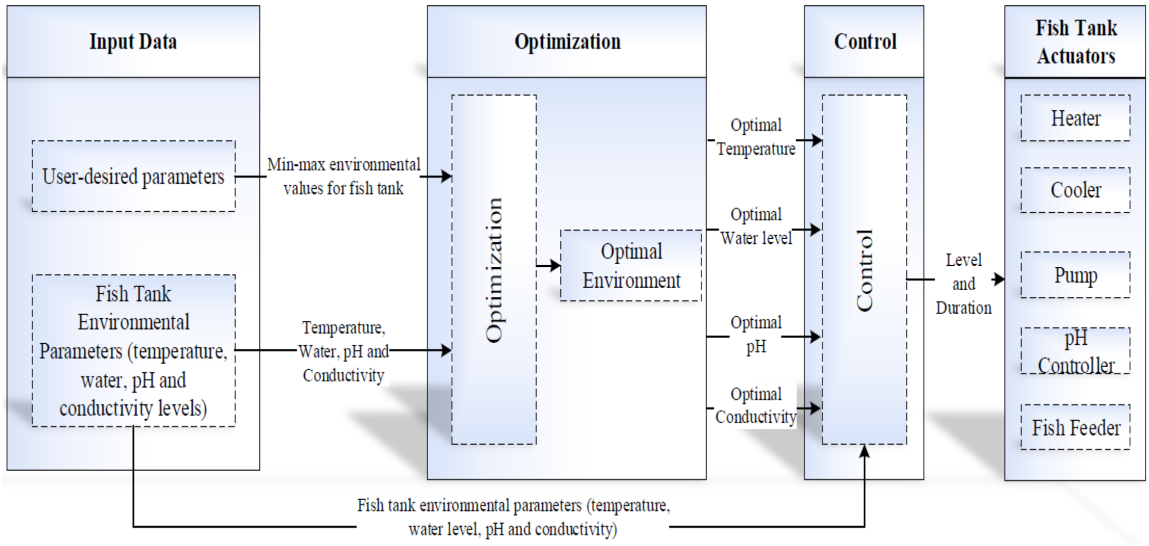


Figure 13: Detailed Conceptual design of the optimization and control based proposed system.

Figure 14 describes the detailed optimization and control based fish tank environmental control scheme using actual environmental parameters. As we mentioned above the proposed system comprises three environments, namely, fish tank environment, embedded hardware environment, embedded software environment. IoT sensors and actuators are installed to the fish tank environment as an embedded hardware environment for collecting temperature, water, pH level and conductivity values. Actual sensing values are used to calculate the optimal parameters based on user-desired parameters in the optimization module. Fuzzy logic control module computes the working level and activation duration to the actuators based on actual environmental and optimal environmental data. Based on these control values heater, cooler, pump, pH controller and fish feeder are controlled automatically.

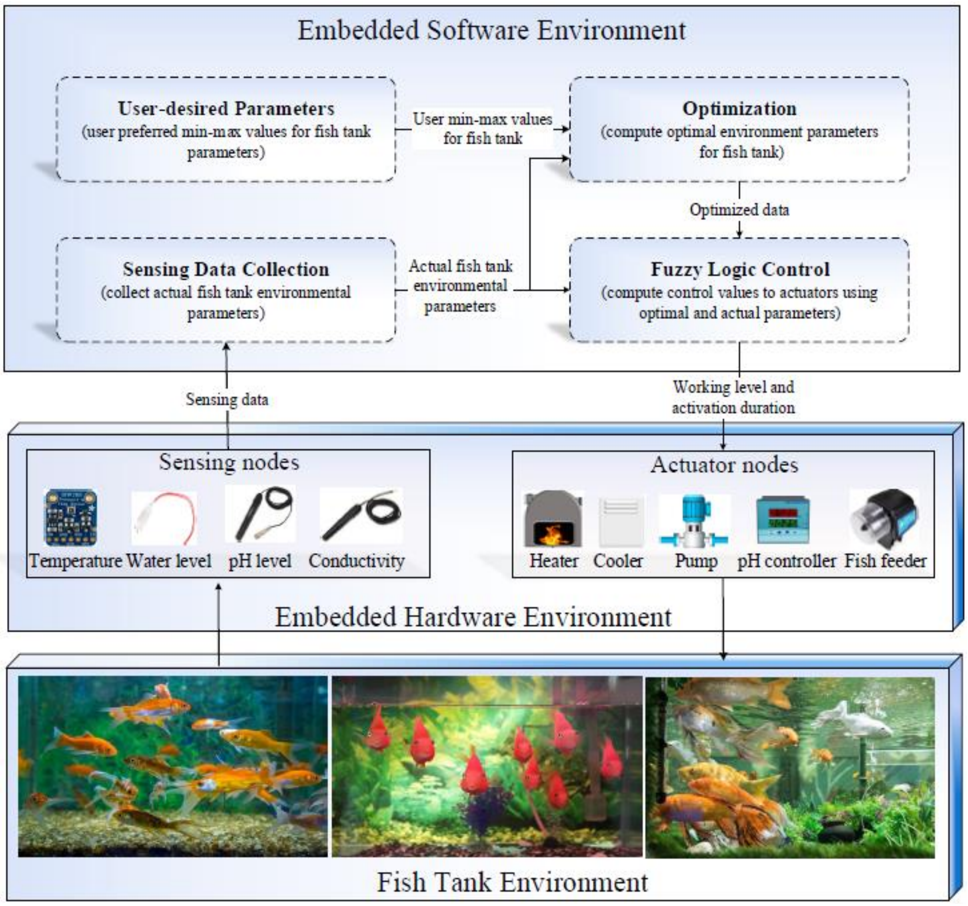


Figure 14: Optimization and control based proposed system architecture.

Figure 15 shows the flowchart diagram of the optimal control mechanism using the actual sensing data. In this study, we consider the prediction, optimization, and control based fish tank environment monitoring system with efficient energy consumption. We implemented the overall system by considering the various cases, as shown in this subsection. This subsection only considers the optimization and control based fish tank environment optimal control system without a prediction model. Optimization scheme computes the most optimal environmental parameters based on actual sensing values and user-desired settings, then fuzzy logic control module computes the working level and activation duration to the actuators using optimized and actual environmental values.

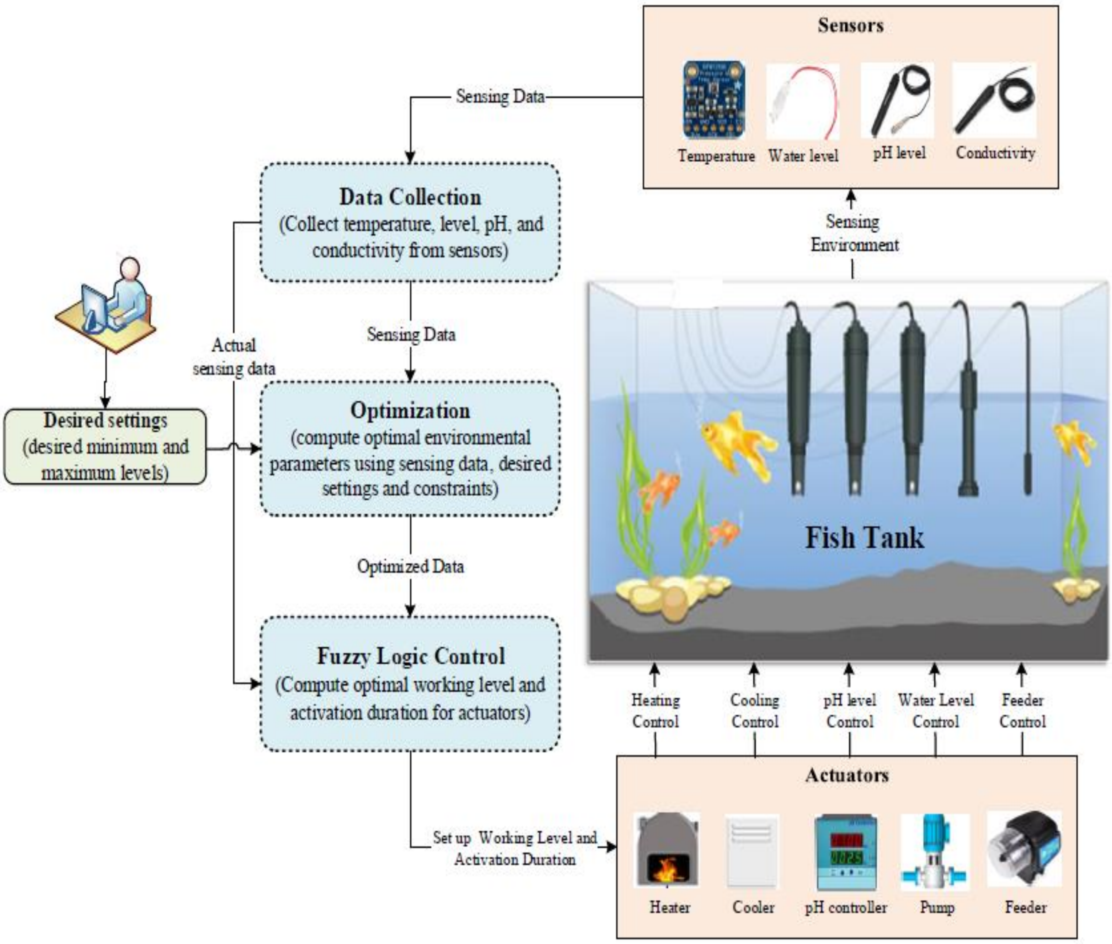


Figure 15: Flowchart diagram of the fish tank environmental control using sensing data.

Figure 16 illustrates the sequence diagram of the proposed optimization and control based fish tank environmental control mechanism using actual sensing values. As we mentioned above, this subsection considers the development of optimal control embedded platform for the fish tank based on optimization and control model without considering the prediction module. As can be seen, the graph includes the fish tank environment, IoT sensors, actuators, the proposed system and user. Sensors are used to collect the actual temperature, water, pH and conductivity levels. The proposed system has data collection, optimization and control functionalities. Based on actual temperature, pH, water, and conductivity values, the objective function computes the optimal environmental parameters to the fish growth based on collected data and user-desired parameters with efficient energy consumption. Then the fuzzy logic-based control unit calculates the working level and activation duration to the actuators using actual and optimal environmental parameters. The role of the user is assigning user-desired parameters to the proposed system and checking the results from the visualized charts.

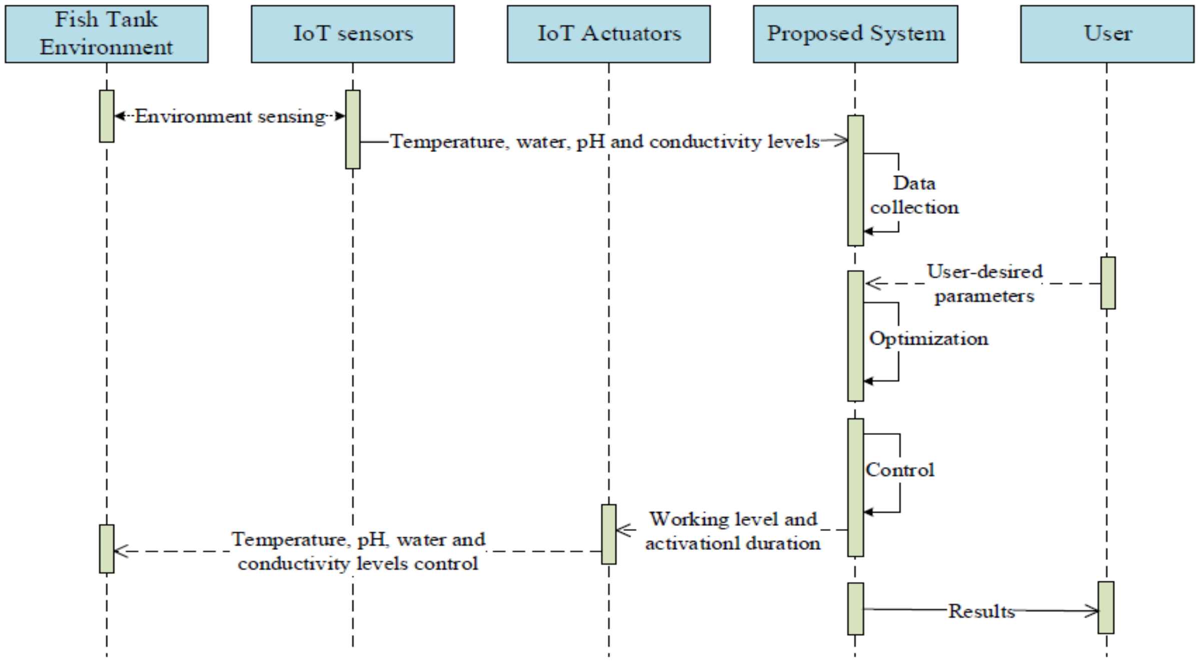


Figure 16: Optimization and control based proposed system architecture.

3.2.2 Proposed Objective Function for Optimization algorithm using Fish Tank sensing data

In this section of the paper, we described our model for fish farm environmental parameters optimization in detail. We developed an objective function for the maximization of fish farm environmental parameters with efficient energy consumption based on actual environmental values, user-desired settings, and system constraints. T, pH, C, and W describe water temperature, pH level, conductivity, and water levels, respectively. The fish tank indoor environmental control time is assumed as one day. One day is divided into T time slots, each slot duration is considered as 15 minutes; as a result, one day divided into T=96 slots. The actual environmental parameters for the fish farm (EPF_a) are described in equation 1

$$EPF_a = [T_a, pH_a, C_a, W_a] \tag{1}$$

Where, T_a, pH_a, C_a, and W_a are the actual temperature, actual pH, actual conductivity, and actual water-level values, respectively, which are collected using Fish Tank IoT sensors. Fish farm user/farmer can choose the range of highly desirable environmental parameters for the fish farm (EPF_d) with desired settings for each value as described in (equation 2).

$$EPF_d = [T_d\ pH_d, C_d, W_d] \tag{2}$$

Table 2 presents a brief description of the used notations in this formulation.

Table 2:Description of notations used in the formulation.

Notation	Description
T	Number of time slots
SD	Slot duration [minute]
EPF_a	Actual environmental parameters for fish tank
EPF_d	User desired environmental parameters
T_a, pH_a, C_a, W_a	The actual temperature, pH, conductivity and water level parameters
T_d, pH_d, C_d, W_d	User desired temperature, pH, conductivity and water level
T^{min}, pH^{min}, C^{min}, W^{min}	The minimum ranges of the desired environmental parameters
T^{max}, pH^{max}, C^{max}, W^{max}	The maximum ranges of the desired environmental parameters
T^{opt}, pH^{opt}, C^{opt}, W^{opt}	The optimal level for environmental parameters
EC	Energy consumption for actuators {heater, cooler, water pump, pH and fish feeder}
OE	Optimal environment for the healthy fish production
α_{EC}, α_{OE}	Objective weights of energy consumption, optimal environment.
EC^{min}	Total energy consumption with the minimum desired parameters ranges
EC^{max}	Total energy consumption with the maximum desired parameters ranges
EC^{opt}	Optimal energy consumption with optimal environmental parameters
g_{max}	Maximum ranges between predicted and desired environmental parameters
Gr	The range between predicted and desired environmental parameters values at time t
A^{max}	Maximum working level for the actuators (fewer time slots and higher energy consumption required)
A^{min}	Minimum working level for the actuators (more time slots and less energy consumption required)
EC*	The convex combination of the energy consumption
*OE**	The convex combination of the optimal condition

Where T_d, pH_d, C_d, and W_d represents the user desired temperature, pH level, conductivity, and water level, respectively. User desired parameters are the most acceptable ranges for the fish growth, which can be inserted from the fish farmer to the system. The proposed objective function calculates the optimal fish farm indoor parameters based on user desired parameters. Because of the optimal temperature, pH level, conductivity need to fulfil the user requirement. User desired setting values are the allowed between the minimum and maximum ranges of each parameter such that,

$$\begin{aligned} T_d &= [T^{min}, T^{max}] \\ pH_d &= [pH^{min}, pH^{max}] \\ C_d &= [C^{min}, C^{max}] \\ W_d &= [W^{min}, W^{max}] \end{aligned} \tag{3}$$

Where T^{min}, pH^{min}, C^{min}, and W^{min} present the minimum user desired ranges for the temperature, pH level, conductivity and water level, respectively. While T^{max}, pH^{max}, C^{max}, and W^{max} describes the maximum user desired parameters for the indoor values in the same order. Based on desired ranges, the maximum values obtain the most desired settings for the environment, and the minimum values are the least acceptable value for the environment parameters. Above mentioned, the minimum and maximum environmental parameters also describe the *boundaries* of the proposed objective function at the same time. For instance, the actual temperature (T_a) is between the minimum (T^{min}) and maximum (T^{max}) temperature boundaries, then no need to optimize the actual temperature because it is already inside of the boundaries or user-desired parameters. If the actual temperature lower than the minimum boundary ($T_a<T^{min}$), then we need to activate the heater to increase the actual temperature until to reach between the minimum and maximum boundaries of the temperature ($T^{min}<T_a<T^{max}$). If the actual temperature is higher than the user desired maximum boundary ($T_a>T^{max}$), then we need to activate the cooler actuator. It is true that a fish farmer obviously wants to boost the production by setting up maximum parameters for each value. However, the maximum configuration of actuators requires high energy consumption. Let us assume the optimal environmental parameters in time *t* that can achieve desired environmental settings are given by (4)

$$EPF^{opt} = [T^{opt}, pH^{opt}, C^{opt}, W^{opt}] \tag{4}$$

Where EPF^{opt} describes the optimal environmental parameters for the fish tank, and T^{opt}, pH^{opt}, C^{opt}, and W^{opt} present optimal temperature, optimal pH level, conductivity, and water level, respectively. Optimal environmental values have to be between the minimum and maximum user-desired ranges, as shown below (5),

$$\begin{gathered} T^{opt} \in [T^{min}, T^{max}] \\ pH^{opt} \in [pH^{min}, pH^{max}] \\ C^{opt} \in [C^{min}, C^{max}] \\ W^{opt} \in [W^{min}, W^{max}] \end{gathered} \tag{5}$$

In the following, the objective function takes into account two terms introduced, overall energy consumption (EC), and optimal environment (OE) to the fish tank. Overall energy consumption can be calculated according to the energy consumption of the actuators' working level and operational duration. With a minimum working level, actuators consume less energy but spend more operational duration for achieving optimal condition as described in equation 6:

$$EC^{min} = \sum_{t=1}^{T} A_{heat}{}^{min} + \sum_{t=1}^{T} A_{cooler}{}^{min} + \sum_{t=1}^{T} A_{pump}{}^{min} + \sum_{t=1}^{T} A_{pHCont.}{}^{min} + \sum_{t=1}^{T} A_{feeder}{}^{min} \tag{6}$$

EC^{min} describes the overall energy consumption of the actuators with activating them minimum working level, and A^{min} is the minimum working level for the heater, cooler, pump, pH controller and fish feeder actuators. EC^{max} is energy consumption of actuators with activating maximum (A^{max}) working levels (6). As we mentioned above, with maximum working level actuators consume more energy but spend less operational duration for achieving optimal condition: Activating the actuators' with minimum working level requires a long time and less energy in per minute.

$$EC^{max} = \sum_{t=1}^{T} A_{heat}{}^{max} + \sum_{t=1}^{T} A_{cooler}{}^{max} + \sum_{t=1}^{T} A_{pump}{}^{max} + \sum_{t=1}^{T} A_{pHCont.}{}^{max} + \sum_{t=1}^{T} A_{feeder}{}^{max} \tag{7}$$

Optimal environment (OE) depends on the working level and activation duration of the actuators. If we run the heater actuator with a minimum working level, it spends different time for achieving the optimal environment and g_{max} (Maximum ranges between actual and desired levels for each fish farm parameter). The below-given equation describes the optimal environment based on the minimum, medium, and maximum working levels of the actuators. Actual input parameters are divided into three categories {Low, Normal, and Very High}, according to the level of the actual input parameter actuators spend different time and activation duration for achieving the optimal environment. For instance, if the predicted temperature level is Low, then we need to activate the heater, and if the heater is activated with minimum working level, then it spends 4-time slots for achieving an optimal environment. By activating the maximum working level, the heater requires 2-time slots to achieve optimal environmental parameters, as shown in equation 8. The same consideration applies to the other actuators too.

$$
\begin{aligned}
OE^{min} &= \boldsymbol{g}_{max} + \sum_{t=1}^{T} \boldsymbol{gr} * A_{heat}^{min} \\
OE^{max} &= \boldsymbol{g}_{max} + \sum_{t=1}^{T} \boldsymbol{gr} * A_{heat}^{max}
\end{aligned}
\tag{8}
$$

Where OE^{min} and OE^{max} present optimal environment of the fish growth according to the minimum (A_{heat}^{min}) and maximum working level activation of the heater (A_{heat}^{max}). gr describes the ranges between actual and desired environmental parameters ranges at time t and T is various time slots for activating actuators. The objective function is a convex combination of the above two cost indices scaled as follows.

$$
\begin{aligned}
EC^* &= (EC - EC^{min})/(EC^{max} - EC^{min}) \\
OE^* &= (OE - OE^{min})(OE^{max} - OE^{min})
\end{aligned}
\tag{9}
$$

Where EC^* and OE^* describe the convex combination of the optimization energyc consumption and environment, respectively. While EC^{min}, EC^{max}, OE^{min}, OE^{max} represent the minimum and maximum values achievable for energy consumption and an optimal environment. The final objective function to be minimized is

$$J = \min(\alpha_{EC}(1-(EC^*)^2) + \alpha_{OE}(1-(OE^*)^2) \quad (10)$$

Where α_{EC} and α_{OE} represent the user desired objective weights for the energy consumption and optimal environment in the range [0, 1], respectively, for instance, if the user pays more attention to the energy consumption, then he or she gives 0.9 value to the energy consumption(α_{EC}) weights and 0.1 value for the optimal environmental parameters (α_{OE}). If the energy consumption is not a problem for the user, then the user can boost the production by giving high weight to the optimal environment (α_{EC} = 0 and α_{OE} = 1).

The system constraints:

$$\begin{aligned}
T_a &< T_d^{min} < T^{opt} < T_d^{max} \\
W_a &< W_d^{min} < W^{opt} < W_d^{max} \\
pH_a &< pH_d^{min} < pH^{opt} < pH_d^{max} \\
C_a &< C_d^{min} < C^{opt} < C_d^{max} \\
0 &< EC^{min} < EC^{opt} < EC^{max} \\
0 &< OE^{min} < OE^{opt} < OE^{max}
\end{aligned} \quad (11)$$

3.2.3 Control Mechanism using Fuzzy Logic in Fish Tank

Over the past several years, Fuzzy Logic Control (FLC) based applications have been considered as one of the main fruitful and active fields in industrial areas, mainly research-based studies. Applying traditional control methods to the industrial processes is difficult due to less available data for the input and output parameters. The basement of the FLC is a fuzzy logic, which is closer to people' reasoning and their language description than the conventional control methodologies [86]. As we mentioned above, we developed the FLC module for computing operational level and activation duration to the actuators based on predicted and optimal environmental parameters.

Input parameters to the fuzzy system are divided into two categories, namely actual and optimized levels of the temperature, water level, water humidity, and conductivity level sensing data. FLC computes control parameters for actuators based on the actual and optimal sensing levels. Figure 17 describes the proposed fuz zy logic control mechanism for controlling the fish tank actuators. These actuators are heater, cooler, pump, pH controller, and fish feeder. As can be seen, the input parameters for the fuzzy logic are actual and optimized environmental parameters. Input actual values are labelled by dividing five categories, namely, very low, low, medium, high, very high and optimized. IF-THEN conditional statements are deployed to compute activation level and operational duration for actuators.

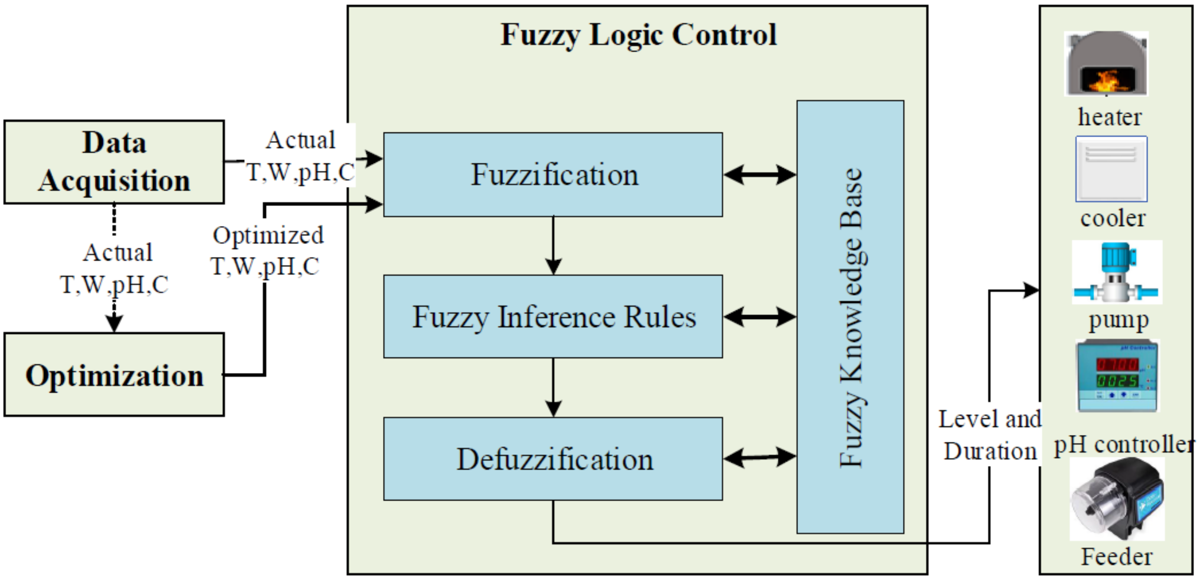


Figure 17: Fuzzy logic control mechanism for controlling Fish Tank actuators.

Fuzzification [90] is a process which converts crisp input parameters to the linguistic values. The below-given parameters describe the input and output parameters for the proposed fuzzy logic control module. Input parameters are actual temperature, pH level, water level and conductivity levels which is divided into five categories based on specific ranges as described in brackets. Second input parameters are optimal temperature, pH, water and conductivity. Whereas, outputs of the fuzzy logic are working level and activation duration for each actuator. Acceptable fuzzy linguistic variables are selected for each fuzzy variable.

•*Input:* Actual Temperature, pH, Water and Conductivity levels {Very Low, Low, Normal, High, and Very High}

•*Input:* Optimized Temperature, pH, Water and Conductivity {Optimal}

•*Output:* Actuator working-level {Minimum, Medium, Maximum}

•*Output:* Actuator activation duration {OffTime, Very Little, Little, Normal, Much, Very Much}

Figure 18 illustrates the detailed fish tank temperature parameters control flow diagram using heater and cooler actuators. As can be seen from the figure, there can be three conditions, a) if the actual and optimized temperature values are equal to each other in time t, then no need to activate the heater and cooler actuators. b) if the actual temperature is lower than the optimized temperature values, then fuzzy logic-based control unit computes and sets working level and operational duration based on below-mentioned rules. If the case a) fails and the actual temperature is higher than the optimized temperature, then the control unit sets working level and activation duration to the cooler actuator.

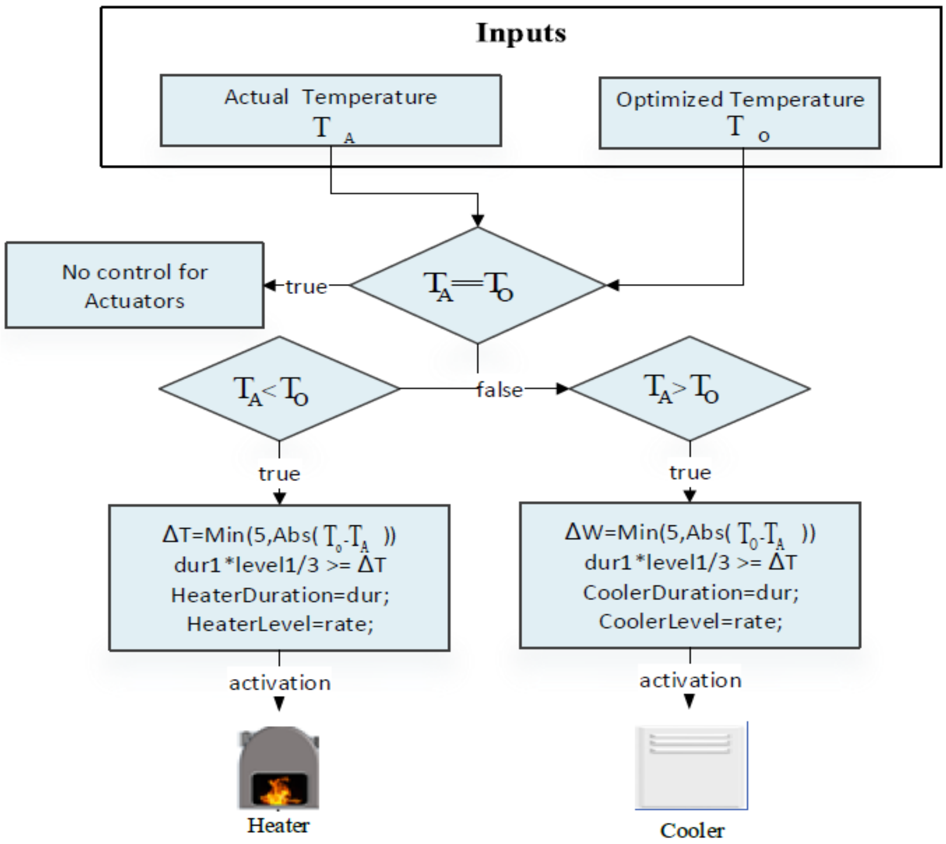


Figure 18: Flow diagram of fuzzy logic-based temperature control.

Water pump actuator control has two input parameters, namely actual water level and optimized water level as presented in Figure 19. The actual water level is the real-time collected data from the fish tank environment using the water level sensor, while the optimized water level is the computed optimal value using the objective function which we have formulated for the fish tank environmental parameters optimization. We do not need to operate actuators if the actual water level is equal to or higher than the optimal water level in case a. If case a) fails and the optimal water level is higher than the actual water level parameters then fuzzy logic-based control unit computes the operational duration and activation level to the water pump actuator.

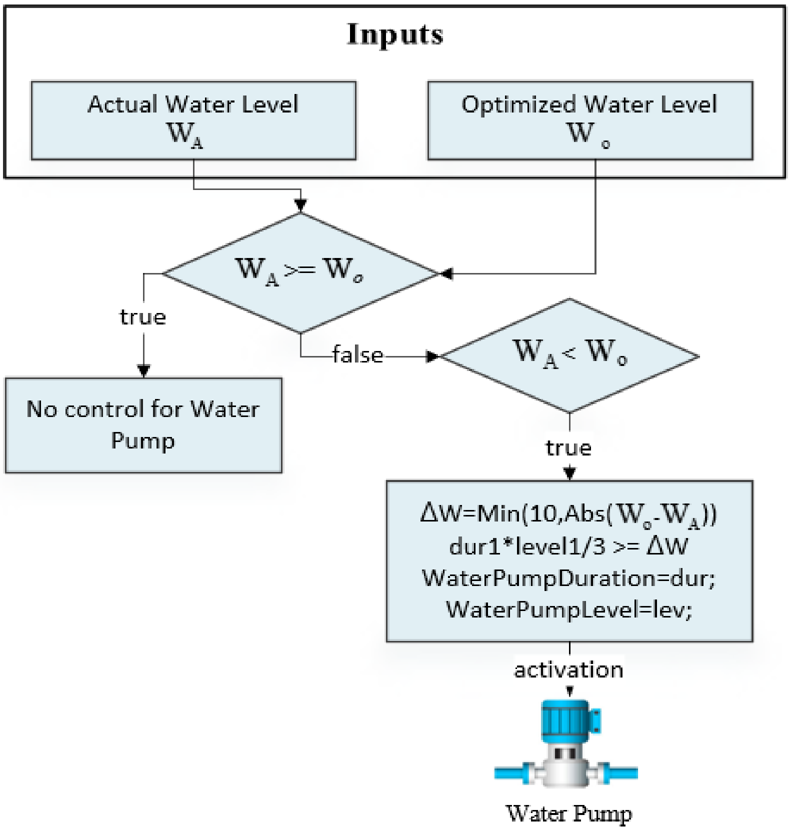


Figure 19: Flow diagram of fuzzy logic-based water level control.

Fish tank pH level control process has two input parameters: the actual pH level and optimal pH level. Figure 20 represents the detailed fuzzy logic-based flow diagram of the proposed fish tank pH level control unit. The actual pH level is the real-time collected data from the fish tank environment using the pH level sensor, while the optimized pH level is the computed optimal pH values using the objective function which we have formulated for the fish tank environmental parameters optimization. As can be seen, there are two possible cases, case (a) when the actual pH level is equal to or higher than the optimized pH level; then any actuators are no need to activate. In case of b) if the actual fish tank pH level is less than the optimized pH level, then fuzzy logic-based control unit computes the operational level and activation duration to the pH controller. For controlling the fish feeding and conductivity level the same rules are considered as we described in above-mentioned figures. Their input parameters are the actual and optimized parameters. The proposed optimization algorithm can be extended easily with other fish tank environmental parameters i.e. dissolved oxygen, humidity, and so on.

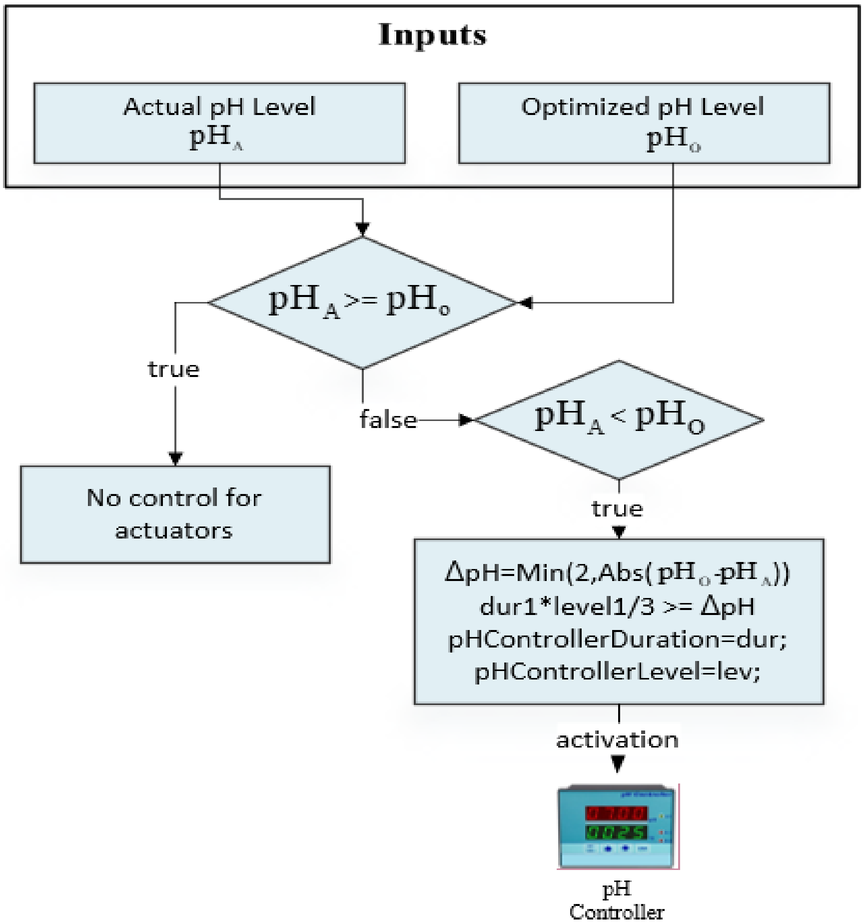


Figure 20: Flow diagram of fuzzy logic-based pH level control.

Table 3 describes the fish farm environmental values, available and optimal ranges. As we mentioned already, this work considers four environmental parameters of the fish tank environment, namely, temperature, pH level, conductivity and water level. The available ranges describe overall cases for each parameter in general, whereas, an optimal range provides the most acceptable values to the fish farm. Fish farm-related researches describe that the available value ranges for the first three parameters are 0-40°C, 0-14 acid, and 10-2000 µS/cm, respectively, while optimal ranges are 20-25 °C, 6.5-8.0 acid, and 150-500 µS/cm. Measurement of the water level is considered according to the height of the fish tank. Our experimental environment fish tank height is 350 mm, and we assumed that 300-320 mm water level is the most acceptable water level.

Table 3: Fishtank environmental values and user-desired ranges for fish growth.

Value name	Available range	User-desired range	
		Min	Max
Temperature	0°- 40°C	20°C	25°C
pH level	0-14 acid	6.5	8.0
Conductivity	10-2000 μS/cm	300 μS/cm	500 μS/cm
Water level	0-350 mm	280mm	320mm

Input parameters show that actual environmental sensing data values are divided into five levels based on their specific ranges. The second input parameters are optimal environmental parameters which are calculated using the objective function. According to the input parameters, fuzzy logic control provides the operational level and activation duration for variable speed actuators. For the purpose of comparisons in this work, we consider actuators' working level in three cases: maximum, medium and minimum operational levels. If variable speed operational level actuators are controlled with various speed, then they require various time and power for increasing or decreasing the actual environment values to the optimal values. Table 4 presents the linguistic description of the actual and optimized input values for the FLC. Actual and optimized levels are labelled as VL, L, N, H, and VH that are abbreviations of Very Low, Low, Normal, High and Very High. If we take fish tank water level as an example, the actual water level is anywhere between 0 and 100 mm, and then fuzzy set for water level is labelled as Very Low. If the water level was between 150 and 225 mm, it is labelled as normal. Above mentioned considerations are set to other fish tank parameters' labels too. The optimized environmental parameters are needed to compute between the minimum and the maximum boundaries. These boundaries also describe the most acceptable ranges for fish growth.

Table 4: Linguistic description of actual input values.

No.	Input Values	Linguistic Description				
		Very Low (x1, x2)	Low (x2, x3)	Normal (x3, x4)	High (x4, x5)	Very High(x6, x7)
1	Actual Temperature (°C)	5–10	5–20	15–30	20-35	30-40
2	Actual pH	0-4	3–7	6–10	9-13	12-14
3	Actual Conductivity (μS/cm)	10-400	350–750	700–1100	1050-1450	1400-2000
4	Actual Water level (mm)	0-100	75–175	150–225	200-300	275-350

*Fuzzy Inference***.** A fuzzy knowledge [91] base is a combination of inference and knowledge conditions to solve particular issues. Generally, this concept is suggested to emulate people's decision to find a solution to various problems using the existing information[92]. Fuzzy rules are evaluated by the performance of Fuzzy Associative Matrix (FAM) tables. FAM is a vital table for the description of the rule editors in a matrix form with describing all existing outputs based on all available input parameters. As we already explained in the above input parameters, actual environmental data is labelled into five levels, such as Very Low, Low, Medium, High, and Very High, as described in Table 5. A novel objective function calculates the second input parameters for the FLC based on user preferable parameters and the proposed system constraints.

Based on the expert explanation, supervisor, and agriculture officers, we have developed labelled output for actuator working level and operational duration. Heater and Cooler work dependently because when the temperature is less compared to the optimal temperature, then the heater is needed to activate and improve the system temperature value until the temperature is levelled of the optimal level. Oppositely, when the actual temperature is more than the optimal temperature value, then the cooler actuator should be activated to decline the actual temperature up to it equalize the optimal temperature level. As a result, if one temperature control actuator is active, the other one's is inactive. Actuators activate in three operational levels (the maximum, medium, and medium) with consuming different energy. Activation duration for actuators is labelled as very much time(vmt), much time(mt), normal time(nt), very little time(vlt) and off time. When actuators activate with the minimum working level, it consumes less energy but spends very much time (VMT). It can be seen from

Table ***5*** there are two off points in both actuators. In the Medium point of the sensing data can be increased or decreased according to the difference between optimized and current sensing data. As can be seen, the first input values to the FLC are the actual sensing data parameters are divided into Very Low, Low, Medium, High and Very High. The second input parameter is the optimal data which is calculated using the objective function. The output values of the proposed FLC unit are the heater and cooler actuators' working level and activation duration. If actual sensing data is very low and optimized data is optimal, then the heater is needed to activate.

Table 5: FAM table for the Fish Tank temperature control.

INPUT		OUTPUT	
Actual Sensing Data	**Objective Function-based Optimal data**	**Heater** (Level * Duration)	**Cooler** (Level * Duration)
Very Low	Optimal data	Minimum*vmt **or** Medium*mt **or** Maximum*nt	Cooler OFF
Low	Optimal data	Minimum*mt **or** Medium*nt **or** Maximum*lt	Cooler OFF
Medium	Optimal data	Minimum*NT **or** Medium*LT **or** Maximum*VLT **or** OFF	Minimum*nt **or** Medium*lt **or** Maximum*vlt **or** OFF
High	Optimal data	Heater OFF	Minimum*mt **or** Medium*nt **or** Maximum*lt
Very High	Optimal data	Heater OFF	Minimum*vmt **or** Medium*mt **or** Maximum*nt

If the heater actuator is activated with minimum working level then it requires the very much time to increase the actual temperature values to the optimal. When the heater actuator is activated with medium working level then it requires much time. Above mentioned Fuzzy Associative Matrix table applies to the fish tank pH level, water level, conductivity levels, as well as the water pump, pH controller, and fish feeder actuators too. Table 6 presents fuzzy logic inference rules for fish tank temperature based on FAM. The rules mentioned below also acceptable for the other fish tank environmental parameters, we have applied these rules for controlling the pH controller, water pump and conductivity control actuators. Our proposed embedded machine learning system provides automatization of fish tank for energy efficiency based on Machine Learning, Objective function and FLC.

Table 6: Fuzzy logic inference rules for the fish tank temperature value control.

1. **if** (Predicted Temperature is *Very Low*) **and** (Optimal Temperature is *Optimized*)
   then ((Heater is *Minimum*) (Duration is *vmt*)
   or (Heater is *Medium*) (Duration is *mt*)
   or (Heater is *Maximum*)(Duration is *nt*)
   and (Cooler actuator status is *OFF*));

2. **if** (Predicted Temperature is *Low*) **and** (Optimal Temperature is *Optimized*)
   then ((Heater is *Minimum*) (Duration is *mt*)
   or (Heater is *Medium*) (Duration is *nt*)
   or (Heater is *Maximum*)(Duration is lt)
   and (Cooler actuator status is *OFF*));

3. **if** (Predicted Temperature is *Medium*) **and** (Optimal Temperature is *Optimized*)
   then ((Actuator is *Minimum*) (Duration is *nt*)
   or (Actuator is *Medium*) (Duration is *lt*)
   or (Actuator is *Maximum*)(Duration is vlt)
   or (Heater or Cooler actuator status is *OFF*));

4. **if** (Predicted Temperature is *High*) **and** (Optimal Temperature is *Optimized*)
   then ((Cooler is *Minimum*) (Duration is *mt*)
   or (Cooler is *Medium*) (Duration is *nt*)
   or (Cooler is *Maximum*)(Duration is *lt*)
   and (Heater actuator status is *OFF*));

5. **if** (Predicted Temperature is *VeryHigh*) **and** (Optimal Temperature is *Optimized*)
   then ((Cooler is *Minimum*) (Duration is *vmt*)
   or (Cooler is *Medium*) (Duration is *nt*)
   or (Cooler is *Maximum*)(Duration is *lt*)
   and (Heater actuator status is *OFF*));

Input values are labeled as *vl*, *l*, *m*, *h*, *vh*, and *opt*. Fuzzy rules are capable of evaluation of input parameters using *if-then* statements, according to these rules actuators operational level and activation duration can be calculated. In the defuzzification step, operational level and activation duration are converted to exact activation duration to actuators. For example, when the required operational time to the system is a low time, then FLC module sets 2 to 4 minutes working time to the actuators. After analyzing the objective function and FLC, the algorithm is developed for the proposed system. Table 7 algorithm only describes temperature, prediction, optimization and control. However, the implemented system also includes an algorithm for other fish tank parameters. The optimal temperature control algorithm consists of “prediction”, “optimization scheme” section and “fuzzy logic control scheme” section.

Table 7: Proposed System Algorithm for Optimal Temperature Level Control

Algorithm Proposed System Algorithm for Optimal Temperature Level Control

Initial: Install *sensors* and *actuators*
Set User desired settings: T_{min}, T_{max} ← Using Equation (1)
Set System Constraints ← Using Equation (10)
Start sensing: T_{act}
procedure PREDICTION MODULE
  Comment: Predict future temperature values using RNN-LSTM trained model
  Predict: T_p
  then
  send: T_{pre}
  to the
  OPTIMIZATION SCHEME();
procedure OPTIMIZATION SCHEME
  Comment: Using Objective Function to calculate optimal temperature.
  Calculate T_{opt} ← Using Equation (9)
  then
  send: T_{pre}, T_{opt}
  to the
  FUZZY LOGIC CONTROL SCHEME ();
end procedure
procedure FUZZY LOGIC CONTROL SCHEME
input 1: T_{pre}
input 2: T_{opt}
 if $T_{pre} == T_{opt}$ **then**
  activateActuator(ALL ,OFF)
 else if T_{pre} == *VeryLow* **and** $T_{min} < T_{opt} < T_{max}$ **then**
  activateActuator(Cooler, OFF)
   activateActuator(Heater, Values=[Minimum*vmt, Medium*mt, Maximum*nt])
 else if T_{pre} == *Low* **and** $T_{min} < T_{opt} < T_{max}$ **then**
  activateActuator(Cooler, OFF)
  activateActuator(Heater, Values=[Minimum*mt, Medium*nt, Maximum*lt])
 else if T_{pre} == *Medium* **and** $T_{pre} < T_{opt}$ **then**
   activateActuator(Cooler, OFF)
   activateActuator(Heater, Values=[Minimum*nt, Medium*lt, Maximum*vlt])
  if T_{pre} == *Medium* **and** $T_{pre} > T_{opt}$ **then**
   activateActuator(Heater, OFF)
   activateActuator(Cooler, Values=[Minimum *nt, Medium*lt, Maximum *vlt])
  else activateActuator(ALL ,OFF)
 else if T_{pre} == *High* **and** $T_{min} < T_{opt} < T_{max}$ **then**
  activateActuator(Heater, OFF)
  activateActuator(Cooler, Values=[Minimum*mt, Medium*nt, Maximum*lt])
 else if T_{pre} == *VeryHigh* **and** $T_{min} < T_{opt} < T_{max}$ **then**
  activateActuator(Heater, OFF)
  activateActuator(Cooler, Values=[Minimum*vmt, Medium*mt, Maximum*nt])
 end if
end procedure

Defuzzification[93]. It is a process which produces a set of output parameters from the crisp logic based on fuzzy sets and membership graphs. As we already mentioned, output values are operational level and activation duration of the fish tank actuators. Heater, cooler, pH controller, pump and feeder actuators are controlled themselves based on actual sensing data and optimal sensing data. When $T_a < T_o$, then the heater is operated, and if $T_o < T_a$ then the cooler is needed to activate. In terms of fish tank water level if $W_a < W_o$ then the water pump is activated. When $W_o < W_a$ then the second water pump is operated in order to decrease the water level. Actuators' power assigns are described in Figure 21. It can be seen that the power rating ranges are divided into three working speeds, namely, maximum, medium and minimum. x1, x2, x3, and x4 illustrate the ranges of degree of membership function for presenting the output values. Each fish tank actuator consumes various energy based on their activation level.

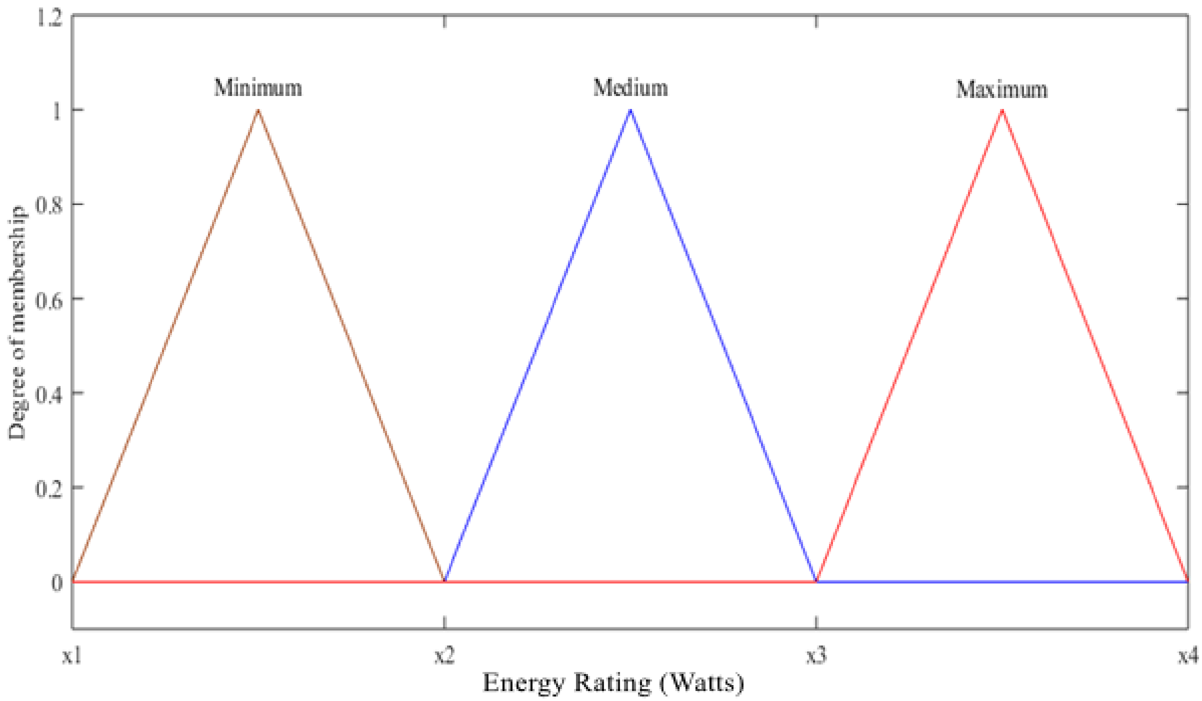


Figure 21: Energy ratings for actuators' working level in Fish Tank.

Table 8 shows the energy consumption rating for fish tank actuators based on maximum, medium, and minimum working levels in a minute. If we take the heater actuator as an example, when heater is operated with a minimum operational level, then it requires energy consumption ranges between 30 (x1) and 120 (x2) watts for a minute. When the heater is operated with the medium operational level, and it spends 120 (x2) to 210 (x3) watts energy in a minute. With activating maximum operational level the heater, the heater requires from 210 (x3) to 300 (x4) energy for per minute. The same consideration is applied to all other fish tank actuators.

Table 8: Energy consumption ratings of actuators' working level in Fish Tank.

No.	Actuators	Energy Rating (Watts)		
		Minimum (x1, x2)	Medium (x2, x3)	Maximum (x3, x4)
1	Water pump	600–1000	1000–1400	1400–1800
2	Heater	30–120	120–210	210–300
3	Cooler	700-800	800-900	900-1000
4	pH Controller	400-500	500-600	600-700
5	Fish Feeder	300–450	450–700	700–850

As mentioned earlier, choosing the right actuators operational time length plays a key role in both the automation of fish farms and the efficient management of energy. If the marking of the actual detection data is very low, the actuator must use one of the operating levels (minimum, medium or maximum). Depending on the operating level or speed of the actuator, the operating time of the actuator also changes until the optimum environment for controlling the actuator environment is reached. In particular, if the water pump operates at the minimum operating level, it will take a long time. Conversely, if the water pump operates at the maximum operating level, little time is required. Figure 22 shows a graphical representation of membership functions as a function of actuator time. The output variable operating time of the actuators has six membership functions. These membership functions are marked as OFF, VLT, LT, NT, MT and VMT and are reduced when the drive is turned off, very little time, little time, normal time, much time and very much time. The drive operating time is described in minutes, and the time range is determined based on agricultural and technical knowledge. This participation function is enabled during operation of all drives. If the current collection data matches the optimal data, the actuator runs for 0 minutes, and the actuator does not need to be activated (OFF). These parameters can be changed based on actuators' operational parameters. With considering these points, we developed the system which user can assign the required control values as an input value to the system from the user interface.

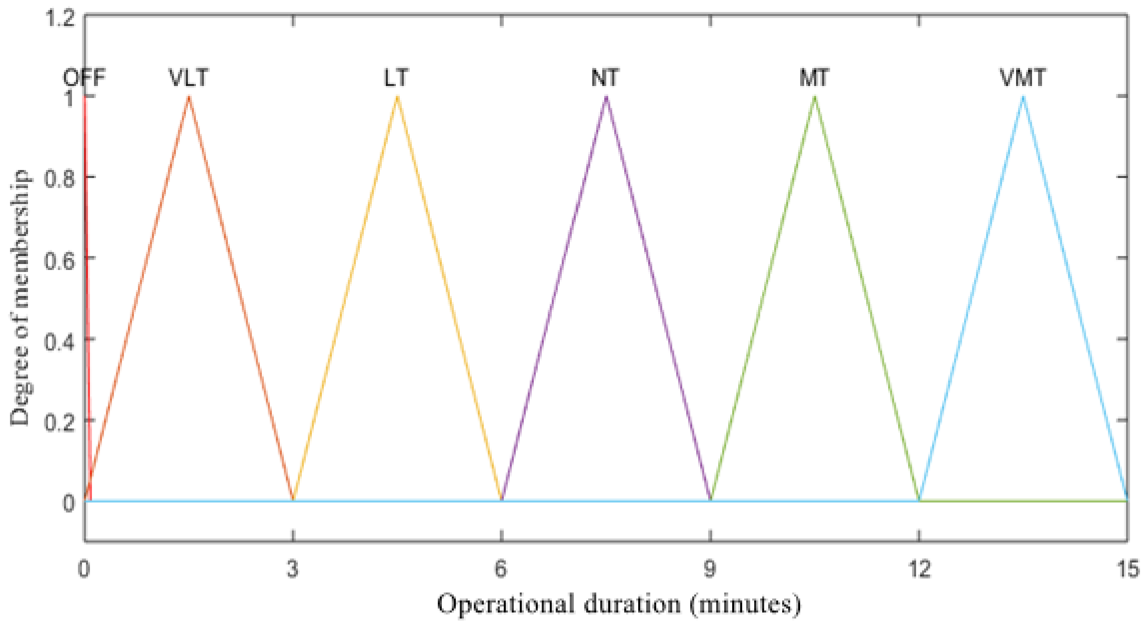


Figure 22: Membership function graph for the actuators' operational duration (min).

3.3 Embedded Predictive Optimal Control Scheme using RNN-LSTM

3.3.1 Embedded Predictive Optimal Control in Fish Tank

In this subsection, we describe our proposed embedded predictive optimal control environment using fish tank parameters. This system includes the prediction module, the prediction module helps to increase the performance environment parameter controlling. Figure 23 describes the conceptual design of the proposed system. As can be seen, we have an IoT based fish tank environment which includes various sensors and actuators to measure and control the environmental parameters of the fish tank. Input parameters for the system are user-desired min-max values and fish tank actual environmental parameters. Context-awareness and prediction model is used to analyze and predict the future environmental parameters using input parameters. The formulated objective function for optimization is used to calculate the optimal environmental parameters to temperature, pH level, conductivity and water level using predicted and user-desired values. The fuzzy logic-based control model computes the operational duration and activation level to the actuators using the predicted and optimal environmental parameters. Based on these control values heater, cooler, fish feeder, water pump actuators increase or decrease the predicted environmental parameters to the optimal environmental values. As a result, the optimal fish growth environment can be achieved with minimum energy consumption.

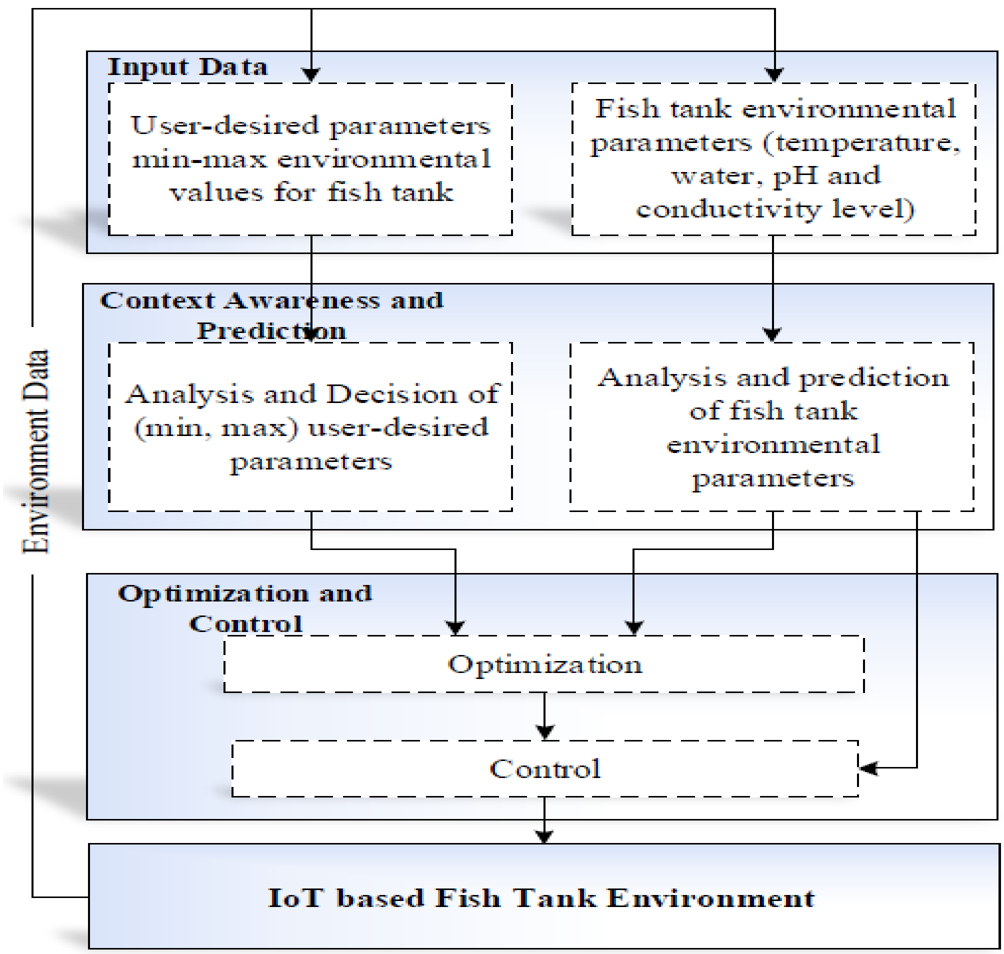


Figure 23: Conceptual design of the embedded predictive optimal control in Fish Tank.

Figure 24 illustrates the detailed conceptual design of the proposed system using the fish tank and user-desired parameters. As shown in the figure, we have input data, context awareness and prediction, optimization and control units. According to the user desired minimum and maximum environmental parameters and predicted environmental parameters, the optimization module calculates the optimal environmental parameters with minimum energy consumption. Then these optimal environmental and predicted environmental parameters the control module sets working level and operational duration to fish tank actuators using IF-THEN rules. For instance, if the predicted temperature is less than the optimal temperature, then we need to activate the heater in order to increase the temperature level of the fish tank. If the predicted temperature level is higher than the optimal temperature level, then we need to activate the cooler actuator to decrease the fish tank temperature level. If the predicted and optimal environmental parameters are the same, we do not need to activate any actuators.

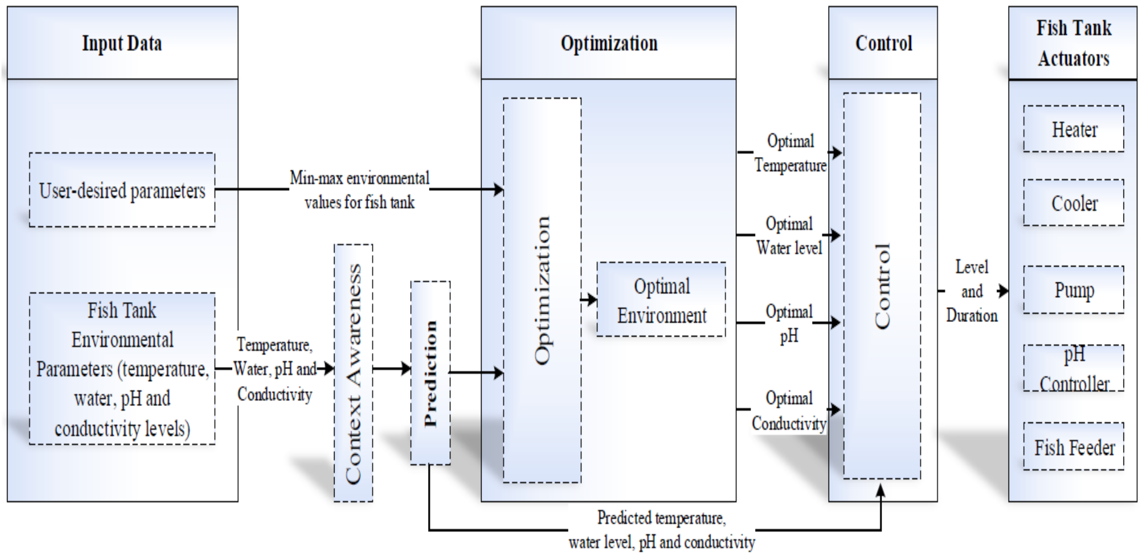


Figure 24: Detailed conceptual design of the embedded predictive optimal control in Fish Tank.

Figure 25 describes the detailed system architecture for the embedded predictive optimal control in the fish tank. As can be seen, we have three environments, namely, fish tank, embedded hardware and embedded software environments. Each environment has various functionalities, such as fish tank environment for breeding, harvesting or producing the fish products. Embedded hardware environment includes a number of sensors and actuators which are used to measure the fish tank temperature, water level, pH level and conductivity levels in real-time, whereas, the IoT actuators are utilized to control these measured parameters with optimal controlling. Embedded software environment comprises the various functionalities which we implemented to control the fish tank environmental parameters with optimal resource utilization. These functionalities are sensing data collection, context awareness, prediction, optimization and control. According to the collected temperature, water level, pH, and conductivity level data, the prediction model predicts the future environmental parameters to the fish tank and based on these predicted parameters the objective function computes the most optimal parameters to the environment with considering the user-desired parameters and the system constraints. According to the optimized and predicted data fuzzy logic control module calculates the operational level and activation duration for the actuators. With these control values heater, cooler, water pump, and fish feeder actuators are activated automatically in the required time in order to provide the optimal environmental values to the fish growth.

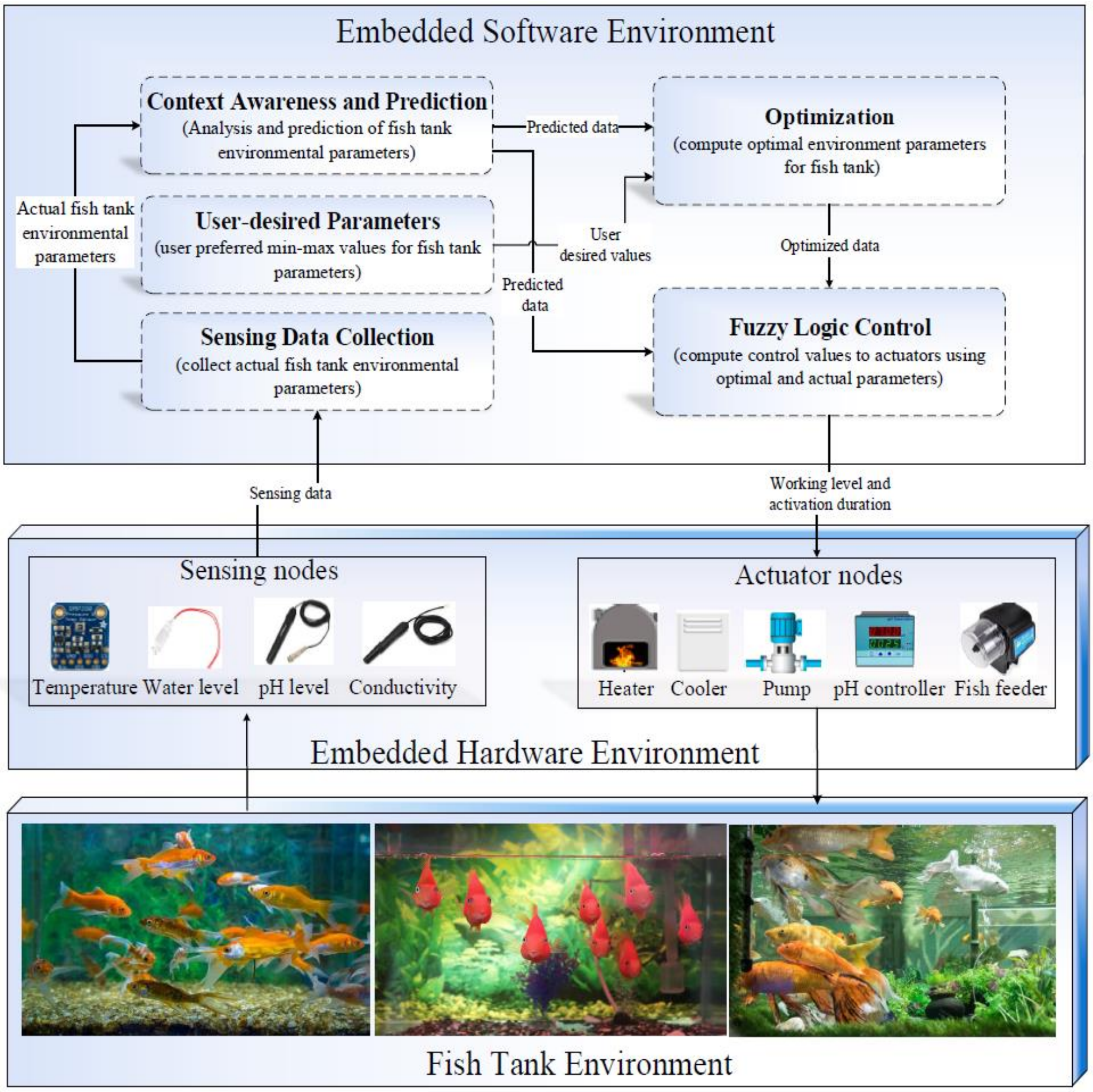


Figure 25: System architecture of the embedded predictive optimal control in Fish Tank.

Figure 26 describes the flowchart diagram of the proposed embedded prediction optimal control scheme using the user-desired and actual fish tank environmental parameters. As we already explained above, RNN-LSTM is used to predict the future temperature, water level, conductivity and pH level parameters to the fish tank using the collected actual environmental parameters, then predicted and user-desired parameters are used as input values to the optimization module. The objective function calculates the most optimal temperature, water, conductivity and pH level environmental values to the fish tank with efficient energy consumption, and then the FLC module assigns operational level and activation duration to the fish tank actuators based on predicted and optimal environmental parameters.

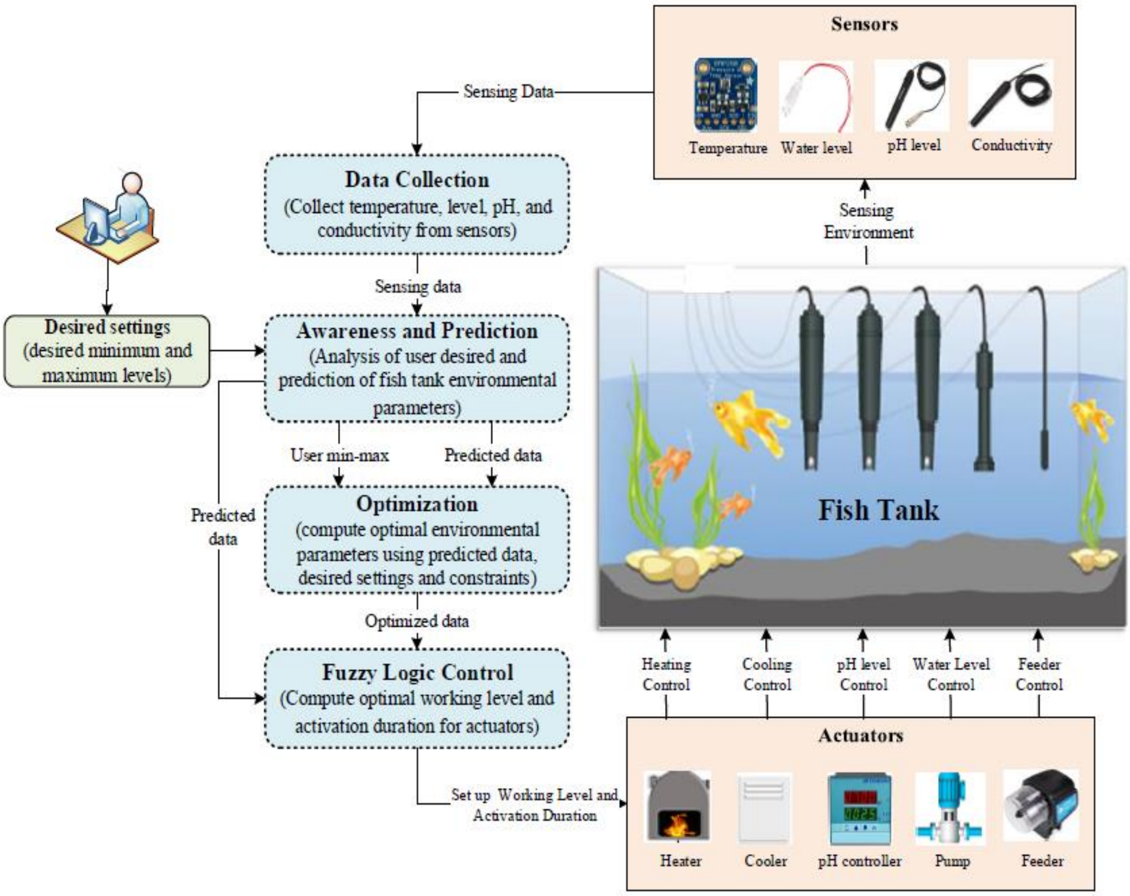


Figure 26: Flowchart diagram of the embedded predictive optimal control in Fish Tank.

Figure 27 describes the sequence diagram of the proposed embedded predictive optimal control scheme. The proposed system has data collection, context awareness and prediction, optimization and control functionalities. Actual fish tank temperature, water level, pH level and conductivity levels are collected to the data collection unit using IoT sensors, and this data is used to train prediction module. As the new sensing values are forwarded to the prediction module this module computes the future environmental parameters for the fish tank, then optimization module computes the optimal fish tank environmental parameters according to the predicted and user-desired parameters. The objective function calculates the optimal temperature, optimal water level, optimal conductivity, and optimal pH level for fulfilling the user-requirement. Then optimal fish tank environmental and predicted environmental parameters the fuzzy logic-based control unit computes the control values to the fish tank actuators, and these control value results are visualized to the user. With controlling the actuators with various working level and operational duration, we can control energy consumption.

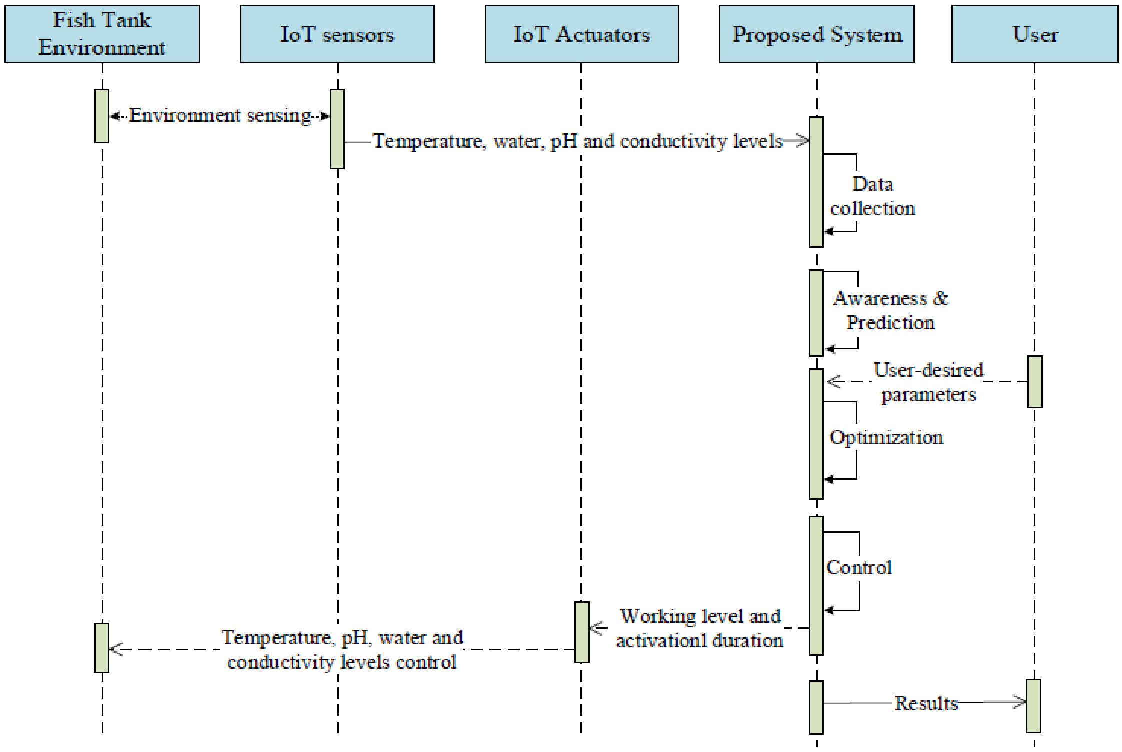


Figure 27: Sequence diagram of the embedded predictive optimal control in Fish Tank.

3.3.2 RNN-LSTM based Prediction Algorithm for Predictive Embedded Optimal Control

In the last decades, the development of advanced technologies has been created a dramatic improvement in a number of industries around the world. Machine Learning has begun to play an essential role in our daily life with extending our ability and knowledge to increase the condition around us. Machine Learning covers various algorithms and models, and they can be used according to the area of interest. However, in this work we have used Long Short-Term Memory Networks (LSTM) for forecasting the future environmental parameters of the fish tank. LSTM is one of the special types of the RNN which have capabilities to learn long-term dependencies. LSTMs were presented by Hochreiter and Schmidhuber [77] in 1997. Compared with many other RNNs types, the LSTM model is a novel recurrent network concept, and support various capabilities in terms of gradient explosions, gradient disappearance, and lack of long-term memory of RNNs [78,79,80,81]. The LSMT network contains a forget and preservation mechanisms that let the network architecture to impact constant fails to flow via the internal state of a particular cell. These portions provide an effective implementation of the non-linear mapping between input values and output values. The LSTM is different from other neural networks in terms of fault tolerance and accurate results. An LSTM layer and a sequence input layer are the central components of the LSMT network. The sequence input layer of the network presents the time-series data or sequence data, which is used as an input parameter to network, whereas the LSTM layer supports the long-term dependency learning process using the time steps of the sequence data.

Figure 28 presents the flow of a time series X with C channels (features) of lengths S through the LSMT layer. As described in the given diagram, the output or hidden state is denoted with ht, while the cell state of the network is illustrated with c_t at time step (t). The first LSTM uses the initial state of the network and the first time step of the sequence to calculate the first output and the updated state of the cell. At time t, the unit calculates the output signal and the updated state of the cell ct using the current state of the network (c_{t-1}, h_{t-1}) and the next sequence time step. A layer state consists of a hidden state (also called an initial state) and a cell state. The latent state at time step t contains the output of the LSTM layer for this time step. The cell state contains information obtained in the previous time step. At each time step, the level adds or removes cell state information. Layers use gates to manage these updates.

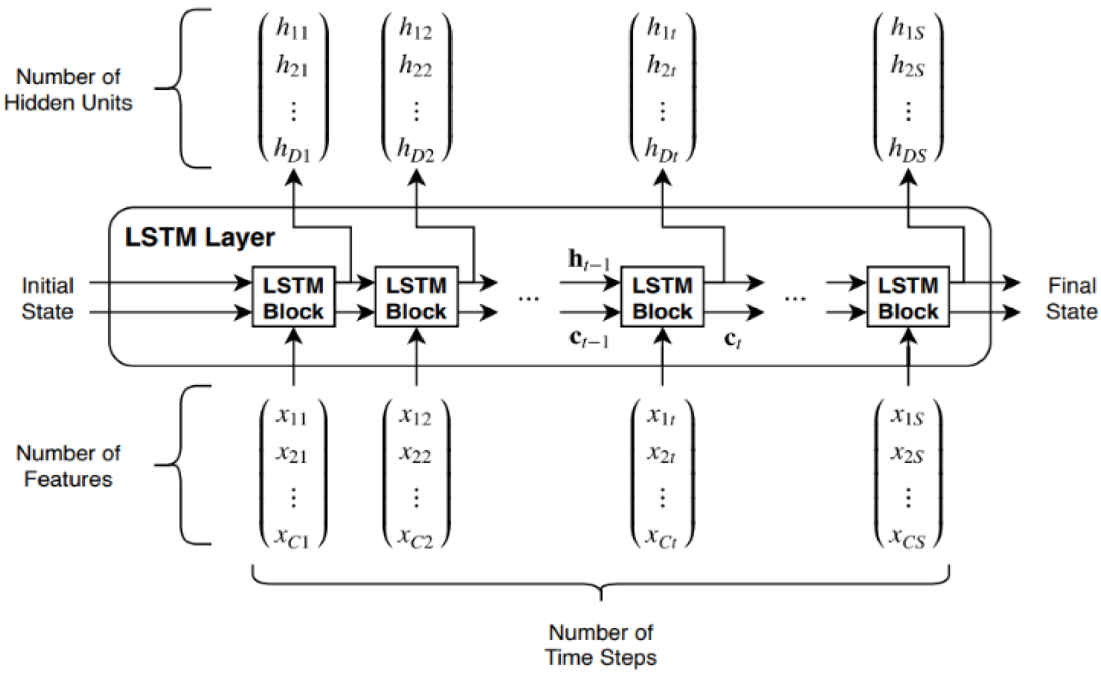


Figure 28: LSTM network layer architecture [82].

The LSMT network hidden layer structure is described in Figure 29. Given a, f, c, o parameters describes the input, the forget, the internal state, and the output gates, respectively. The sigmoid activation function is represented with σ, whereas the hyperbolic tangent activation function is given with tan h. Table 9 presents the components of the LSMT networks with their purpose. The main role of the input gate is controlling the current internal state's input. The forget gate is used to discard or retain the timing data, only the output $h(t_{i-1})$ of the network is forwarded to this unit. The network state is updated by the internal state. The final output signal of the network is determined jointly by the output valve and the internal state and will be used as the input of the entire network module at the next moment and controlled by the input valve. As presented in Figure 29, The input parameter for the LSTM networks is the input value $x(t_i)$ of the time series data at time t_i, the LSTM network output value $h(t_{i-1})$ at time t_{i-1}, and the internal state $c(t_{i-1})$ at time t_{i-1}.

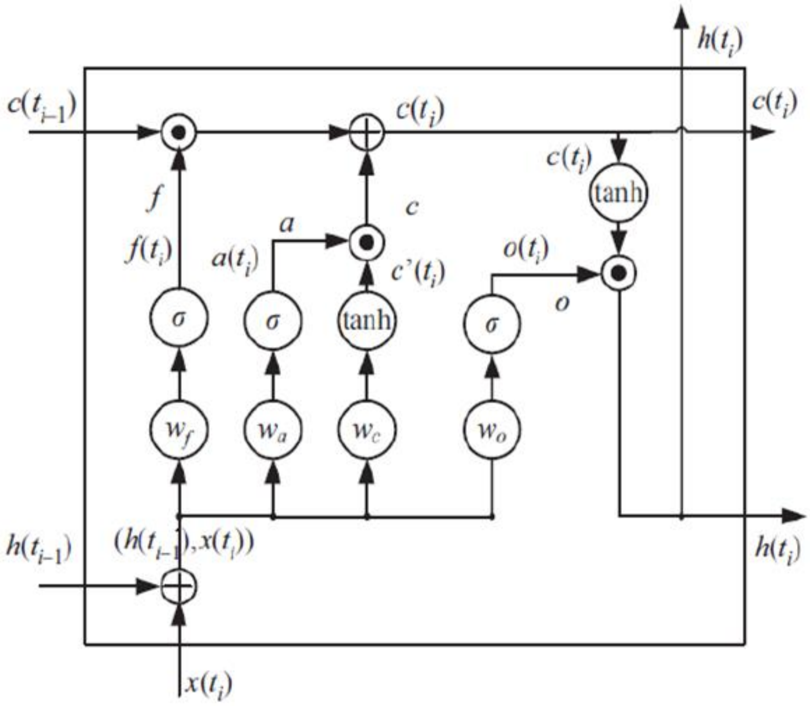


Figure 29: Hidden layer structure of the LSTM.

The output parameters of the LSTM networks is the LSTM network output value $h(t_i)$ at time t_i, and the network internal state $c(t_i)$. Where in the time series data $x(t_i)$ presents the data at time t_i, the output value of the network is $h(t_{i-1})$ at the time t_{i-1} and the initial statue value of $h(t_{i-1})$ is 0. Threshold layer has the threshold values, which is described as $b = \{b_a, b_f, b_c, b_o\}$, each parameter of the threshold presents the input gate, the forget gate, and the internal state and the output gate. Weight matrixes for the threshold layer for the input gate, forget gate, the internal state and the output gate are assigned as $w_1 = \{w_a, w_f, w_c, w_o\}$, respectively. Below given formulas describe the forward learning in sequence:

$$a(t_i) = \sigma(w_a x(t_i) + w_{ha} h(t_{i-1}) + b_a) \tag{12}$$

$$f(t_i) = \sigma(w_f x(t_i) + w_{hf} h(t_{i-1}) + b_f) \tag{13}$$

$$c(t_i) = f_t \times c(t_{i-1}) + a_t \times \tan h(w_c x(t_i) + w_{hc} h(t_{i-1}) + b_c) \tag{14}$$

$$o(t_i) = \sigma(w_o x(t_i) + w_{ho} h(t_{i-1}) + b_o) \tag{15}$$

$$h(t_i) = o(t_i) + tan\ h(c(t_i)) \tag{16}$$

The LSTM network output value weight matrixes to the threshold layer are described as $w_2 = \{w_{ha}, w_{hf}, w_{hc}, w_{ho}\}$, for each gate. The output result of the LSTM network is $a = \{a(t_i), f(t_i), c(t_i), o(t_i)\}$, where each parameter comprises the output result input gate, forget gate, internal status and output gate. The role and description of the RNN-LSTM hidden layer gates are described detailly in Table 9.

Table 9: RNN-LSTM hidden layer gates and their purpose.

Component	Purpose
Input gate(a)	Management layer of cell state update
Forget gate(f)	Management layer of cell state reset (forget)
Internal state(c)	Adds information to cell state
Output gate(o)	Management layer of cell state added to the hidden state

The training process in the LSTM network model utilizes a time-based backpropagation with a time algorithm that comprises four-phase calculations, as described in Equation 12 to 16. The LSTM network error terms are computed in revers, and the error is transferred to the output, internal, forget, and the input gates. The gradient value of the weights in each gate is successively computed based on the corresponding error term. The weight values of all gates are updated using the optimization algorithm. After iterative computation, the optimal threshold *b* and weight *w* are used to predict the fish farm temperature, water level, pH, and conductivity data of the fish tank.

The detailed framework of the specific LSTM based prediction model is described in Figure 30. As can be seen, the figure comprises five functional modules, namely, the input layer, hidden layer, output layer, network training, and network output layer. The proposed system supports a multi-input multi-output prediction model based on indoor and outdoor environmental values time series data, the prediction model output will be predicted temperature, predicted pH level, predicted water level and predicted conductivity results. However, for the formulation of the proposed system is described with temperature values of the fish farm in order to simplicity of the explanation.

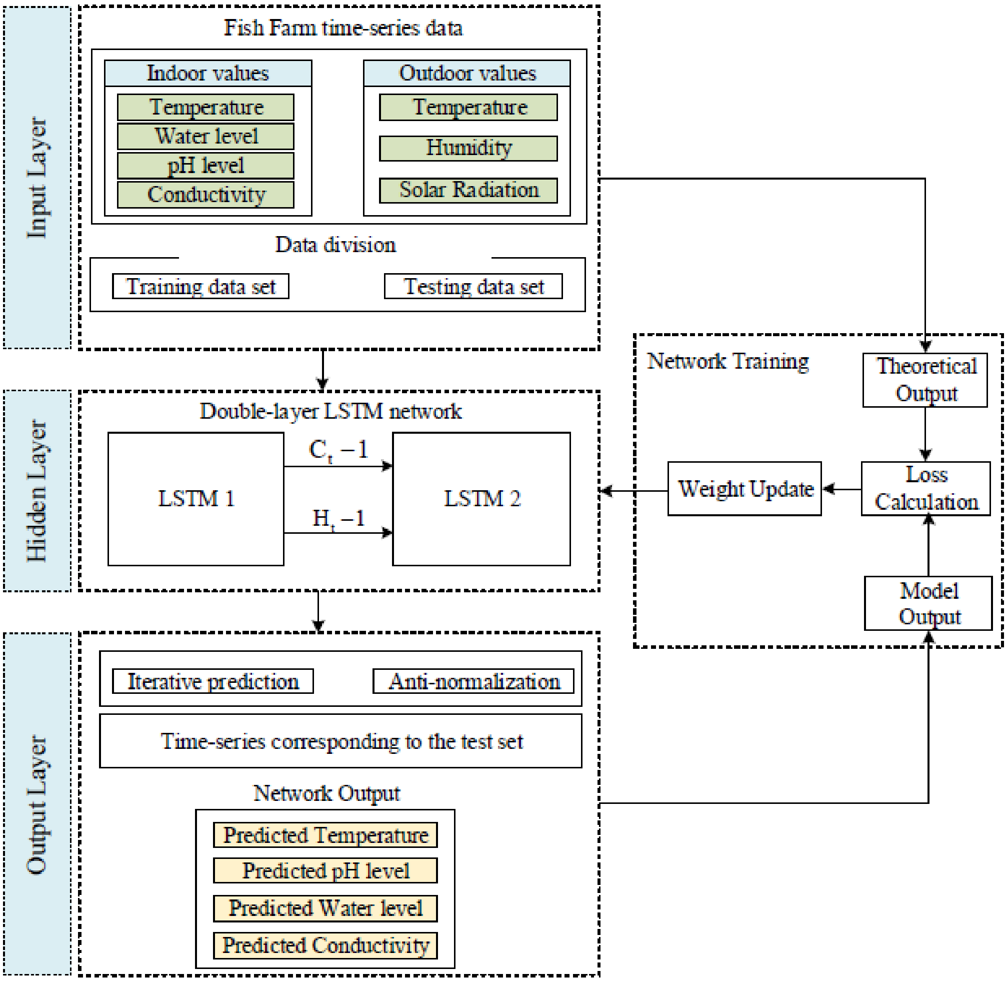


Figure 30: Proposed configuration of sensing data prediction using RNN-LSTM in Fish Tank.

In the input layer step if the time axis of the water temperature data of fish farm is $t_1, t_2, t_3, \ldots, t_N$, after that the water temperature value corresponding to $t_1, t_2, t_3, \ldots, t_N$ is $x_1, x_2, x_3, \ldots, x_N$, then the water temperature data of the fish farm can be demonstrated as $\{x(t_i), i = 1, 2, 3, \ldots, N\}$, and N describes data length.

The water temperature data $x(t_i)$ of fish tank is split into two sets, which are the set for training $\{x_{tr}(t_i), i = 1,2, \ldots, m\}$ and the testing set $\{ x_{te}(t_i), i = m + 1, m + 2, \ldots, N\}$, satisfying the constraints $m < N$ and $m, N \in N+$, whereas $N+$ describes a positive integer values. The training set values of the training comprise the sequence $\{ x_{ve}(t_i), i = r + 1, r + 2, \ldots, m\}$, satisfying the constraints $r < m$ and $r \in N+$, and it is mainly used to establish the model. The verification set sequence is used to adjust the network parameters in the model construction and assist the training set sequence to establish the model.

The training set x is converted to $x_{reshape}$ by using the python function called reshape, which is described as:

$$\boldsymbol{x_{reshape}} = [\boldsymbol{r_1}, \boldsymbol{r_2}, \ldots, \boldsymbol{r_{m-L,}}] \tag{17}$$

*In the hidden layer step***.** The sequence x of fish farm temperature training set pre-processed by the input layer. As described in Figure 30, the network has the hidden layer includes a double layer LSTM neural Network. The output of the training set sequence x after the hidden layer can be expressed as:

$$P = [P_1, P_2, \ldots, P_{m-L}]^T \tag{18}$$

$$P_q = LSTM_{forward}(x_q, C_2(t_{i-1}), H_2(t_{i-1})) \tag{19}$$

where $C_2(t_{i-1})$ and $H_2(t_{i-1})$ are, respectively, represented as the state and output of the second layer LSTM network at time t_{i-1}, $LSTM_{forward}$ represents the forward propagation algorithm formulas (1)–(5) mentioned in above.

In the network training module. The actual output value of the input layer and the output value of the hidden layer are passed to the network training module; and the loss function (loss) in the network training process was defined as follows:

$$\boldsymbol{loss} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{L(m-L)}} (\boldsymbol{y_i} - \boldsymbol{P_i})^2 / (\boldsymbol{L}(\boldsymbol{m} - \boldsymbol{L})) \tag{20}$$

3.3.3 Deployment of RNN-LSTM module to the IoT device using TensorFlow Lite

TensorFlow Lite is a special tool which can be used to deploy and run TensorFlow models on IoT, embedded and mobile devices. Machine Learning algorithms can be delay can be activated with small size and low latency[83]. TensorFlow Lite comprises two main modules:

The TensorFlow Lite interpreter works with specially optimized models on various types of equipment, including cell phones, embedded Linux devices, and microcontrollers [84].

The *TensorFlow Lite converter* that can convert TensorFlow models to an efficient format that can be used by interpreters and provides optimization techniques to decrease file size in binary format and supports high-level performance [85].

Figure 31 describes the conversion diagram of the TensorFlow based module to the TensorFlow Lite format.

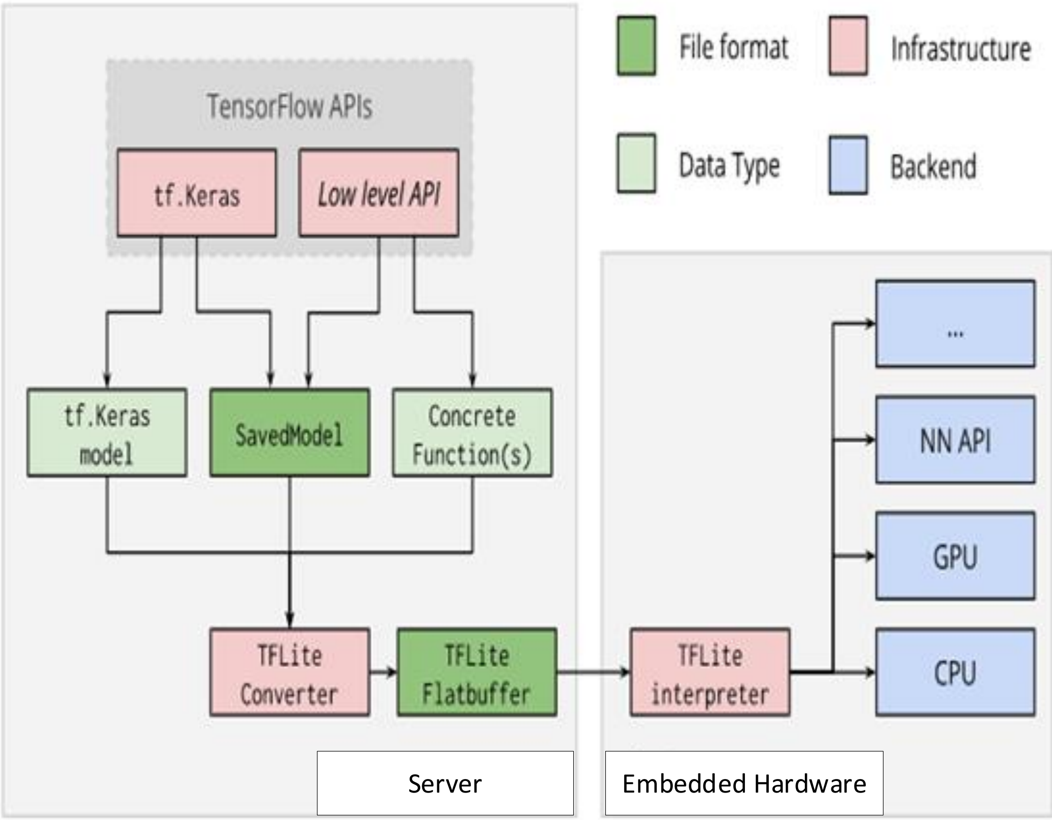


Figure 31: Deployment of a prediction model based on RNN-LSTM using TensorFlow Lite[86].

TensorFlow Lite is built to simplify machine learning on a "at the edge" network device, not to send and receive data from a server. TensorFlow Lite can be deployed to various types of devices, from small microcontrollers to powerful IoT devices and mobile devices. There are several advantages of running machine learning algorithms on devices, which can support:

- *Low latency:* all processes are directly performance on devices and no need to send the data or files to the server;
- *High privacy:* There is no data forwarding to the server or cloud using the Internet, so privacy is high;
- *Cheap connection:* Internet connectivity is not mandatory;
- *Less Energy requirement:* Internet connectivity requires extra devices and simultaneous activation period, then devices require a lot of power for activation.

The deployment of Tensorflow Lite requires four essential processes as described in the below-mentioned steps:

- *Model selection:* Training new TensorFlow model, or finding TensorFlow models from the Internet, or selection of model from Pre-trained models.
- *Model Conversion:* After training or selection of conventional TensorFlow model, then convert this model to the TensorFlow Lite format using the TensorFlow Lite converter with Python code.
- *Model deployment:* In this step, the converted model is needed to deploy to the end devices using the TensorFlow Lite interpreter.
- *Model Optimization:* In this step, the deployed model size, efficiency and accuracy can be improved using the model optimization toolkit to reduce your model's size and increase its efficiency with minimal impact on accuracy. TensorFlow time is improving the Tensorflow lite capabilities for supporting high-performance on end devices for deploying any TensorFlow model.

3.4 Embedded Predictive Optimal Control Scheme using Outdoor Environmental Data

In this subsection, we describe the proposed embedded predictive optimal control scheme using outdoor and fish tank sensing data. The main difference between this scheme and the above-mentioned scheme is the outdoor environmental parameters. Outdoor environmental parameters influence on the fish tank environmental parameters. For instance, if the outdoor temperature becomes very cold, then it impacts on the fish tank indoor temperature. If the outdoor temperature is remarkably warm, then these temperature parameters can increase the fish tank water temperature, so we need to consider the outdoor environmental parameters for achieving the optimal environmental control. Figure 32 shows the conceptual design of the embedded predictive control scheme using outdoor and fish tank environmental parameters.

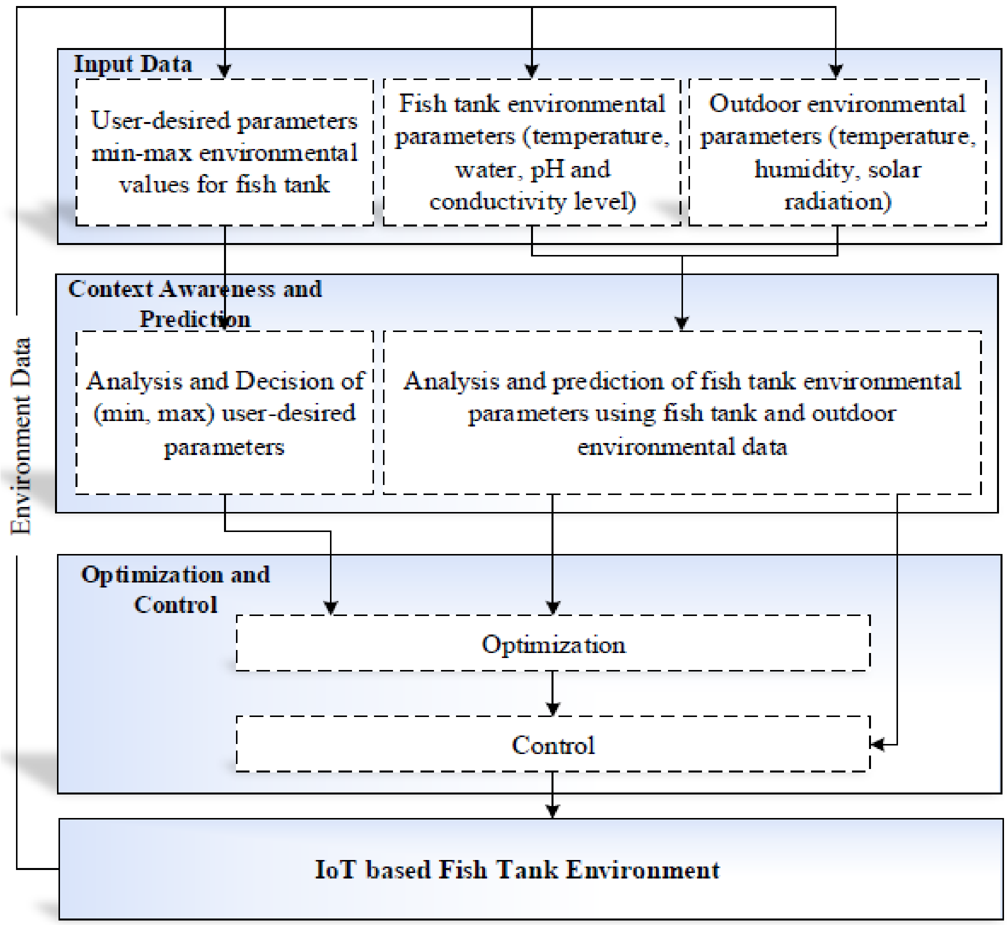


Figure 32: Conceptual design of the embedded optimal control scheme using fish tank and outdoor parameters.

It can be clearly seen, input parameters to the context awareness and prediction model are user-deisred min-max environmental parameters, fish tank environmental parameters and outdoor environmental values. Outdoor environmental parameters are used to increase the accuracy of the proposed prediction module. Figure 33 illustrates the detailed embedded optimal control scheme conceptual design, which is based on fish tank and outdoor environmental parameters. Input data to the prediction module is outdoor temperature, humidity and solar radiation, and fish tank environmental parameters namely temperature, water level, pH level and conductivity. Based on this input data prediction module forecasts the future environmental temperature, water level, pH level and conductivity levels, while the optimization module uses these predicted values to compute optimal environmental parameters to the fish growth based on user desired parameters. Fuzzy logic-based control module computes working level and operational duration to the actuators.

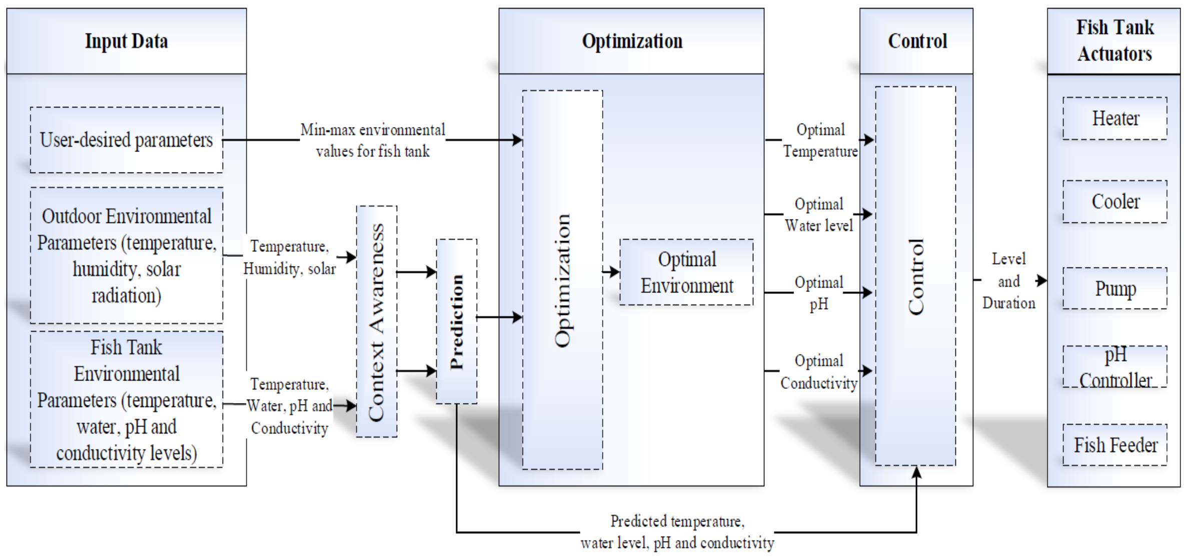


Figure 33: Detailed Conceptual design of the embedded optimal control scheme using fish tank and outdoor parameters.

Figure 34 presents the embedded optimal control scheme architecture in detail. As we mentioned above, the proposed system architecture comprises the layers, namely, fish tank environment, embedded hardware environment and embedded software environment. The fish tank and embedded hardware environment have the same functionalities which were described above. However, the embedded software environment is implemented with considering the outdoor environmental parameters in order to increase the capability of the prediction module. Prediction module forecasts the future fish tank temperature, water, pH and conductivity levels using indoor and outdoor environmental parameters. Predicted parameters and user-desired min-max values are used as input parameters to the optimization module.

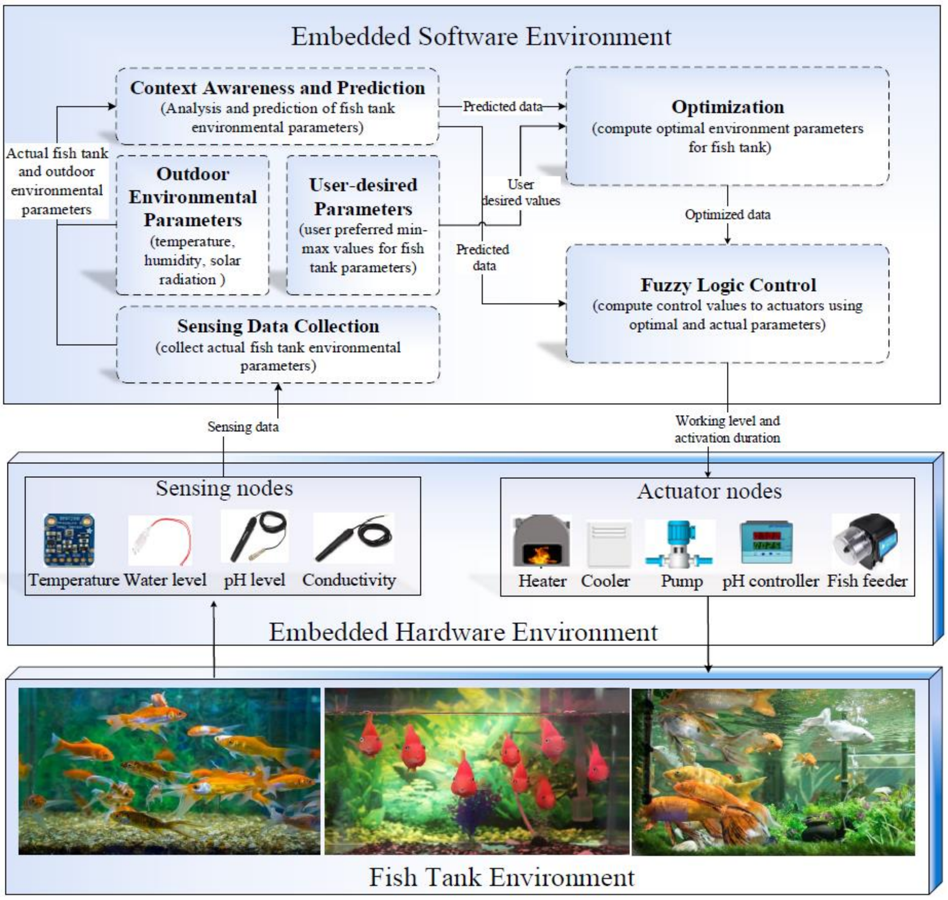


Figure 34: System architecture of the embedded predictive optimal control using Fish tank and outdoor parameters.

An objective function based optimization module computes the most optimal temperature, water level, conductivity and pH level values for the fish tank. Fuzzy logic control unit computes the working level and activation duration to the actuators based on predicted and optimized data. Then actuators are activated automatically in the required time in order to control actuators namely, heater, cooler, water pump, pH controller and fish feeder actuators. Heater and cooler actuators are used to control the water temperature values. The water pump is used to control the water level in the fish tank. pH controller is used to controlling the pH level of the fish tank. Figure 35 represents the flowchart diagram of the proposed embedded predictive optimal control scheme architecture. As can be seen, the input parameters are desired settings and outdoor parameters for the prediction module. Outdoor environmental parameters are used to increase the performance of the prediction module. As we know, outdoor environmental parameters impact on the prediction model.

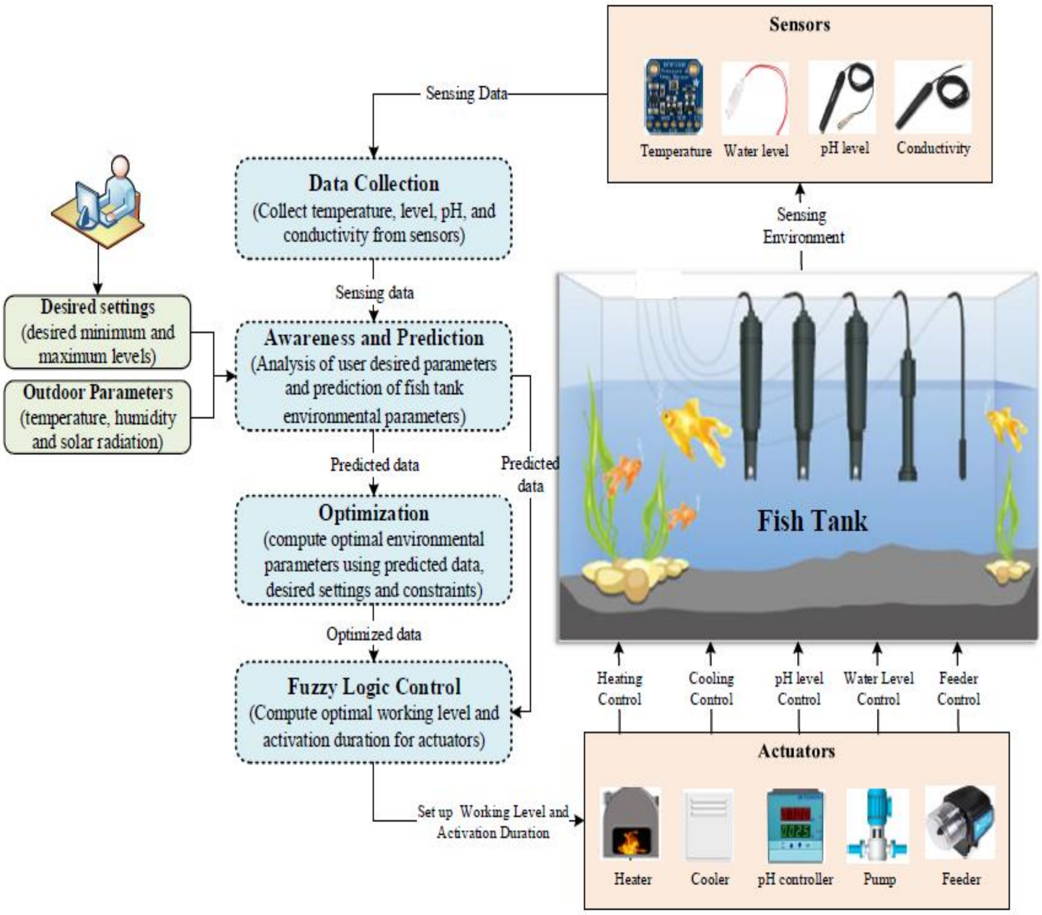


Figure 35: System architecture of the embedded predictive optimal control using Fish tank and outdoor parameters.

Figure 36 presents the sequence diagram of the proposed embedded predictive optimal control scheme using Fish Tank internal and external environmental parameters. The indoor and outdoor environmental parameters are used to predict the future fish tank temperature, water, pH and conductivity levels. Then predicted parameters and user-desired minimum and maximum temperature, water level, pH level and conductivity levels are used as input parameters to the objective function. Objective function is used to calculate the optimal environmental parameters to the fish tank. Based on optimal and predicted temperature, pH level, conductivity and water level, FLC module assigns the operational level and activation duration for fish tank actuators.

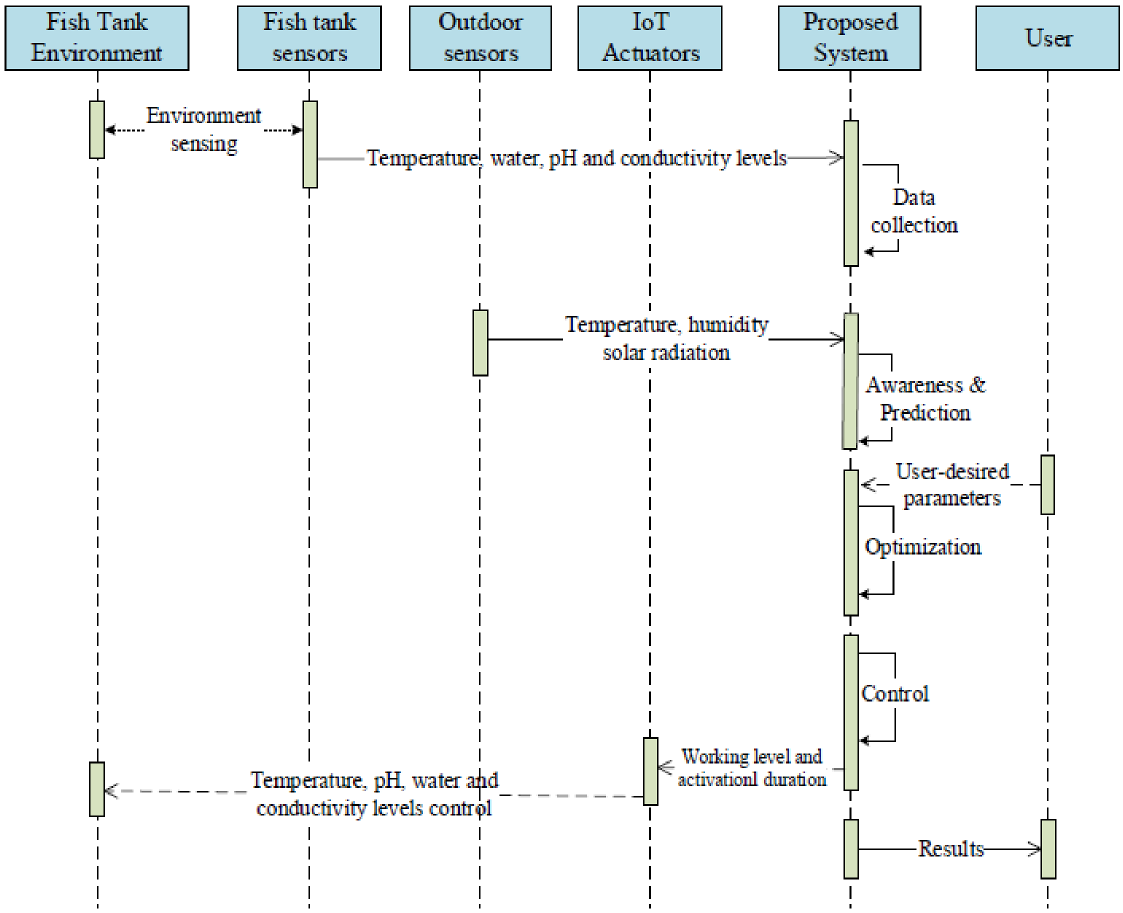


Figure 36: Sequence diagram of the embedded predictive optimal control using Fish tank and outdoor parameters.

3.5 Embedded Predictive Optimal Control Scheme based on Actuators' Control Parameters

In this subsection, we describe our proposed embedded predictive optimal control scheme based on actuators' control parameters in order to minimize energy consumption. As we mentioned above, actuators' control settings are their operational level and activation duration. Usually, variable and fixed speed heaters, coolers, water pumps, and fish feeders are used in fish tanks. The fixed speed technologies can only activate in the same levels and consume a fixed quantity of power because they do not have the speed or working level increasing/decreasing function. Conversely, the variable speed or operational level actuators are able to be activated with various speed levels to provide required resources according to the requirement. These variable speed devices consume the various energy based on activation speed, more precisely if the device is activated with higher speed, then the device requires higher energy by compared to lower speed activation. In fish farming or the greenhouse environment, the power consumption of the devices can be optimized by controlling actuators in variable speed, but this type of activation requires various time to finish the specific task. For instance, if the pump requires to be activated with the flow rate of 80 $\boldsymbol{ft^3/min}$ for 4 hours in a day, then operating the same water pump with 20 $\boldsymbol{ft^3/min}$ will require 16 h of operation in a day. So actuators' control parameters are needed to consider to achieve high efficiency. Figure 37**Figure *36*** presents the conceptual design of the proposed embedded predictive optimal control scheme using energy control parameters.

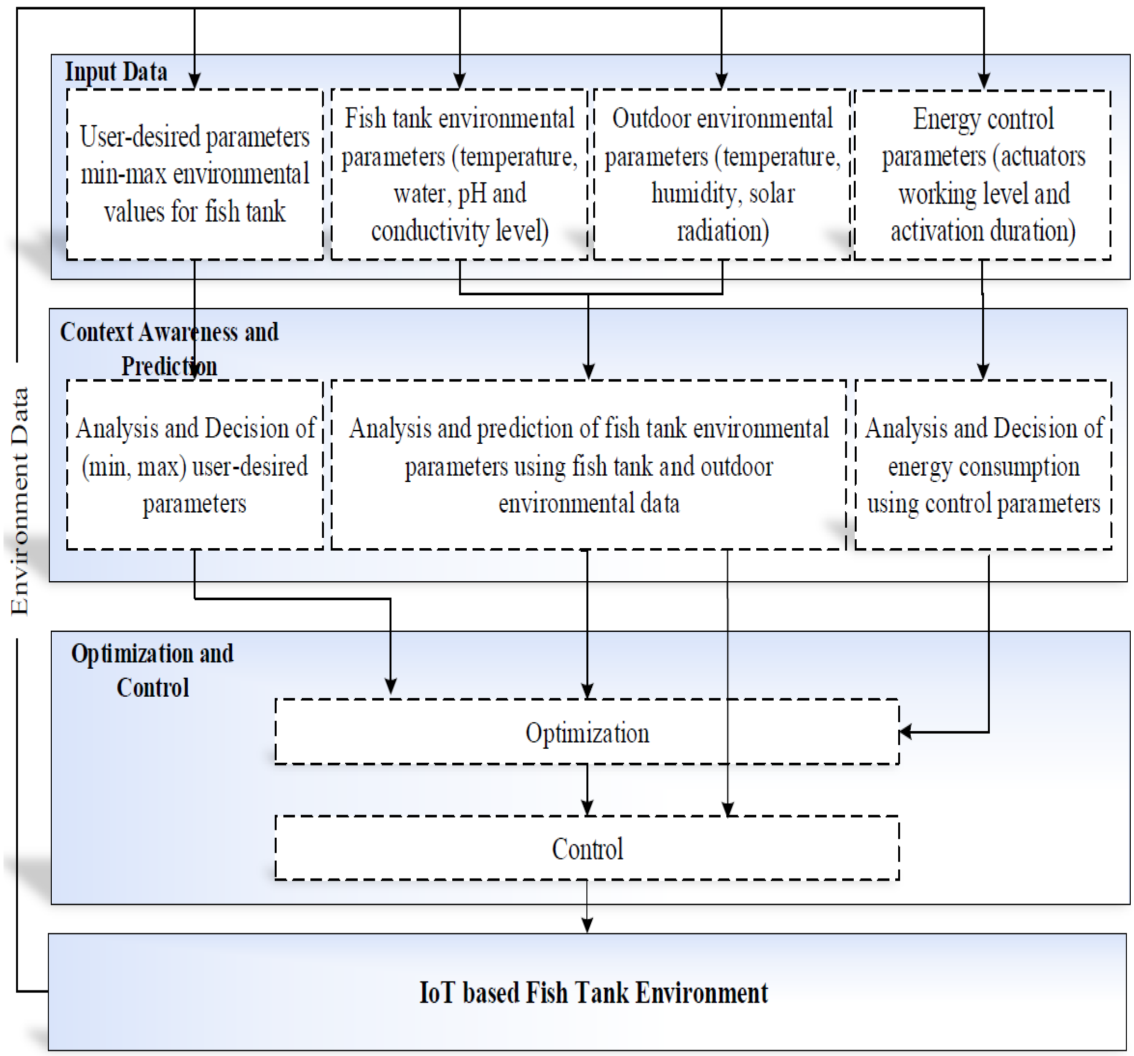


Figure 37: Conceptual design of the embedded predictive optimal control scheme using energy control parameters.

Energy control parameters actuators' operational level and activation duration are one of the input parameters to the system. Context-awareness module is used to analysis and decision for the energy consumption parameters according to the control values. Then actuators' working level and activation duration are used as the input parameter to the optimization module with user-desired and predicted environmental parameters. Optimization module computes the optimal environmental parameters to the fish tank with efficient energy consumption and finds the optimal working level to the fish tank actuators. Figure 38 presents the detailed conceptual design of the proposed embedded predictive optimal control scheme using energy control parameters. The energy control parameters actuators working level and operational duration are the input parameter to the optimization module. Optimization module outputs are optimal energy consumption and optimal environment parameters.

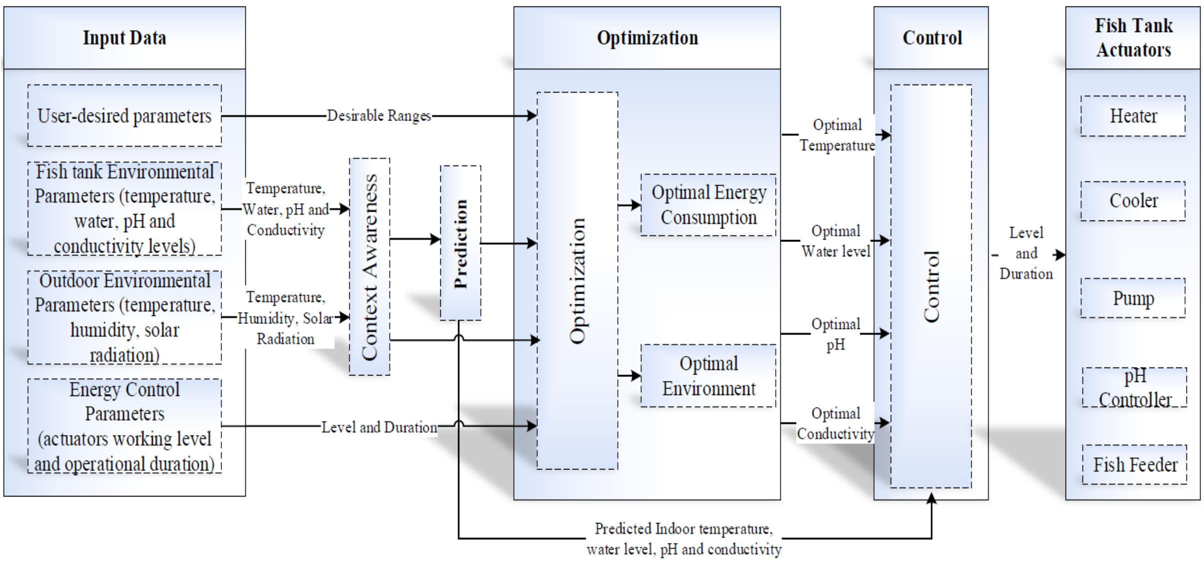


Figure 38: Detailed conceptual design of the embedded predictive optimal control scheme using energy control parameters.

Figure 39 and Figure 40 present the proposed system architecture for the proposed embedded predictive optimal control scheme by considering the actuators working level and activation duration. As we use actuators' control parameters to the objective function as one of the input parameters, then we can formulate their energy consumption too. As a result, we can achieve the minimum energy consumption from the actuators and maximum and healthy fish productivity by providing the optimal environmental parameters to the fish tank.

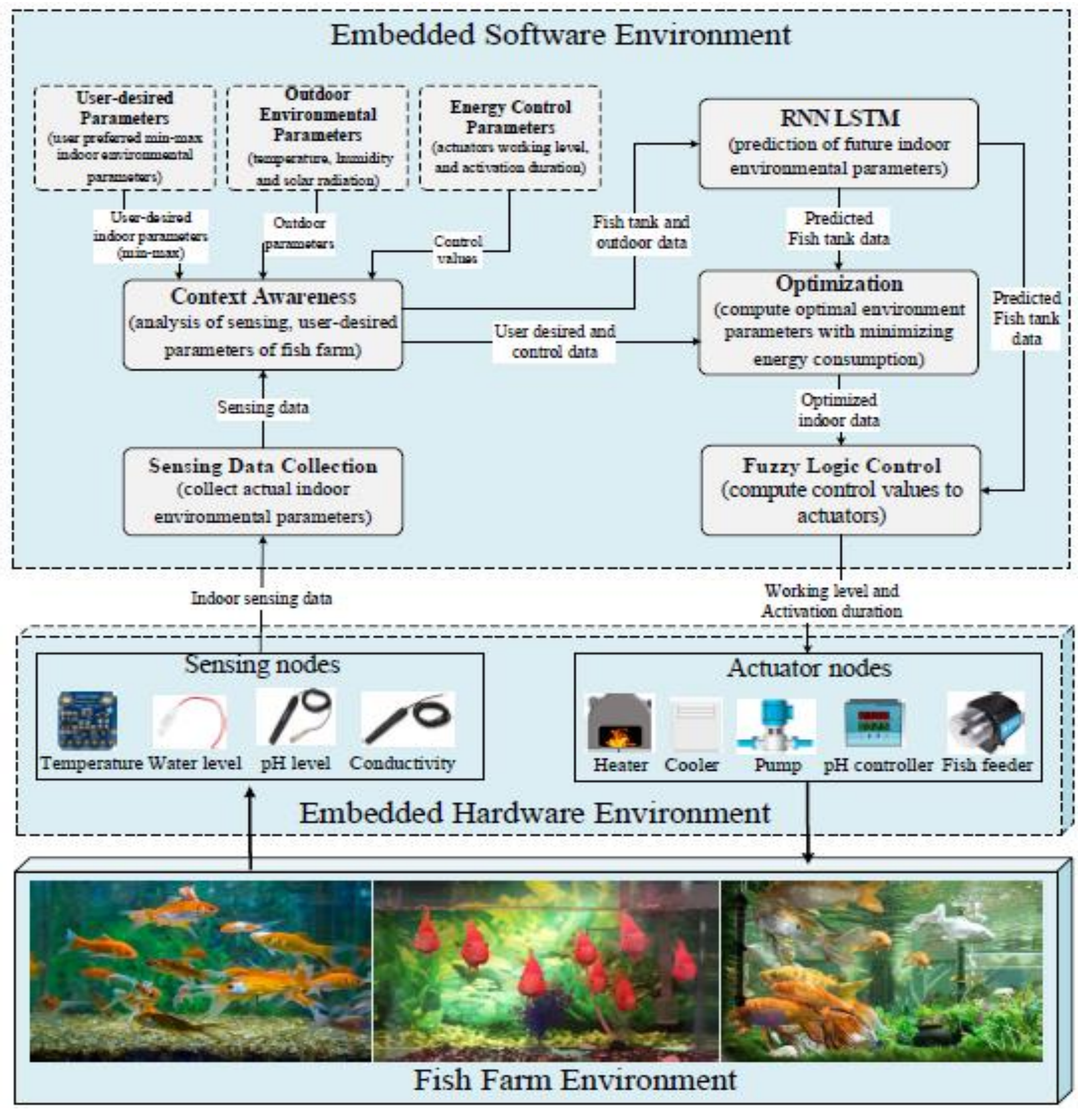


Figure 39: Proposed system architecture of the embedded predictive optimal control scheme using energy control parameters.

RNN-LSTM based prediction module predicts the future indoor environmental parameters to the fish tank, and this predicted data, user-desired parameters and control data are used as input parameters to the optimization module. Predicted environmental parameters are predicted temperature, predicted pH level, predicted water level and predicted conductivity levels in time-series. Optimization module computes the most optimal future environmental parameters to the fish growth with efficient energy consumption. Figure 40 presents the flowchart diagram of the proposed embedded predictive control scheme based using energy control parameters. As can be seen, input parameters to the awareness and prediction module are user-desired parameters, outdoor environmental parameters and actuators' working level and operational duration. Based on these input parameters, the prediction model forecasts future environmental values to the fish tank.

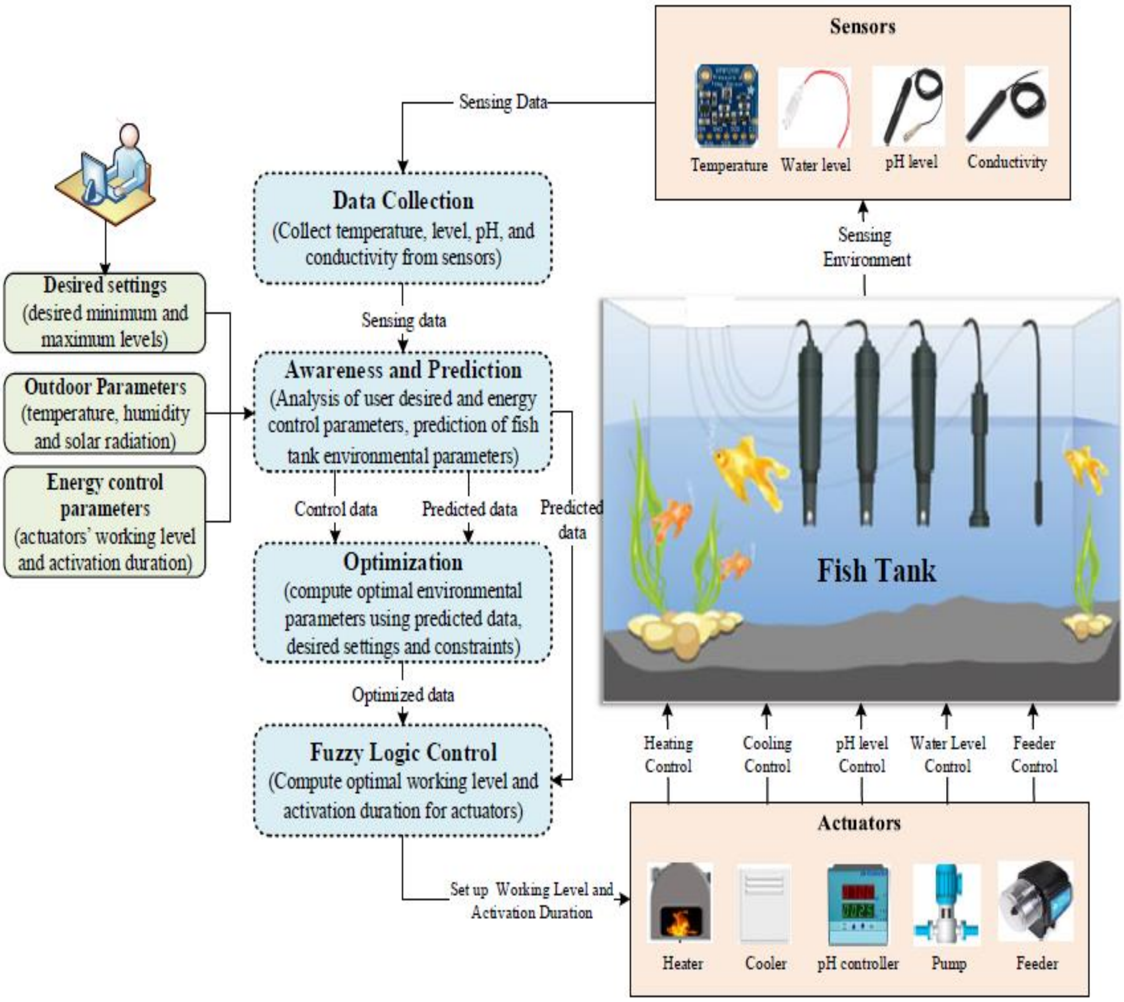


Figure 40: Flowchart diagram of the embedded predictive optimal control scheme using energy control parameters.

Figure 41 presents the sequence diagram of the proposed embedded predictive optimal control scheme using energy control parameters. The indoor and outdoor environmental parameters are used to predict the future fish tank temperature, water, pH and conductivity levels. Then predicted parameters and user-desired minimum and maximum temperature, water level, pH level and conductivity levels are used as input parameters to the objective function. The objective function computes the optimal environmental parameters to the fish tank. Based on optimal and predicted temperature, pH level, conductivity and water level, the fuzzy logic control module sets the working level and operational duration to the actuators.

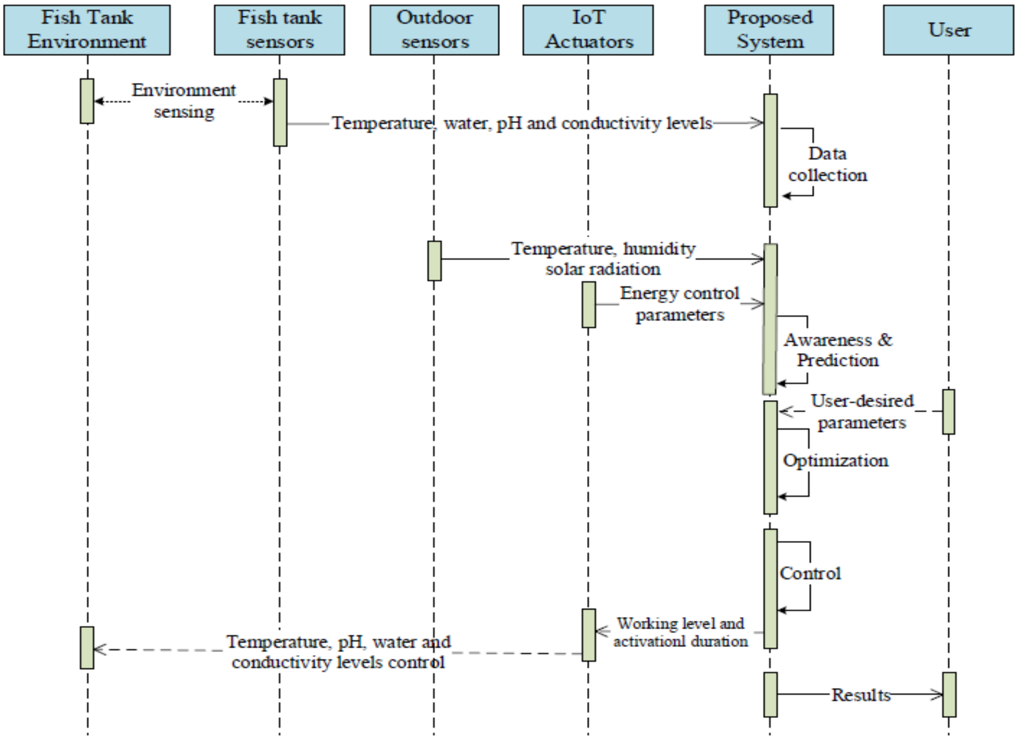


Figure 41: Sequence diagram of the embedded predictive optimal control scheme using energy control parameters.

3.6 Embedded Predictive Optimal Control Scheme based on Power Policy

In this subsection, we describe our proposed embedded predictive optimal control scheme with power policy data. Power policy is used to calculate the price of energy consumption. Based on the proposed novel objective function, we can achieve energy efficiency with optimal resource utilization. Figure 42 presents the proposed embedded predictive optimal control scheme, including the power policy parameters. As can be seen, in this suggestion, we have all input parameters as describes in section 3.1. Input parameters are user-desired environmental parameters, actual temperature, water level, conductivity, pH level values, and outdoor environmental parameters and power policy value. Context Awareness module is used to analyze all input parameters, while the prediction module predicts fish tank environmental parameters using fish tank and outdoor environmental data. Then minimum and maximum user-desired values, predicted environmental parameters and actuators energy consumption values are used as inputs to the optimization module. Optimization module computes the most desirable values to the fish tank with achieving minimum energy requirement.

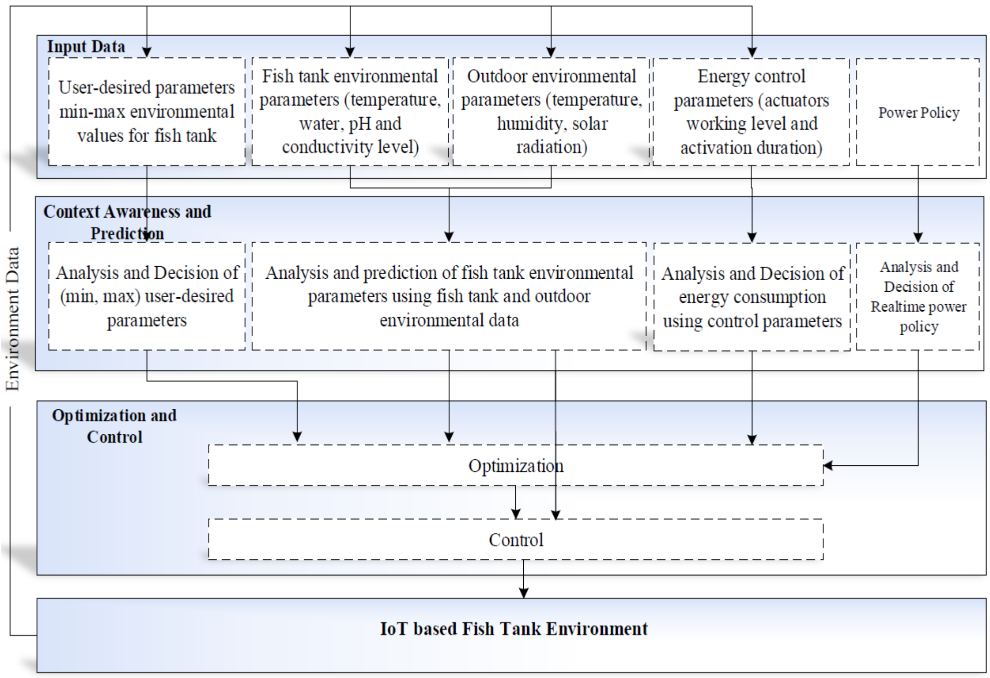


Figure 42: Conceptual design of the embedded predictive optimal control scheme using power policy parameters.

Then, user-desired, predicted, energy control parameters, and power policy parameters are used as input values to the optimization module. Optimization module computes the fish tank environmental parameters to the fish tank with efficient energy consumption and optimal price. Figure 43 describes the detailed conceptual design of the proposed predictive optimal control scheme using power policy parameters.

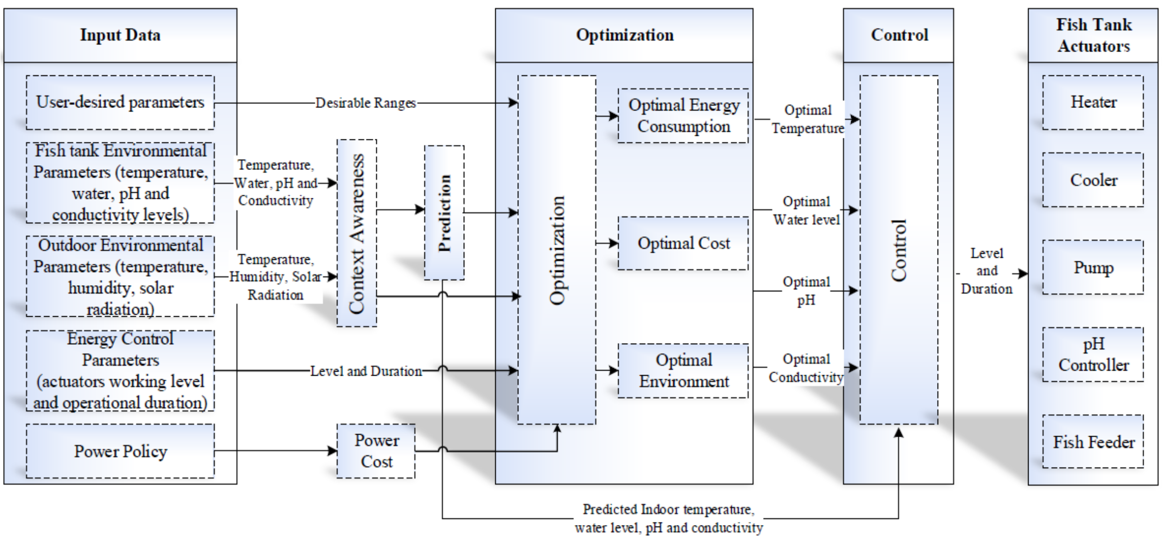


Figure 43: Detailed conceptual design of the embedded predictive optimal control scheme using power policy parameters.

Figure 44 represents the proposed system architecture of the embedded predictive optimal control scheme using power policy. The optimization module is used to calculate the optimal environmental parameters based on user preferred and the system constraint settings. FLC is used as a control algorithm for the proposed system to calculate and set the optimal working level and activation duration. In this work, we use a heater, cooler, pump, pH controller, and fish feeder actuators to control the environmental and feeding processes in the fish tank. The FLC module assigns the activation level and working duration for fish farm actuators. Based on these control values, actuators control the temperature, water level, pH, and conductivity level in an optimal condition by minimizing the energy consumption and maximizing the cost.

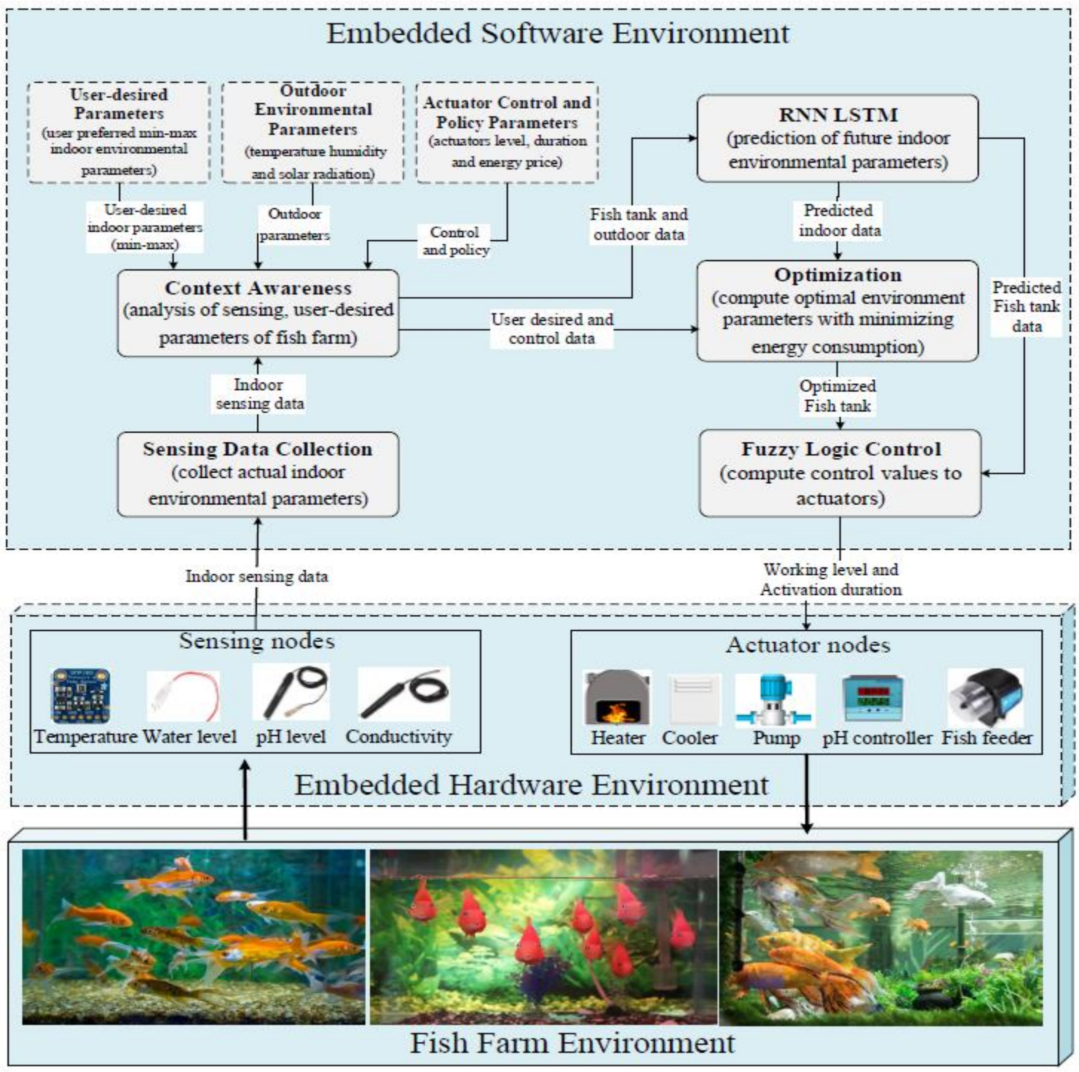


Figure 44: Proposed system architecture of the embedded predictive optimal control scheme using power policy.

Figure 45 illustrates the flowchart of the proposed IoT based fish tank embedded control framework. As it was described above, the overall procedure comprises four phases. First, we monitor the fish tank by collecting the various environmental data (e.g., temperature, water level, ph level, and conductivity) using IoT sensors, and these collected environmental data is stored to the data collection module. In the second phase, we apply the context awareness and prediction unit to analyze the used desired min max settings, environmental parameters with predicting future indoor parameters for the fish tank. Thirdly, the optimization module is used to calculate optimal indoor parameters for fish growth with energy efficiency based on user preferred values, control parameters, and constraints. At the end of the process, the FLC control is utilized to compute operational level and activation duration to the fish tank actuators according to optimal and predicted environmental data.

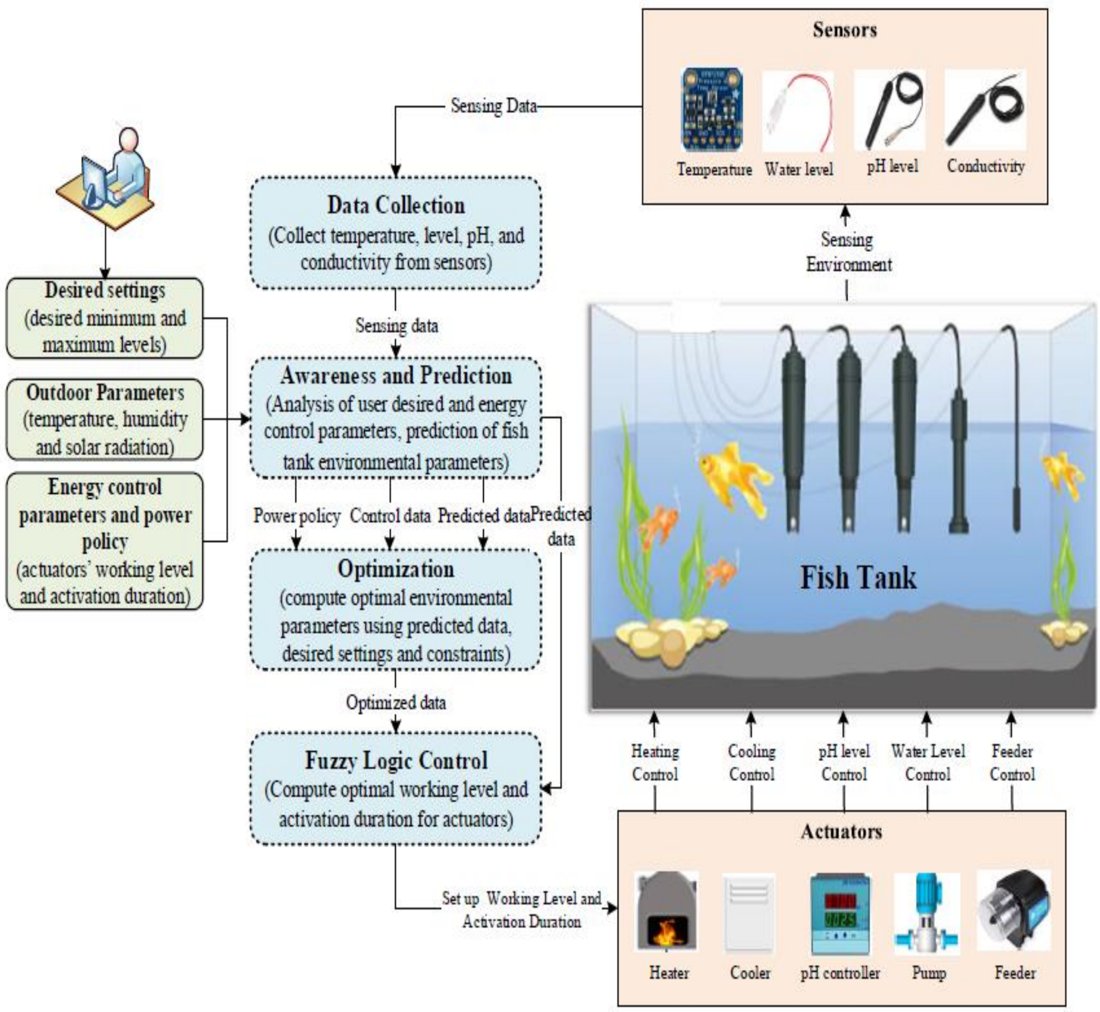


Figure 45: Flowchart diagram of the embedded predictive optimal control scheme using power policy.

Figure 46 presents the sequence diagram of the proposed embedded predictive optimal control scheme using power policy. The indoor and outdoor environmental parameters are used to predict the future fish tank temperature, water, pH and conductivity levels. Then predicted parameters and user-desired minimum and maximum temperature, water level, pH level and conductivity levels are used as input parameters to the objective function. The objective function computes the optimal environmental parameters to the fish tank. Based on optimal and predicted temperature, pH level, conductivity and water level, FLC module calculates the operational level and activation duration to the actuators.

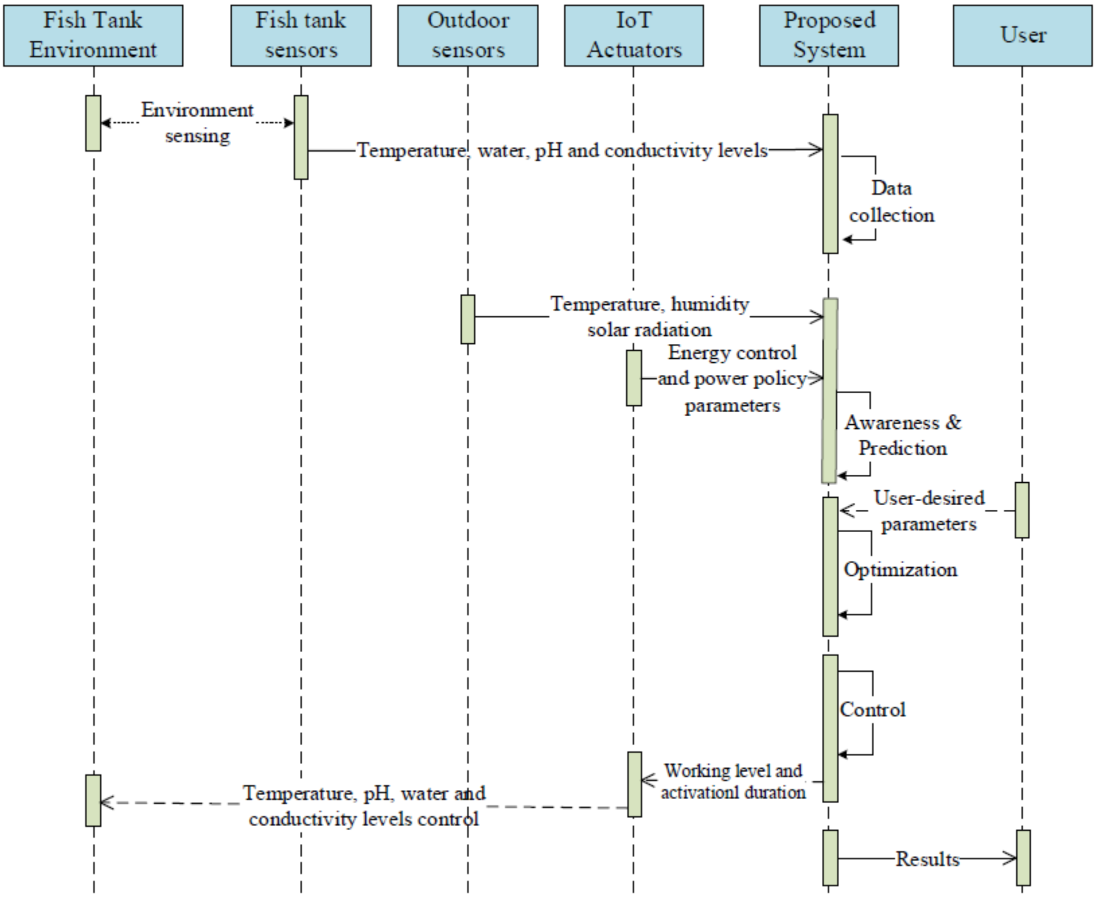


Figure 46: Sequence diagram of the embedded predictive optimal control scheme using power policy.

4. Experimental Embedded Optimal Control Platform in Fish Tank.

4.1 Embedded Hardware Environment of Fish Tank

In this section, we represent the implementation technologies and experimental environment of the proposed fish tank environment control platform in detail. The experiment was conducted in MCL laboratory; at D423 room at Jeju National University during the period January 2020 to May 2020. Figure 47 shows the real fish tank environment, which we designed as a case study. There are several connectivities, such as sensors and actuators' connection to the one Arduino board. Arduino plays a role as an IoT gateway. As we mentioned above the proposed system includes various types of sensors and actuators, also some functionalities which we deployed to the IoT devices including prediction, optimization, control algorithms.

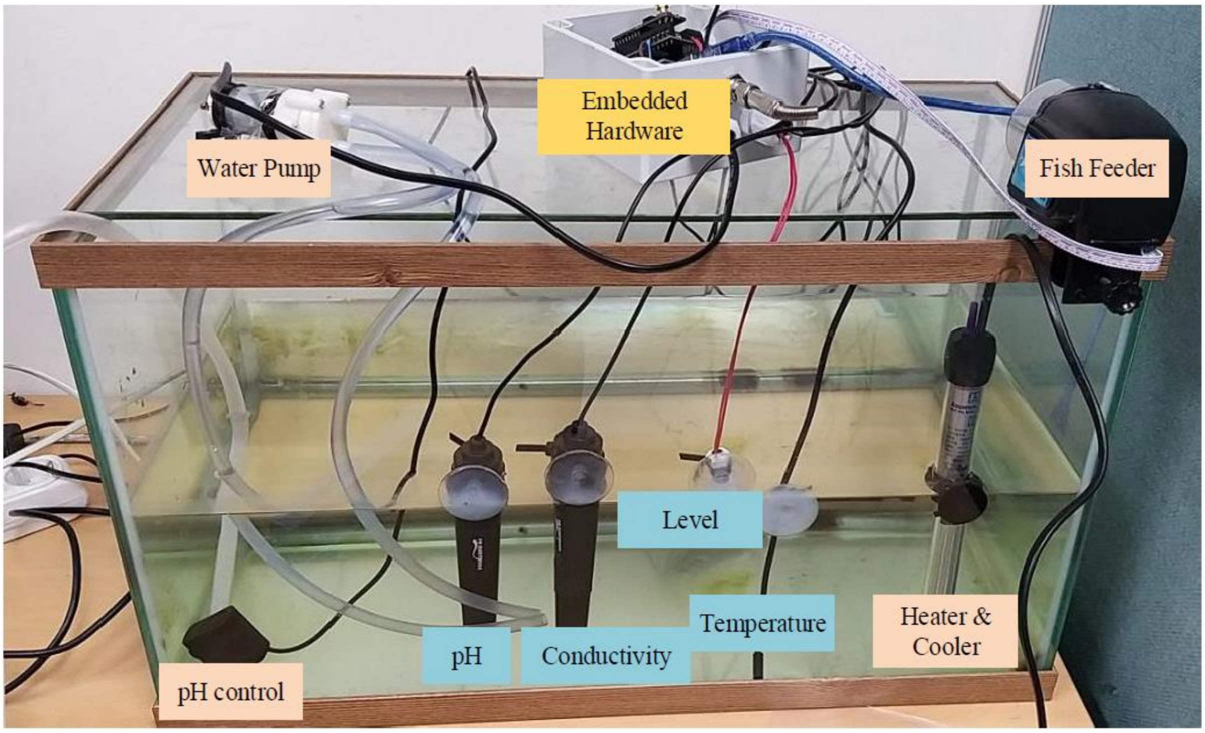


Figure 47: Experimental Environment of the proposed system.

Before moving to the implementation section, we have described the sensors and actuators' installation process for the experimental purpose of this work. For our experimental fish tank environment, we utilized Open Aquarium Fish Tank Monitoring tools manufactured by LibeLium. Open Aquarium has been fabricated for the management of fish tanks and ponds environment without human interference. Open Aquarium includes two various types of complementary kits, namely, Basic and Aquaponics, as well as some extra accessories. Open Aquarium platform includes five types of sensors, namely, temperature, conductivity, water, and pH level sensors. Also, the platform includes four different actuators for automatization of water temperature controlling, feeding process control, activating the water pumps for the controlling water level, and LED lamp for the intensity of the required light. The experimental environment presents four types of sensors, namely, temperature, water level, conductivity, and pH level sensors. Five types of actuators: heater, cooler, water pump, fish feeder, and pH-conductivity controller were installed to the Fish Tank. Figure 48 illustrates the relationship diagram among IoT devices and their role. In our proposed system we have used four types of IoT sensors, five types of actuators, Arduino and raspberry board. IoT sensors are used to get environmental sensing values, whereas, the actuators are utilized to control the environmental values with increasing and decreasing the actual environmental parameters. Arduino board plays a role as IoT gateway for the collection of the data from the environment and forwarding the sensing values to the Raspberry Pi board.

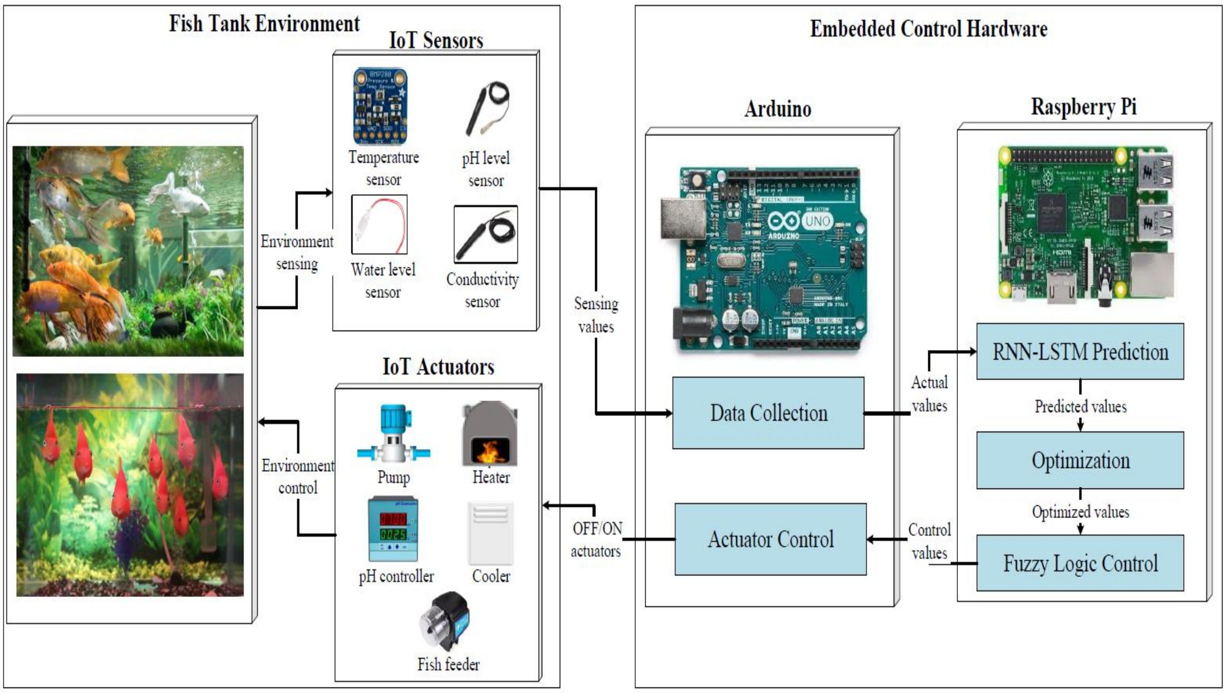


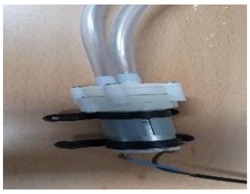
Figure 48: Embedded Control Environment of IoT sensors, actuators and embedded hardware.

We have deployed Embedded ML, Optimization and Fuzzy logic control functionalities to this board. We deploy RNN-LSTM based prediction module using TensorFlow Lite to the Raspberry Pi as Embedded ML, and this model forecasts environmental parameters. Then predicted values are used as input parameters to the optimization module. The Optimization module calculates the optimal environmental values with minimizing the energy consumption to the environment based on user desired parameters and the system constraints. The fuzzy logic control module calculates control values based on predicted and optimized values. These control values comprise working level and activation duration to the actuators. Arduino board has actuators' control functionality, which can activate or deactivate the actuators in the required time. Table 10 and Table 11 describe the IoT sensors and actuators which were used in this work, respectively.

Table 10: Description of IoT sensors for the experimental fish farm environment.

IoT Device (Sensors)	Item	Description
Water Level Sensor		Water level sensor produced by Geekri and is used for measurement of water level, activation voltage 3–5 V DC, operating current less than 20 mA.
pH Level Sensor		Measures the pH level of the water. Detection ranges: 0~14pH, Can be used temperature: 0~60°C, connection type: BNC and the length of the cable 2.9 meter
Conductivity sensor		A conductivity sensor measures the electrical conduction of can be used in temperature: 0~60°C, connection type: BNC and the length of the cable 2.9 meter, Analogic output
Temperature sensor		Temperature sensor is sealed is used to measuer temperature levels, power range 3.0-5.5V, can detect -55°C to+125°C temperature ranges, accuracy ±0.5°C 1 wire connection

Table 11: Description of IoT actuators for the experimental fish farm environment.

IoT Device (Actuators)	Item	Description
Water Pump Actuator		Variable speed peristaltic pump for fish tank, power ranges: 10-30 W, flow: 20-60 ml/min, 12V DC input voltage.
pH Control Actuator		Immersible pH control actuator for open garden and aquarium, power range: 0.5W-5W, power supply: 3.5~12V DC,65mA-500mA.
Fish Feeder Actuator		Programmable fish feeder, power range: 3,3 V, size:11 x 6.5x0.7 cm
Heater & Cooler Actuator		Energy: 100W, voltage: 220/240V 50/60Hz length: 22cm diameter: 2.2cm length of power cord: 85cm recommended tank size: 20 to 33 gallon temperature range between 17°C and 35°C).
Arduino and Open Aquarium Shield		Provides connection of all sensors and actuators to the one board and server. Manufactured by Libelium, power supply 12V-2A.

As can be seen from the list of sensors, these sensors can measure water level, pH level, conductivity, and temperature sensing values from the environment in real-time. According to the measured fish tank environmental parameters, we have five types of fish tank actuators, as presented.

It is important to note that all actuators are programmable, which means these devices can be activated at various speeds or working levels. As we know, the Arduino board can not support a wide range of sensors and actuators connected to the one board. When the user wants to add some extra technologies like wifi, Bluetooth, motor-drives, actuators, etc., it can be pretty tricky for connecting all of them for the Arduino. It can be seen that we have enough actuators for controlling each environmental values. For instance, the temperature sensor is used to measure the water temperature parameters, and according to the optimized parameters and predicted temperature values fuzzy logic control module activates or deactivates the heater or cooler actuators.

So we need extra devices, which are called IoT Shield, for connecting the four sensors and five actuators to the one board in order to centralize the control unit. We have used Open Aquarium IoT shield, which was produced by Libelium, external power supply 12V-2A for attaching all sensors and actuators to the one board. Figure 49 presents the open aquarium IoT shield, as can be seen, this IoT shield has the capability for connecting various sensors and actuators to the one board. For instance water level connector, Arduino/raspberry jumpers, light Led, digital input/output connectors, temperature connectors, RF connector, water leak sensor connector, pH level sensor connector, peristaltic pump connector and so on.

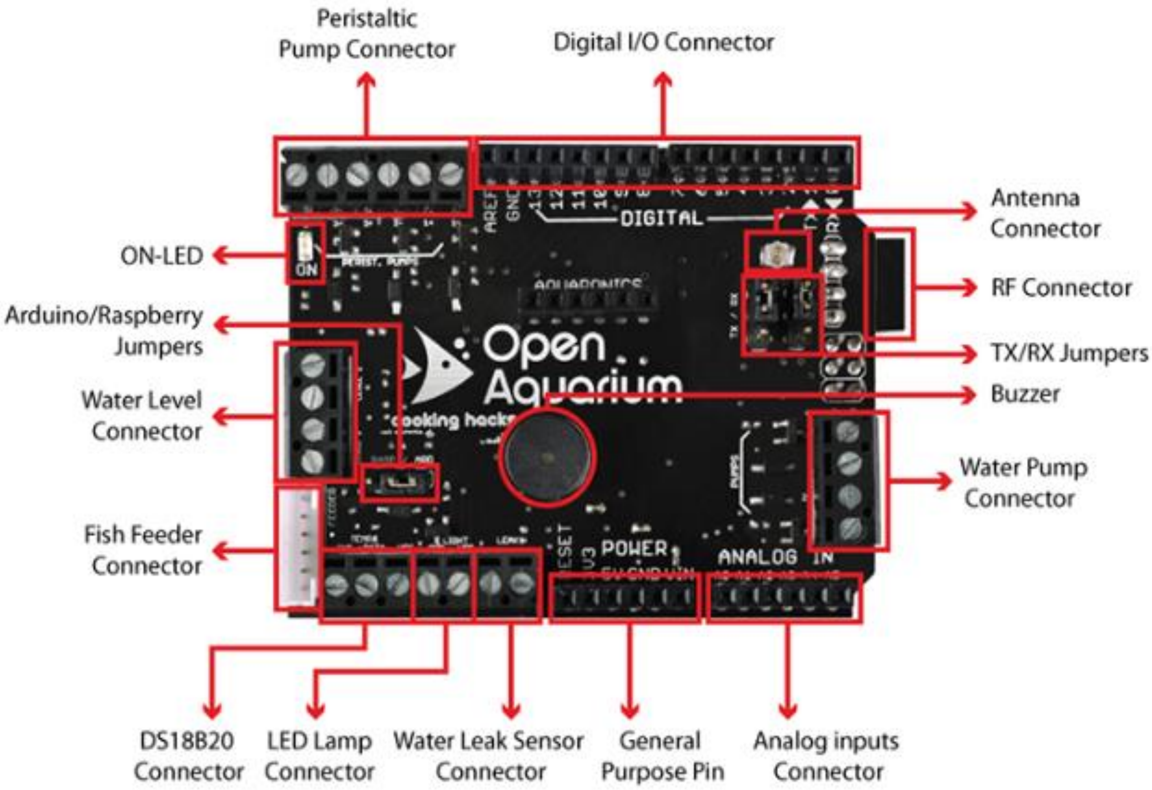


Figure 49: Open Aquarium IoT Shield for connecting various IoT sensors and actuators to one board.

We have connected temperature, water level, pH level, conductivity level sensors and heater, cooler, water pump, pH controller, fish feeder actuators to IoT shield in this work. However, the proposed system architecture, the objective function is adaptable and flexible for other fish tank environmental values. The architecture, prediction, optimization and control modules can be easily extended with other sensor parameters, such as dissolved oxygen, humidity, and CO2 level.

Figure 50 describes the embedded hardware environment for the data collection and actuator control units using IoT shield and Arduino board.

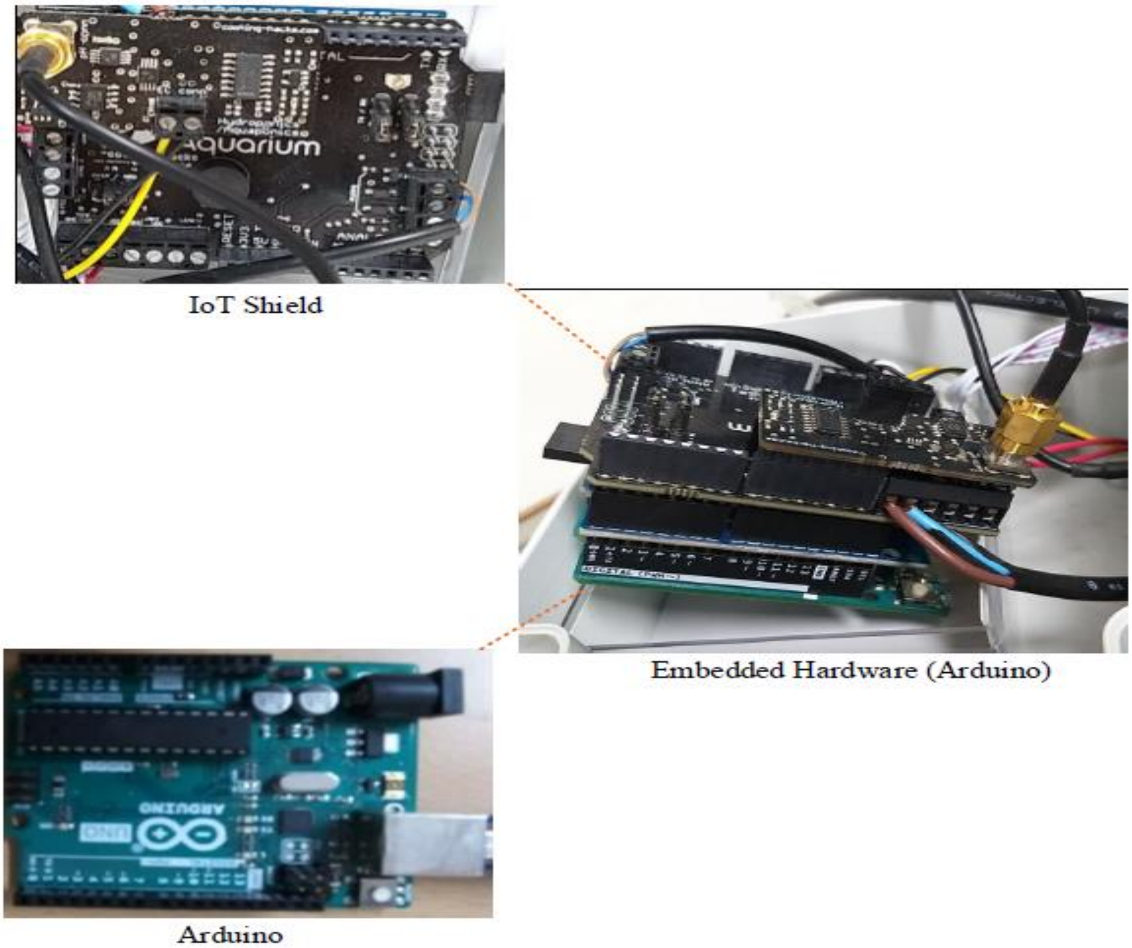


Figure 50: Embedded hardware environment for data collection and actuator control using Arduino and IoT Shield.

Arduino is an open-source lightweight electronic platform that can provide hardware and software services. There are several advantages of the Arduino platform, such as they are inexpensive, can operate in different operating systems, open-source, clear programming environment, and extensible hardware. As we already mentioned above, the Arduino board can not support a wide range of device connectivity, so we have used an open aquarium IoT shield to centralize the connectivity and control of sensors and actuators to the one board. After connecting all sensors and actuators to one board, we attached the IoT shield to the Arduino board as shown in Figure 50. Arduino board is played a role as IoT gateway between the fish tank environment and Raspberry Pi. More precisely, the Arduino board has two main functionality environmental Data Collection from the fish tank using sensors and sending the actual values to the Raspberry Pi and Actuator control unit for the activation and deactivation of the actuators with turning off and on the actuators in the estimated time. Fish Tank sensors measure the indoor environmental values from the fish tank and forward these data to the embedded software which were deployed to the Raspberry PI using USB connectivity. Figure 51 presents an embedded hardware environment of the proposed system using Raspberry Pi. As we have mentioned above, IoT sensors and actuators are connected to the Arduino board using IoT shield for receiving the sensing values. Then the Arduino board is connected to the Raspberry PI device. Also, this device has network connectivity, the connection to the monitor, power connectivity, and memory.

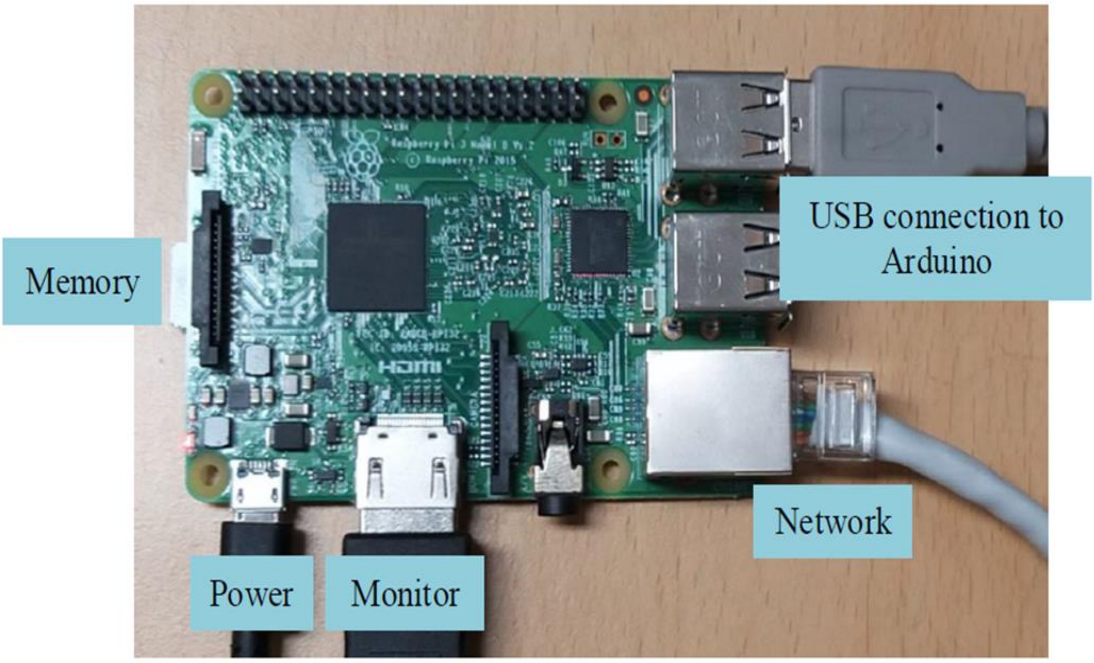


Figure 51: Embedded hardware environment for prediction, optimization, and control using Raspberry Pi.

We deploy RNN-LSTM based prediction, optimization, and control functionalities to this device. As the actual sensing values come from the environment via the Arduino board, an embedded system calculates the optimal environmental parameters and required control parameters to the actuators. Then control values are forwarded to the Arduino's control unit, and this unit switches on and off the actuators to manage the environmental parameters.

4.2 Software Experimental Environment of Fish Tank

The implementation environment and the development of the proposed platform are divided into two phases, firstly we wrote and developed the proposed system in our personal computer then, we have deployed these models to the embedded IoT device. Table 12 presents the tools utilized on a general-purpose PC for the development of the proposed framework. RNN-LSTM based prediction model is developed using the Tensorflow library using external and internal environmental data which are described in Section 3. For the implementation of the proposed optimization system, we developed a C# based desktop application. The fuzzy logic control module algorithm is implemented in MATLAB and integrated with the desktop application. Indoor temperature, pH level, conductivity and water level values are sent to the PC server using serial cables, and these values are stored to the database. Direct communication provided between Fish Farm and the application using Arduino IDE. Operating system of the PC is Windows 10, and primary memory is 12 GB. .NET, PyCharm, Arduino, MATLAB integrated development environments were used to implement the proposed desktop-based system. Model training libraries for the prediction model are Pandas, Tensorflow, and Sklearn. As we mentioned above the proposed system firstly implemented on PC and then deployed to the IoT device.

Table 12: Implementation environment of the general-purpose PC.

Component	Description
Operating System	Windows 10
CPU	Intel (R) Core (TM) i5-4570 CPU @ 3.20 GHz
Primary Memory	12 GB
Programming Language	Python, C#
Integrated Development Environment (IDE)	.NET, PyCharm, Arduino, MATLAB
Model Training Libraries	Pandas, TensorFlow, SKlearn
Framework	.NET Framework
Connectivity	Serial connection

TensorFlow is a comprehensive open-source machine learning platform. Researchers can easily implement several applications using this complete and flexible tool, libraries and ecosystem of community resources to help advance ML's cutting-edge technology, and developers can quickly create and deploy ML-based applications. Building a model using Tensorflow has the following advantages:

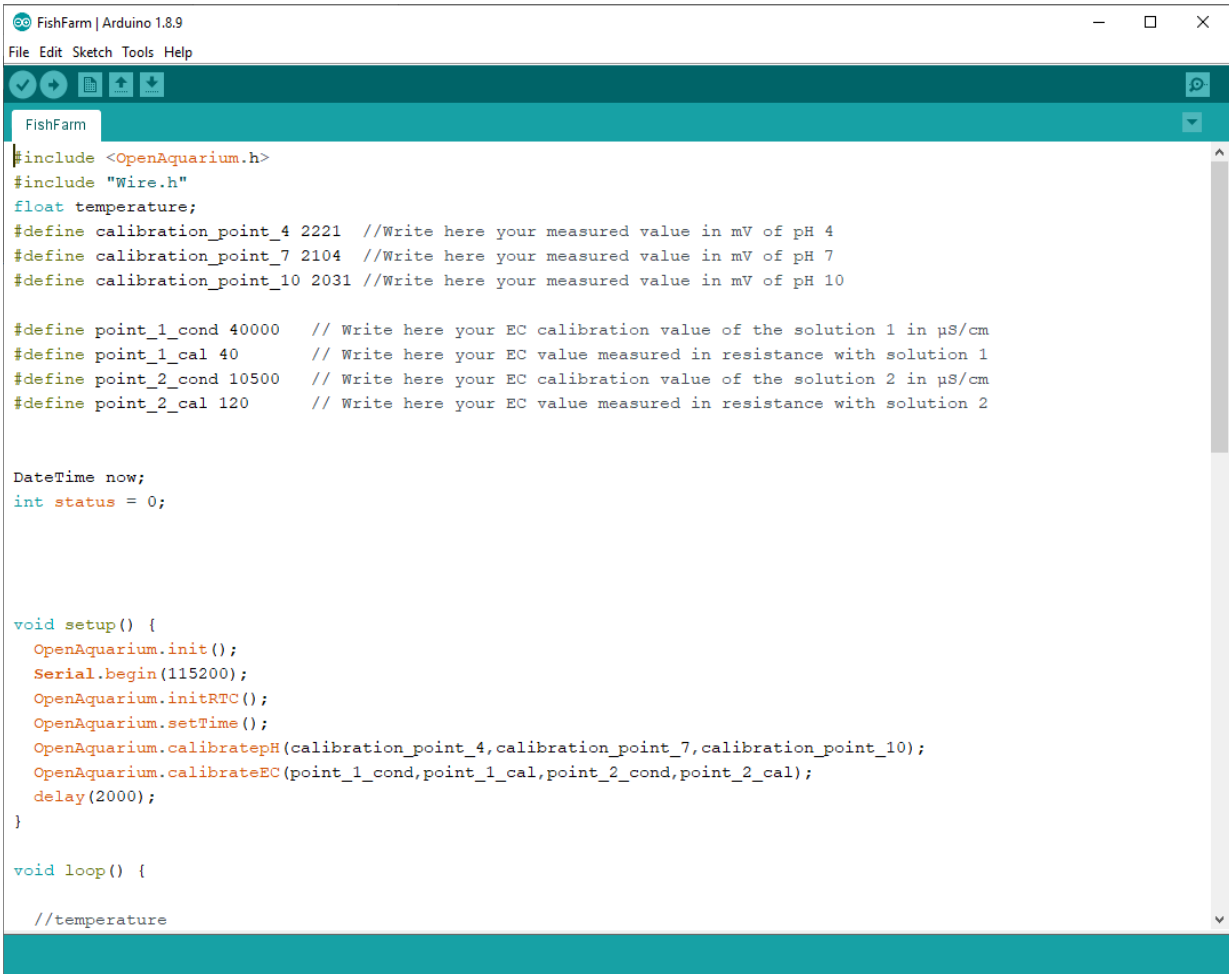
- Simple modelling: With quick execution, we can easily create and train ML models using intuitive, advanced APIs like Keras to iterate and debug ML models instantly.
- Reliable ML production anywhere: Simple training and model delivery of the model from the cloud, place, browser or device regardless of the language used.
- Powerful research experiments: A simple and flexible architecture for conveying new ideas from concept to code, including the latest models and quick publishing.

After implementing the proposed system successfully in PC, we deployed the proposed model to the Raspberry Pi and Arduino board, as described in Figure 51. Table 13 shows the technologies used for the embedded software implementation environment. For the implementation of the embedded software environment we have used Raspberry Pi and Arduino, the programming language is Python. PyCharm, Arduino Studio, .NET framework are used for the integrated development environment. Pandas, Tensorflow, and Sklearn based Trained libraries are deployed to the Raspberry Pi using Raspbian OS and TensorFlow lite. The core programming language is Python.

Table 13: Implementation environment of the embedded software.

Component	Description
Hardware	Raspberry Pi 3 Model B, Arduino
Operating System	Raspbian OS
Memory	32 GB
Programming Language	Python, C#
Integrated Development Environment (IDE)	Visual Studio, PyCharm, Arduino
Framework	.NET Framework, TensorFlow Lite
Connectivity	Serial connection

As we have mentioned above, we have deployed Embedded ML, Optimization and Fuzzy logic control functionalities to embedded hardware. We deploy RNN-LSTM based prediction module using TensorFlow Lite to the Raspberry Pi as Embedded ML, and this model forecasts environmental parameters. Then predicted values are used as input parameters to the optimization module. The Optimization module calculates the optimal environmental values with minimizing the energy consumption to the environment based on user desired parameters and the system constraints. The FLC module calculates control values based on predicted and optimized values. These control values comprise working level and activation duration to the actuators. Arduino board has actuators' control functionality, which can activate or deactivate the actuators in the required time. Table 5 describes the IoT sensors which were used in this work. Figure 52 describes the implemented modules for the proposed embedded control environment with their description. Mainly we have three modules, namely, sensing data collection, prediction, optimization, and control. We have used temperature, pH level, conductivity, and water level sensors to collect the data from the environment using Arduino board, and this Arduino board is connected to the Raspberry Pi for the connection to another functionality.




```
#include <OpenAquarium.h>
#include "Wire.h"
float temperature;
#define calibration_point_4 2221  //Write here your measured value in mV of pH 4
#define calibration_point_7 2104  //Write here your measured value in mV of pH 7
#define calibration_point_10 2031 //Write here your measured value in mV of pH 10

#define point_1_cond 40000   // Write here your EC calibration value of the solution 1 in µS/cm
#define point_1_cal 40       // Write here your EC value measured in resistance with solution 1
#define point_2_cond 10500   // Write here your EC calibration value of the solution 2 in µS/cm
#define point_2_cal 120      // Write here your EC value measured in resistance with solution 2


DateTime now;
int status = 0;




void setup() {
  OpenAquarium.init();
  Serial.begin(115200);
  OpenAquarium.initRTC();
  OpenAquarium.setTime();
  OpenAquarium.calibratepH(calibration_point_4,calibration_point_7,calibration_point_10);
  OpenAquarium.calibrateEC(point_1_cond,point_1_cal,point_2_cond,point_2_cal);
  delay(2000);
}

void loop() {

  //temperature
```

Figure 52: Sensing data collection module of Fish Tank.

Figure 53 presents the RNN-LSTM based prediction model using TensorFlow and python, and this trained model is deployed to the embedded device using TensorFlow lite.

```
multi_step_model = tf.keras.models.Sequential()
multi_step_model.add(tf.keras.layers.LSTM(32,
                                          return_sequences=True,
                                          input_shape=x_train_multi.shape[-2:]))
multi_step_model.add(tf.keras.layers.LSTM(16, activation='relu'))
multi_step_model.add(tf.keras.layers.Dense(72))

multi_step_model.compile(optimizer=tf.keras.optimizers.RMSprop(clipvalue=1.0), loss='mae')
```

Figure 53: RNN-LSTM based Prediction model in Fish tank.

An objective function based optimization formulation and Fuzzy logic based control unit using C#. C# is developed in the .NET framework, so it is challenging to use the .NET framework in Raspbian because it has limited memory, so we deployed the .exe file of the C# based application to the embedded system using Mono. Mono is a free open-source and cross-platform implementation of the .NET Framework.

4.3 Fish Tank Environment Modeling

In this section of the thesis, we describe the proposed a fish tank environment modeling for the deploying the proposed system for the various environments with formulating mathematically various fish tank data acquisition and device control processes according to the studies [96,97,98]. This work considers the fish tank as a parallelepiped shape which comprises tank side height (T_{sh}), tank length (T_l), and tank width (T_w) as described in Figure .

Fish tank floor area T_{area} can be computed using the following equation, where T_l presents the length of the tank, and T_w is the width of the tank.

$$T_{area} = T_l \times T_w$$

The overall volume of the fish tank can be calculated with computing the length, width, and side height of the fish tank as described in

$$T_{vol} = T_l \times T_w \times T_{sh}$$

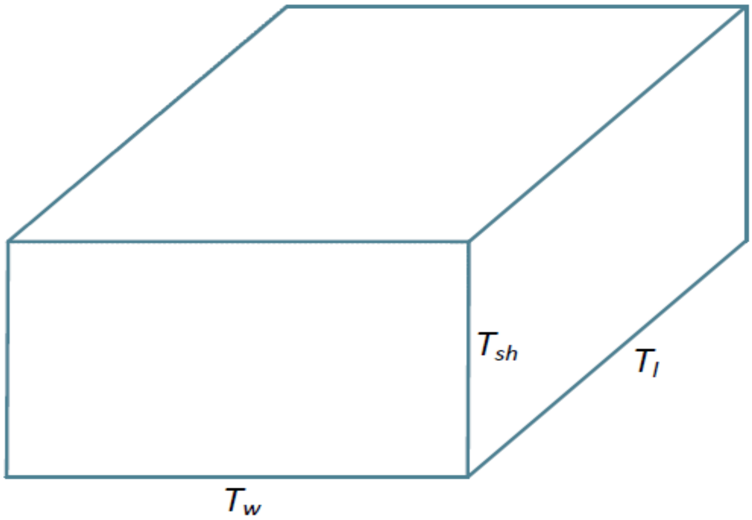


Figure 54: Fish Tank modelling with parallelepiped shape.

Figure 54 presents the fish tank model used in this study. As we mentioned earlier, four fish tank parameters are considered for controlling the fish tank indoor environment, i.e. temperature, pH, conductivity, and water level. Figure 55 describes the used parameters for the fish tank environment and actuators. Fish tank parameters are internal temperature, pH level, conductivity level and water level.

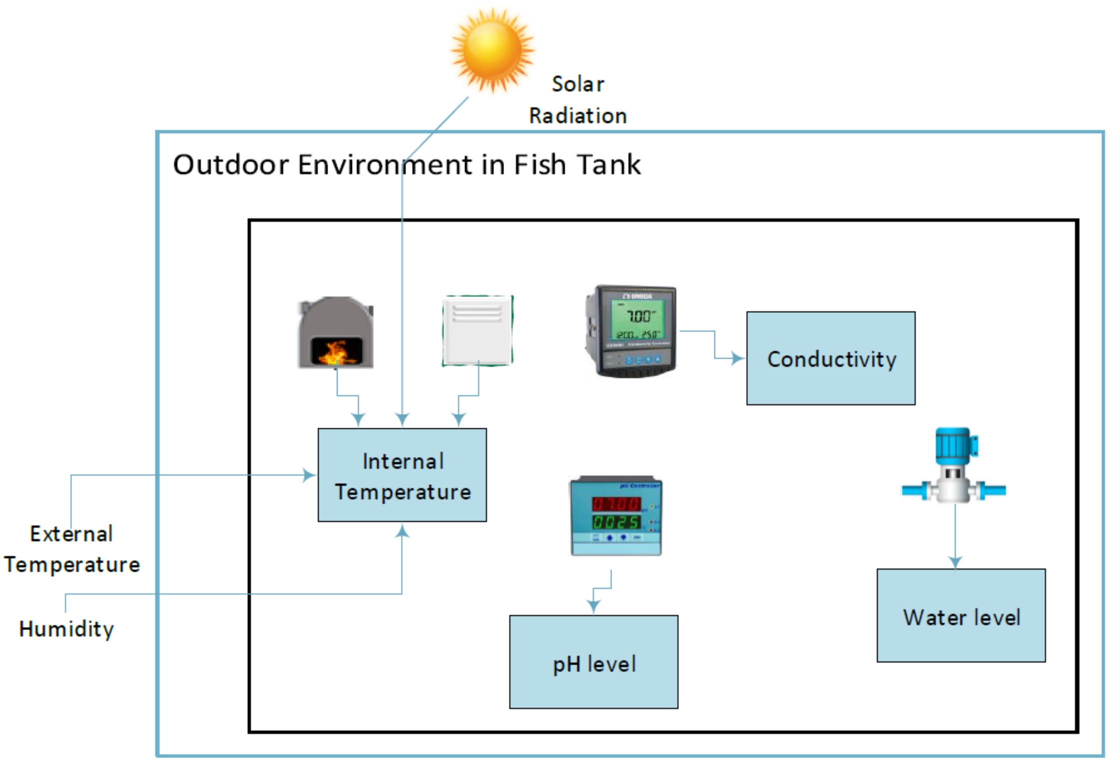


Figure 55: Outdoor environment configuration with essential components and processes in Fish Tank.

For experimental analysis, we have used real sensing data from the fish tank, which we constructed in Mobile Computing Laboratory at Jeju National University. Temperature, water level, pH level and conductivity level sensors are used to collect the real-time data from the environment as an indoor environmental data. We also used outdoor environmental data, which were collected from online weather site Meteoblue [95] for Jeju as described in Figure 56, South Korea. The outdoor environmental data includes outdoor temperature, humidity, and solar radiation information collected half-hourly interval based. In this thesis work, our objective is to provide optimally indoor temperature, pH level, conductivity, water level, and fish feeding based on user-desired settings with efficient energy consumption.

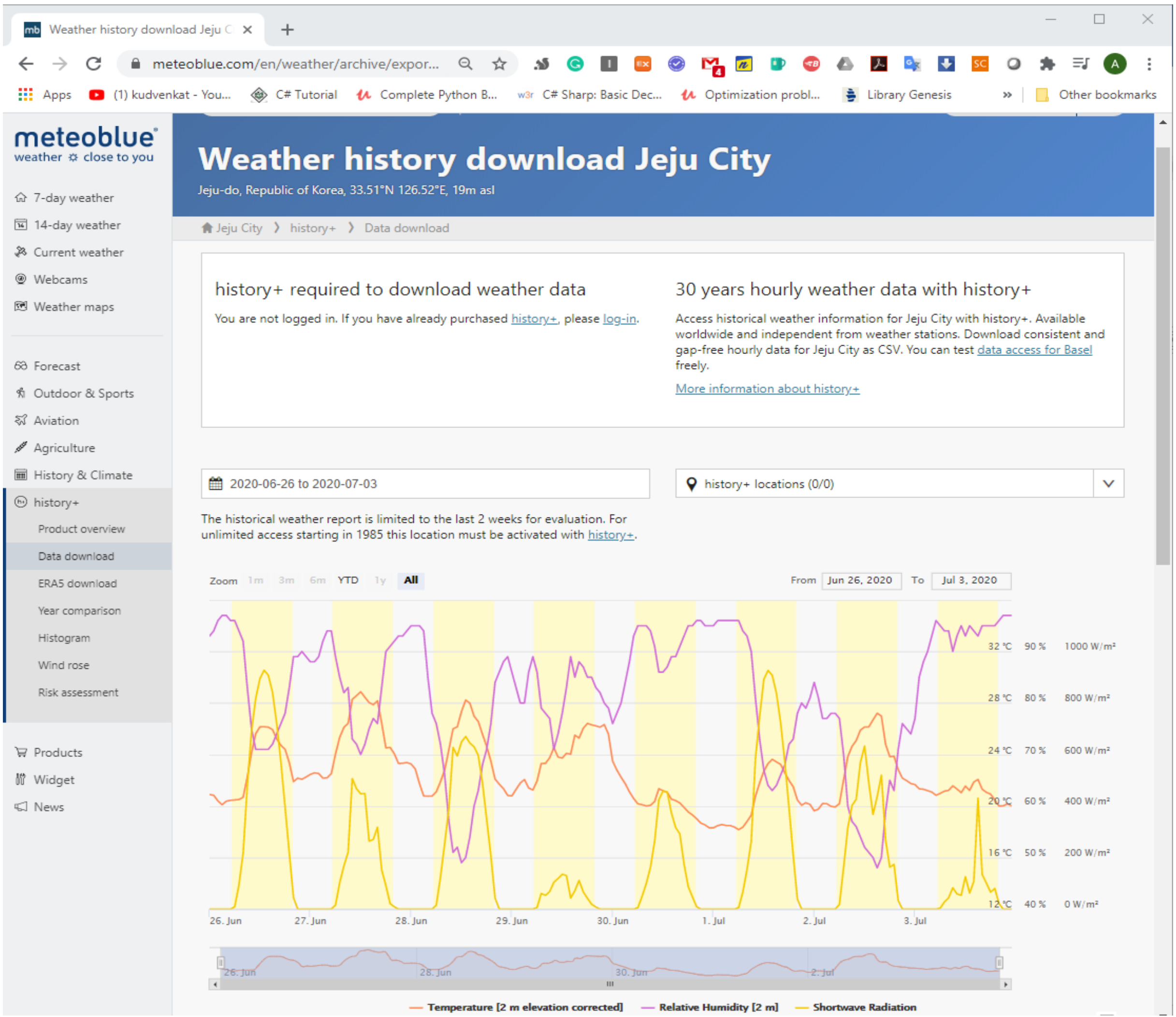


Figure 56: External data collection from Meteoblue website.

Table 14 describes the sample data collection, which is used in this study. As can be seen the dataset includes the number of data, date time, indoor temperature, pH level, conductivity, water level. In addition we use outdoor environmental temperature, humidity and solar radiation parameters. In these experiments, we have used 70% of available data for training and rest of the 30% is used for testing. For training and testing the accuracy of learning modules, we have conducted a repeated number of experiments and collected the data.

Table 14: Dataset example which is used in this study.

No	Date	Time	Indoor Temp	pH	Conduct	Water level	Outdoor Temp	Outdoor Humid	Solar Rad
1	1/31/2020	11:30:00 PM	18.7166	6	812.60	247	1.08333	93.1	403.6
2	2/1/2020	12:00 AM	19.1803	6.26	775.33	245	0.90556	93.2	403.1
3	2/1/2020	12:30 AM	21.340	6.62	733.40	242	-1.6278	90.1	404.8
4	2/1/2020	1:00:00 AM	19.953	6.49	730.32	243	-1.36667	93.5	404
5	2/1/2020	1:30:00 AM	18.043	6.8	665.43	235	-2.0333	85.3	405.4
6	2/1/2020	2:00:00 AM	23.276	6.9	628.54	239	-2.112	80.2	404.4
7	2/1/2020	2:30:00 AM	20.366	6.38	642.03	240	1.38	81.2	402.2
8	2/1/2020	3:00:00 AM	18.084	6.4	640.04	241	1.40	79.8	400.1
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
3000	4/3/2020	10:30 AM	16.734	6.38	613.20	265	17.03889	10.2	405.6
3001	4/3/2020	11:00 AM	18.516	6.4	620.15	268	16.68889	12.2	405.4

4.4 Implementation Results of the Proposed System

In this subsection we present the implementation results of the proposed system. Figure 57 describes the implementation result of the data collection unit using the Arduino board. Arduino board is attached with an IoT shield which comprises the various sensors for the collecting the real data from the fish tank environment. As can be seen, the indoor environmental parameters temperature, pH level, conductivity and water level are collected successfully using Arduino board in Rasbian OS.

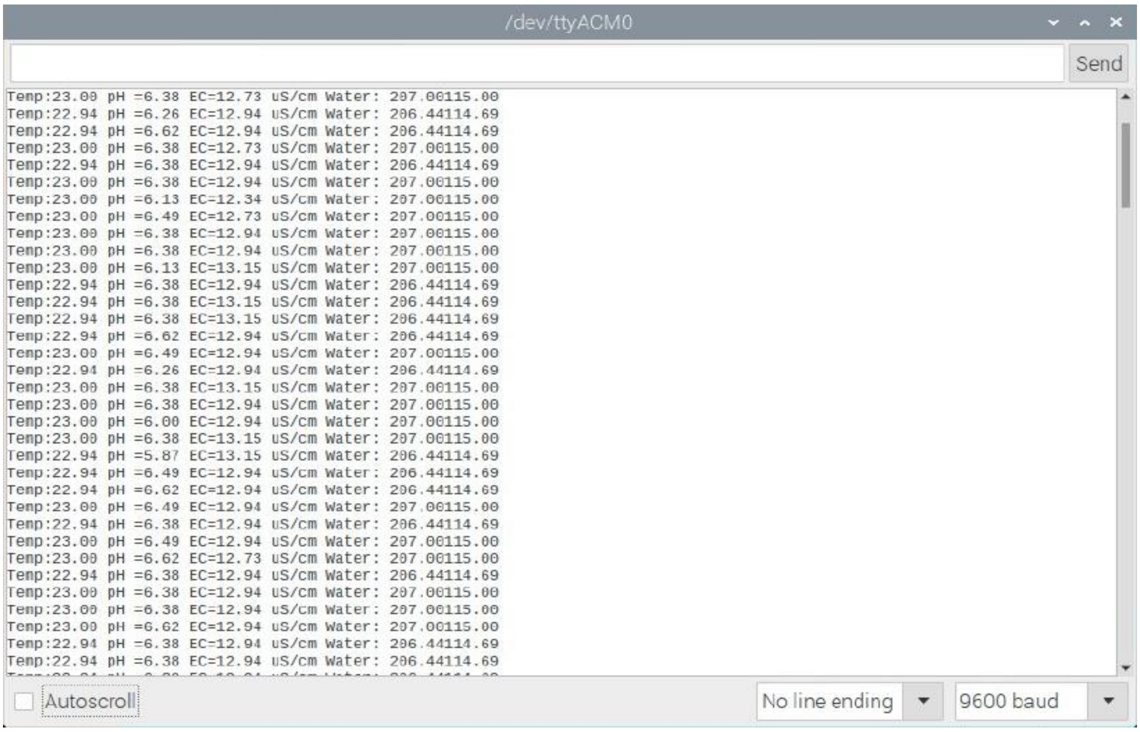


Figure 57: The implementation result of the data collection unit in Fish Tank.

Figure 58 describes the optimization and control unit simulator interface, which is deployed to the Raspbian OS using Mono cross-platform. Using user-interface users can easily monitor the system status, and update the user desired parameters. This interface is used for the visualizing results. As can be seen, the simulator has sensors and actuators modules which are numbered with 1 and 2, respectively. User can connect temperature, pH level, water and conductivity level sensors with ticking them and clicking the connect sensor button. Heater, cooler, water pump, pH controller and fish feeder actuators can also be connected with this section. User-set points assignment which is described with number 3, is used to insert minimum and maximum user-desired temperature, pH level, water level, and conductivity level parameters based on user requirement by clicking apply changes button user can easily update user-desired parameters. Based on updated user-desired parameters, the objective function computes the optimal environmental parameters to the fish tank. Prediction model section helps to activate the RNN-LSTM based prediction algorithm to predict the future environmental parameters. By clicking the optimization scheme button proposed system computes the most optimal environmental parameters to the fish tank. The FLC can be started, paused or cancelled using the fuzzy logic control module section. In the results section, the user can see the prediction, optimization, fuzzy logic control, and energy consumption results.

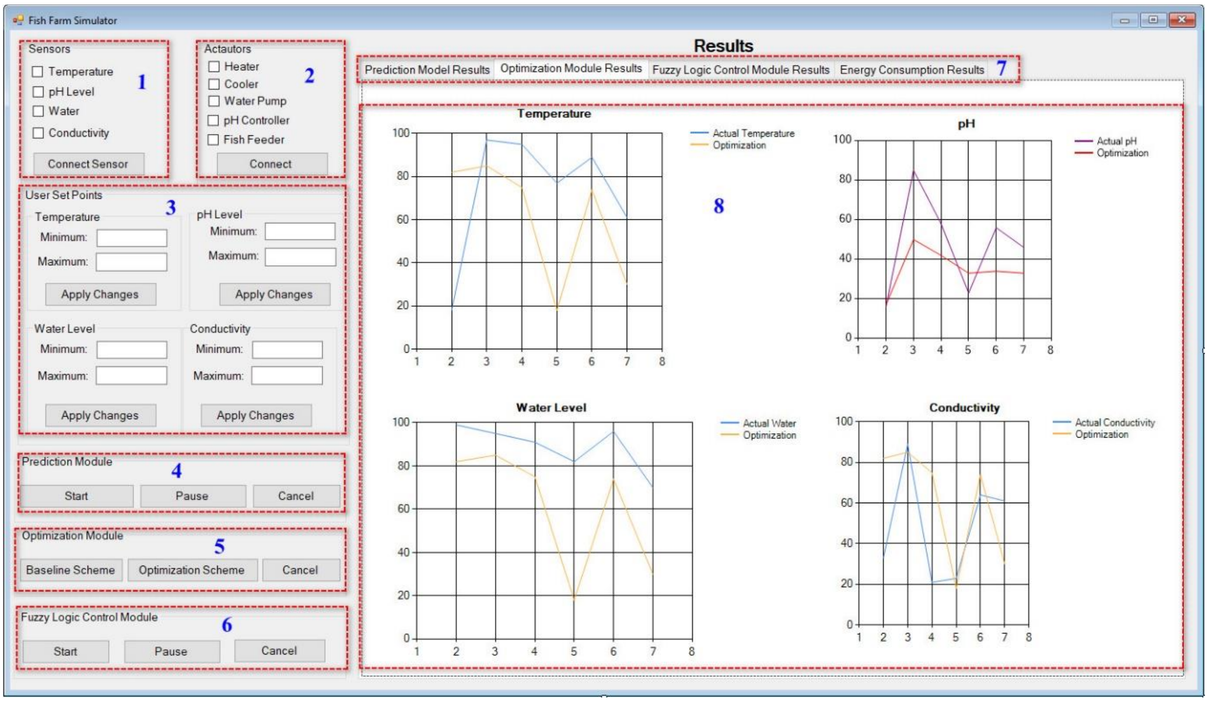


Figure 58: The implementation results of the optimization and control units.

Figure 59 describes the implementation result of the overall system in using Main.py code. The primary role of the Main python code is providing communication among all of the developed modules. As we developed several modules, then we can control all modules using the *python Main* command. As we run the *python Main* command using the Raspbian OS command prompt, then the system automatically describes the actual sensing data collection results, prediction module results, optimization module results and control module results in the black window. Table 3 illustrate the summary of the collected temperature and pH level data values with the user desired minimum and maximum points. We have included the actual temperature and pH level data from Kaggle.com [94]. Actual temperature values are around 25°C in most of the time because data is actual and collected from the already fixed fish tank environment. However, in this work we propose the novel objective function which can calculate the optimal temperature, pH level, conductivity and water level for the fish tank based on various input data.

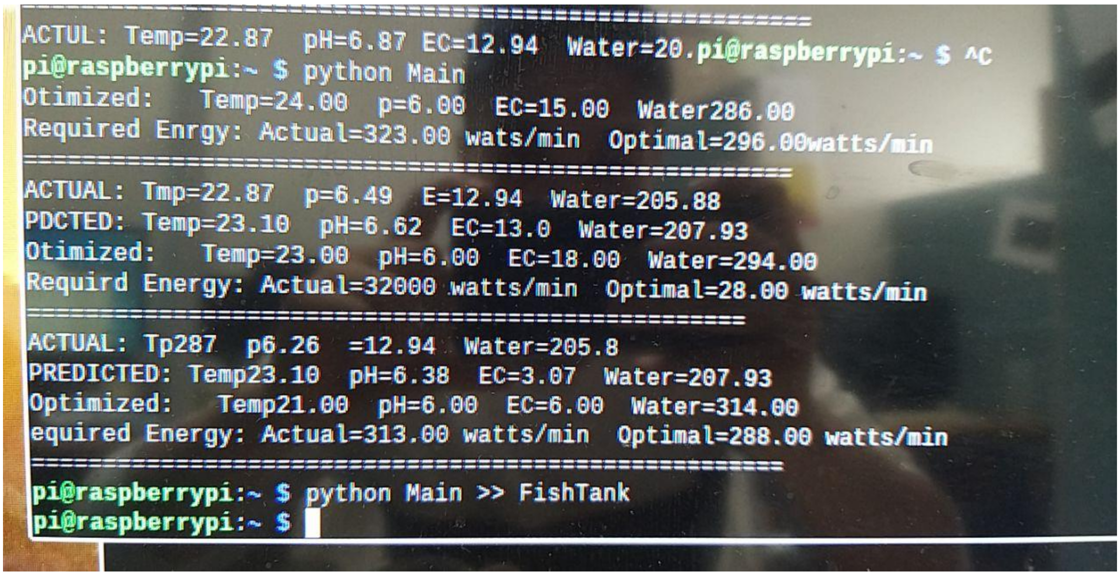


Figure 59: The implementation results of the main python module.

If the input data for the optimization module becomes nearly the same parameters, then the testing of the optimization module is difficult. Our target is finding the optimal parameter for the fish tank according to the various input parameters and controlling the heater and cooler actuators for increasing and decreasing the water temperature. In order to test the accuracy and performance of the proposed system were need to consider various input data for the optimization module, as described in Table 4.

4.5 Performance Results of Embedded Optimization and Control Scheme using Fish Tank Sensing Data

In this subsection of the paper, we describe the proposed embedded control scheme performance evaluation results in detail. As we mentioned above, two parameters are used as an input, namely, user-desired parameters and actual environmental values. Based on user-desired parameters, the proposed platoform calculates the optimization and control values to the actuators. Figure 60 presents the optimization of the temperature parameters in the fish tank based on actual sensing data. As can be seen, the actual temperature parameters are between 10-40°C in the fish tank. Using an optimization algorithm, the system calculates the optimal temperature values to the environment between user desired maximum and minimum values. User-desired minimum and maximum values are 20 and 25°C, respectively.

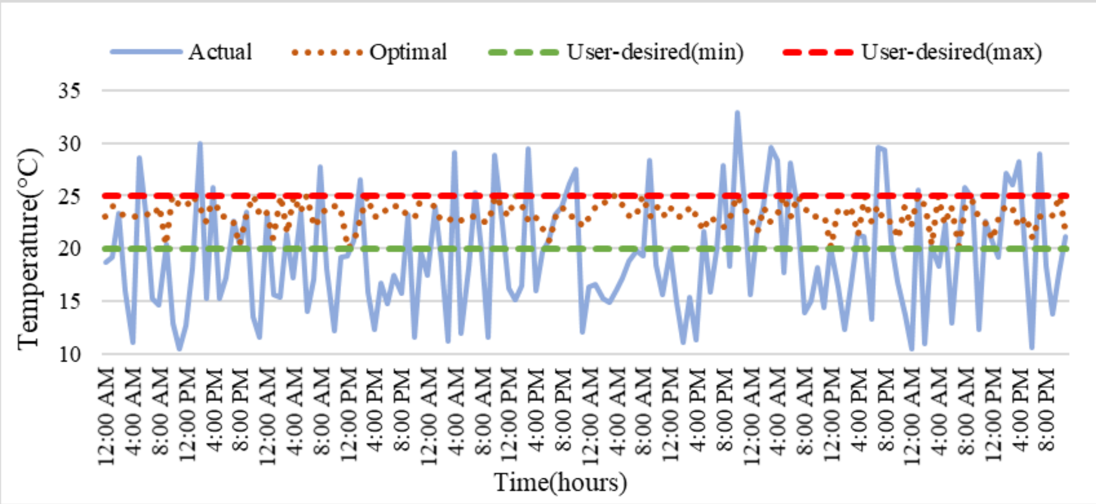


Figure 60: Temperature optimization results based on actual temperature data.

Figure 61 presents the actual pH level optimization result based on proposed novel objective function. It can be seen that the actual pH level parameters are between 0-14 acid in fish tank. With using an optimization algorithm, the system calculates the optimal pH level values to the environment between user desired maximum and minimum values. Optimization scheme is based on an objective function which calculates the optimal pH level values based on that formulation.

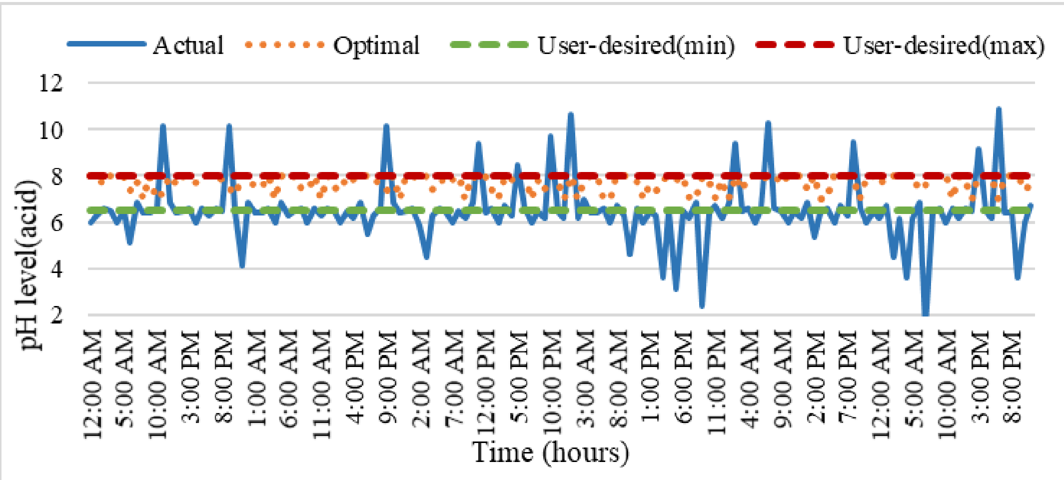


Figure 61: pH level optimization results based on the actual pH level.

Figure 62 presents the conductivity level optimization results of the proposed embedded optimal control framework. It can be seen that the actual conductivity level parameters are between 10-2000 in the fish tank. Using an optimization algorithm, the system calculates the optimal conductivity level values to the environment between user desired maximum and minimum values.

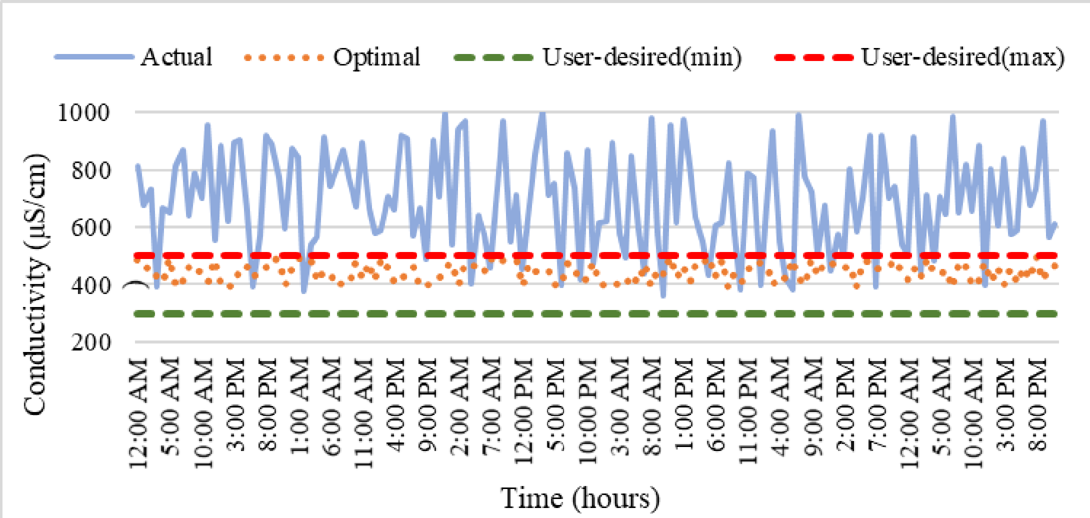


Figure 62: Conductivity level optimization results based on the actual conductivity.

Figure 63 describes the proposed embedded optimization and control scheme results for the water level optimization in the fish tank based on actual and user-desired parameters. It can be seen that the actual water level parameters are between 0-350 mm in fish tank. Using an optimization algorithm, the system calculates the optimal water level values to the environment between user desired maximum and minimum values. As can be seen, the proposed optimization module computed the optimal water level between the user desired parameters. By controlling the water level, we can decrease the wastage of the water level from the fish tanks.

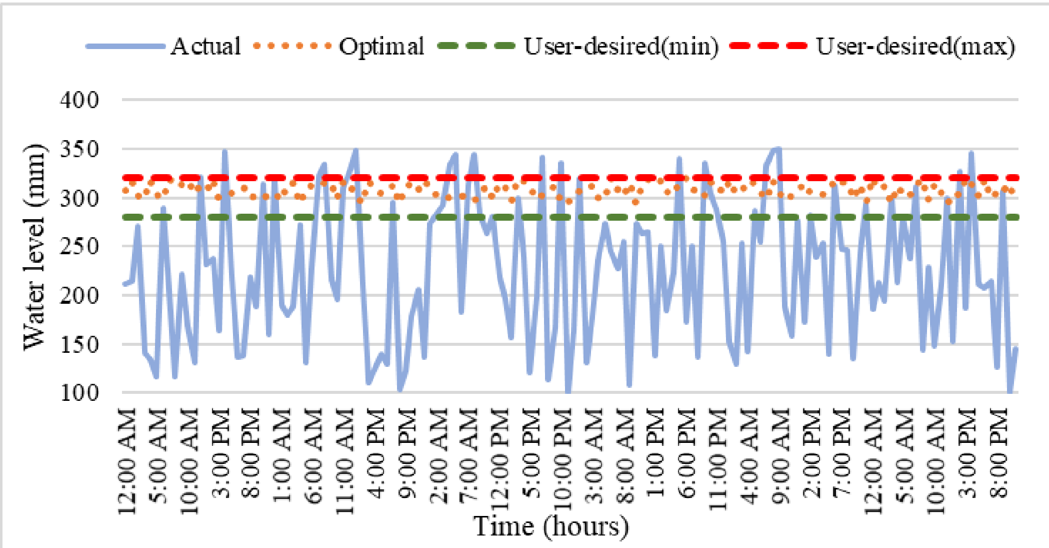


Figure 63: Water level optimization results based on the actual water level.

Based on optimized temperature, pH level, conductivity, and water level parameters and actual environmental parameters, fuzzy logic control module compute the working level and activation duration to the actuators. In this work, we consider a heater, cooler, water pump, pH controller, and fish feeder actuators. Figure 64 presents the actuator control results based on actual and optimized environmental parameters. The FLC module computes the required working level and duration.

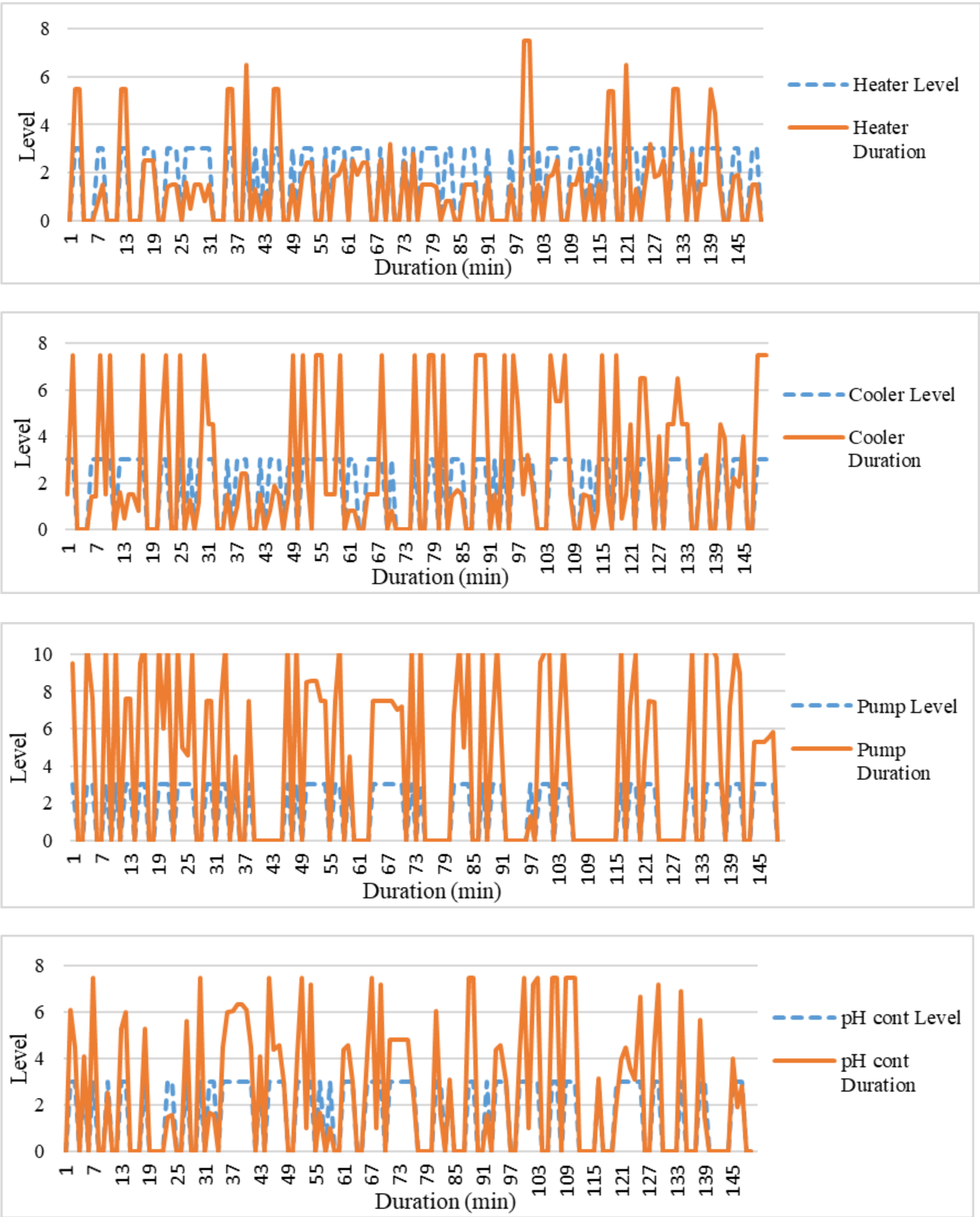


Figure 64: Actuator control results based on actual and optimal parameters.

4.6 Performance Results of Embedded Predictive Optimal Control Scheme using RNN-LSTM

In this subsection of the thesis, we describe the proposed embedded predictive optimal control scheme results based on prediction, optimization, and control using the fish indoor environmental parameters. For the implementation of the proposed RNN LSTM prediction module, we have conducted a number of experiments using the collected time series data. As we know, A Recurrent Neural Network (RNN) is a type of neural network well-suited to time series data. RNNs process a time series step-by-step, maintaining an internal state summarizing the information. Figure 65 describes the time series based on indoor environmental parameters data which is used for the training of the proposed prediction model.

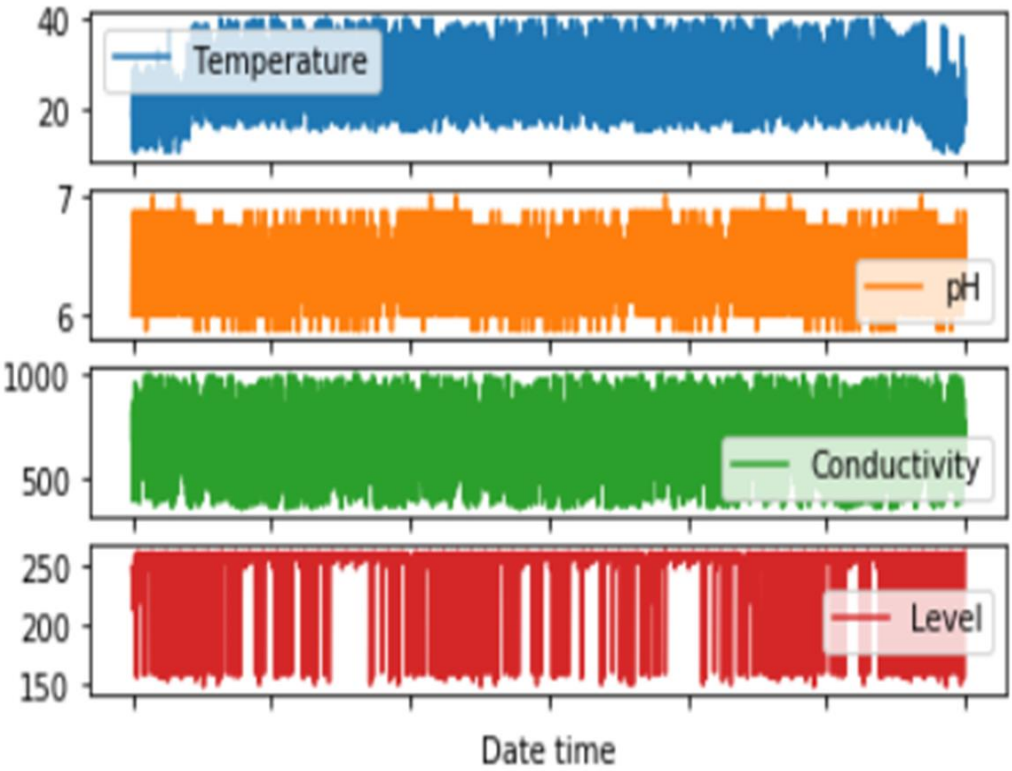
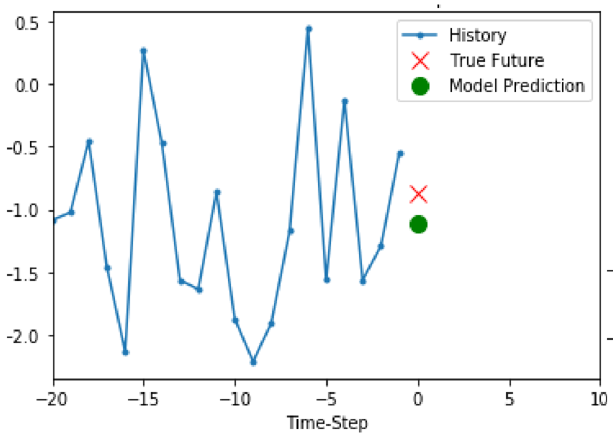
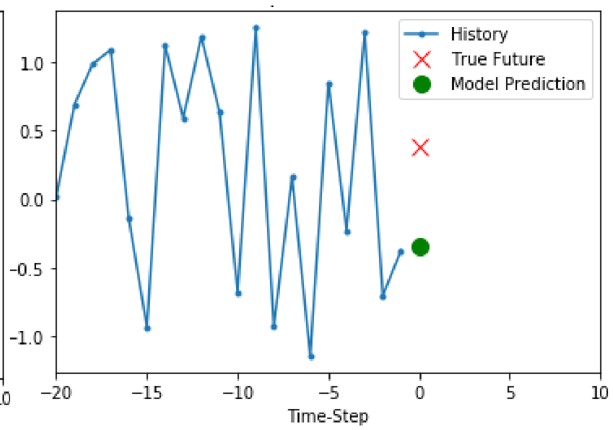


Figure 65: The experimental results of the uploaded indoor environmental data for the training.

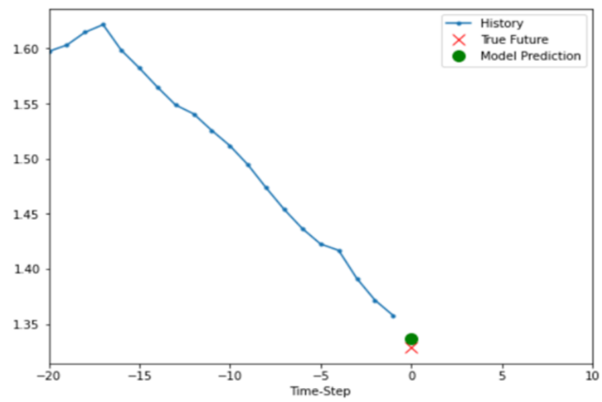
In the beginning, we have used the one-step forward prediction concept to analyze the accuracy of the historical data, actual future, and model prediction values. Figure 66 describes the one-step forward prediction module results for each fish tank parameter. In a single step setup, the model learns to predict a single point in the future based on historical data. One-step forward prediction model results show that fish tank water level and conductivity level prediction results' model prediction and true future results are nearly the same values, which means the prediction model is accurate. However, there are a few differences between model prediction and the true future in temperature value prediction. In terms of pH level prediction, there is a remarkable high difference between the true future and model prediction.



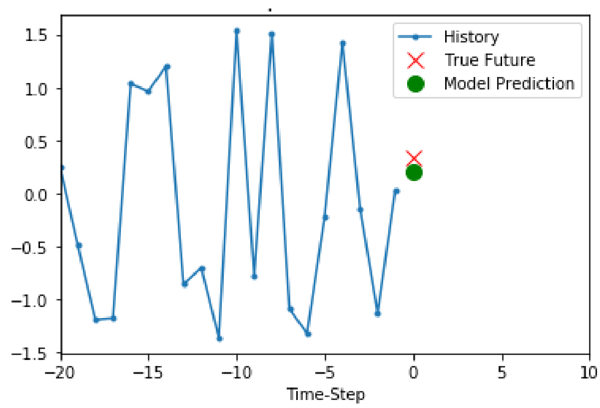
a) Temperature



b) Water level



c) Conductivity



d) pH level

Figure 66: The experimental results of the one step forward prediction model results: a) temperature, b) water level c) conductivity and d) pH level.

The prediction module results provide predicted temperature, predicted water level, predicted conductivity and predicted pH level results. Then these predicted values and user-desired setpoints are used as input parameters to the optimization module. Optimization module computes the most desirable temperature, water level, conductivity and pH level results in the fish growth with energy efficiency.

Figure 67 presents temperature level optimization based on predicted temperature parameters. As can be seen, user-desired minimum and maximum environmental temperature values are 20 and 25 °C, respectively. Predicted environmental parameters help to analyze the future environmental temperature and utilize this temperature data for the optimization module as an input parameter. Then based on predicted temperature parameters, the optimization module computes the optimal temperature level for the healthy fish growth.

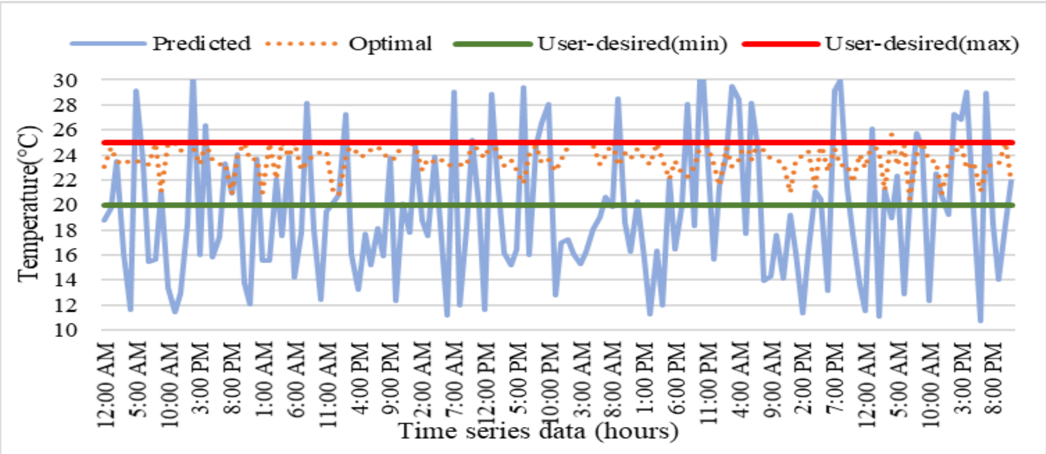


Figure 67: Temperature optimization results based on predicted temperature.

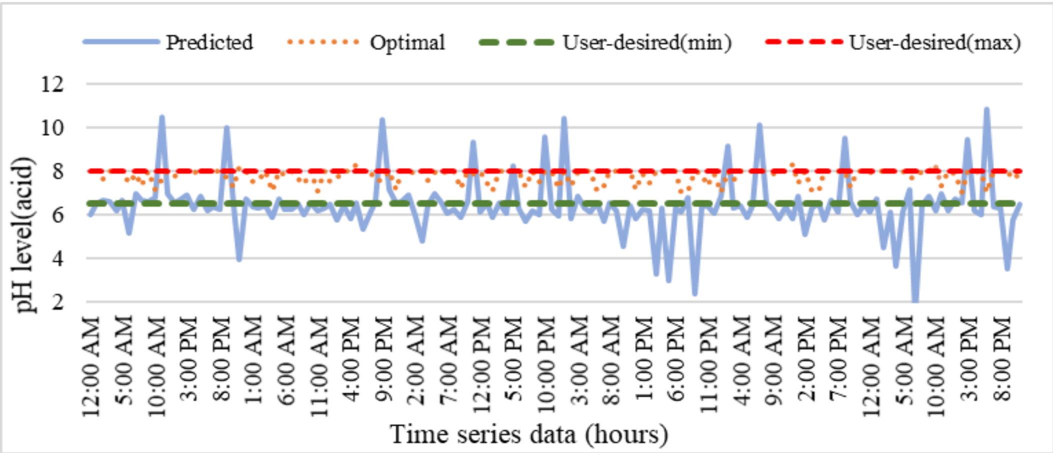


Figure 68: pH level optimization results based on predicted pH level.

Figure 68 presents the pH level optimization results of the proposed embedded predictive optimal control framework for the fish tank using indoor environmental parameters and user-desired settings. Predicted pH level parameters of the fish tank are between 2-11 acid in time t, at each predicted value are applied to the optimization module to calculate the most desirable environmental parameters to the fish tank pH level, and optimal environmental parameters are between the user-desired parameters.

Figure 69 describes the conductivity level optimization results of the proposed embedded predictive optimal control framework for the fish tank using indoor environmental parameters and user-desired settings. Predicted conductivity level parameters of the fish tank are between 400-1000 in time t. However, the user-desired optimal environmental values are between 300 and 500. Each predicted value are applied to the optimization module to calculate the most desirable environmental parameters to the fish tank conductivity, and optimal environmental parameters are between the user-desired parameters.

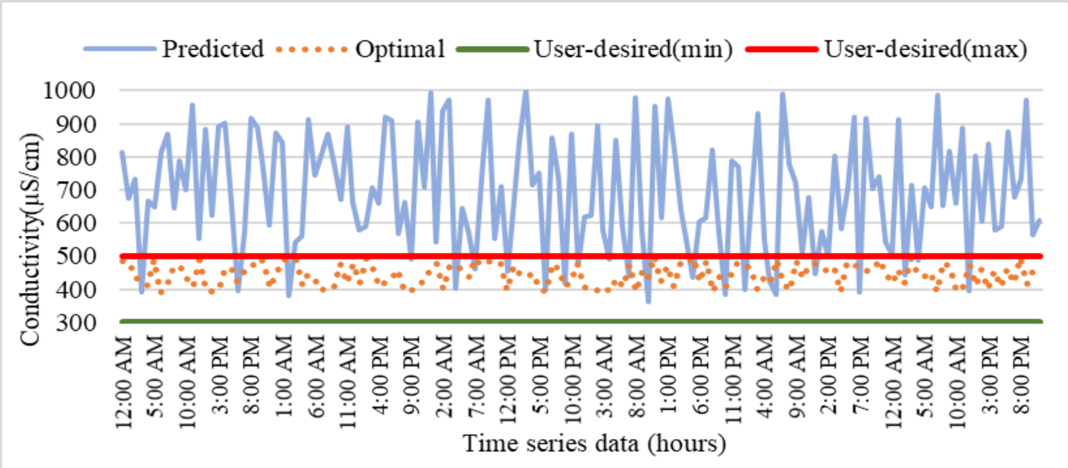


Figure 69: Conductivity level optimization results based on predicted conductivity level.

Figure 70 presents the water level optimization results of the proposed embedded predictive optimal control framework for the fish tank using indoor environmental parameters and user-desired settings. As can be seen the optimal water level is between user-desired water level.

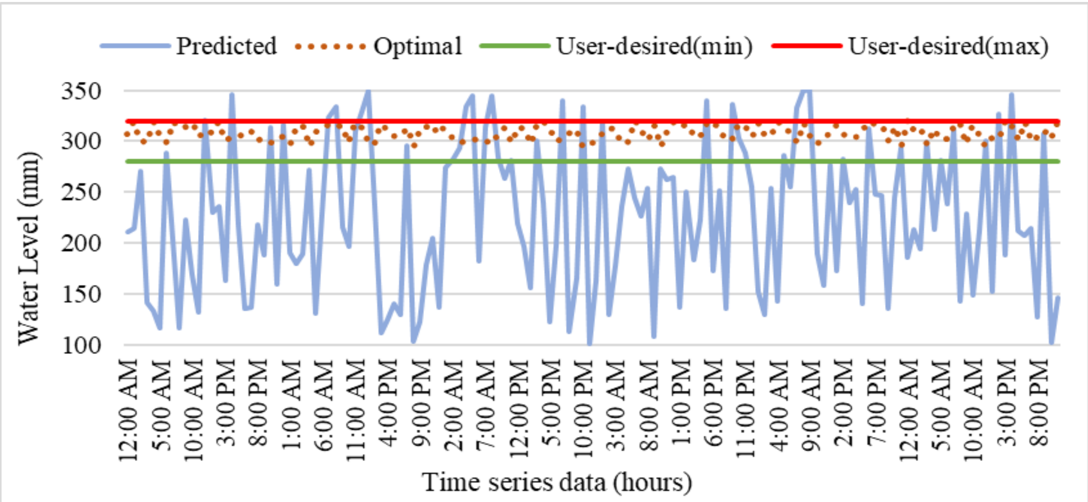
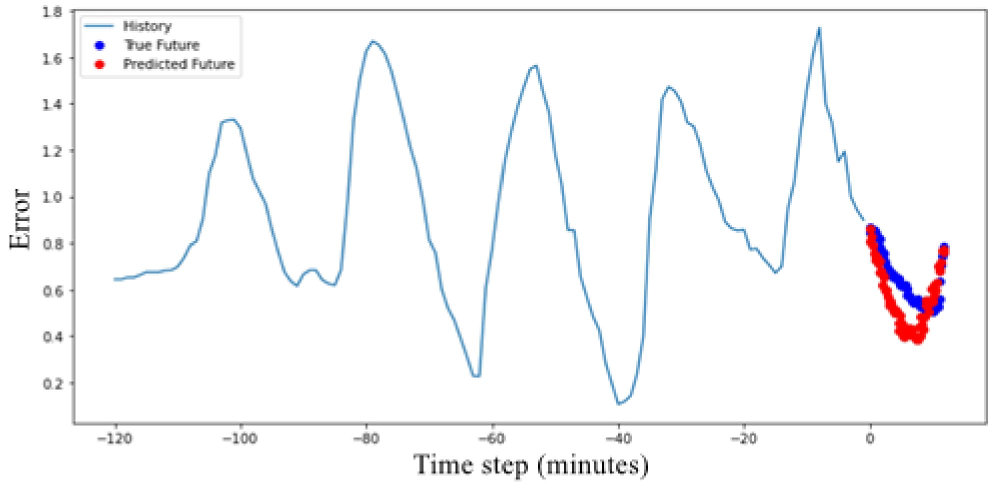


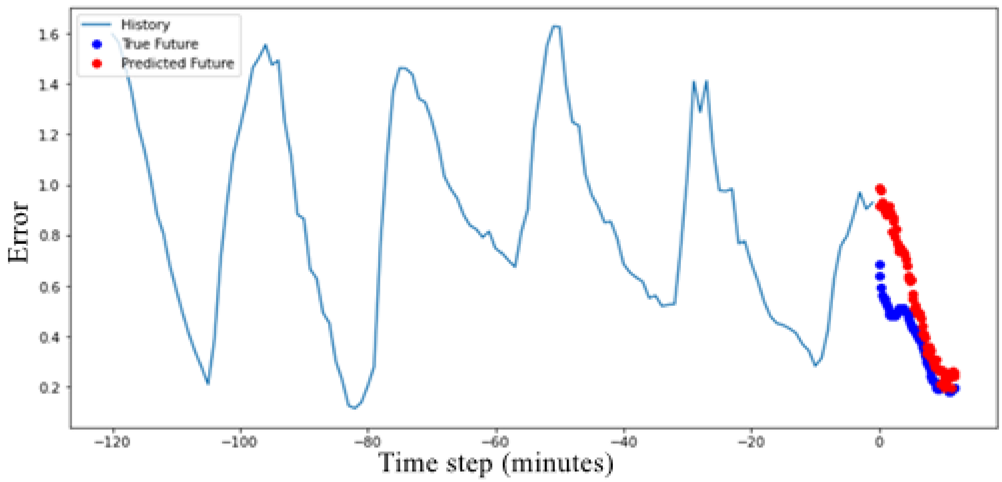
Figure 70: Water level optimization results based on the predicted water level.

4.7 Performance Results of Predictive Optimal Control Scheme using Outdoor and Fish Tank sensing data.

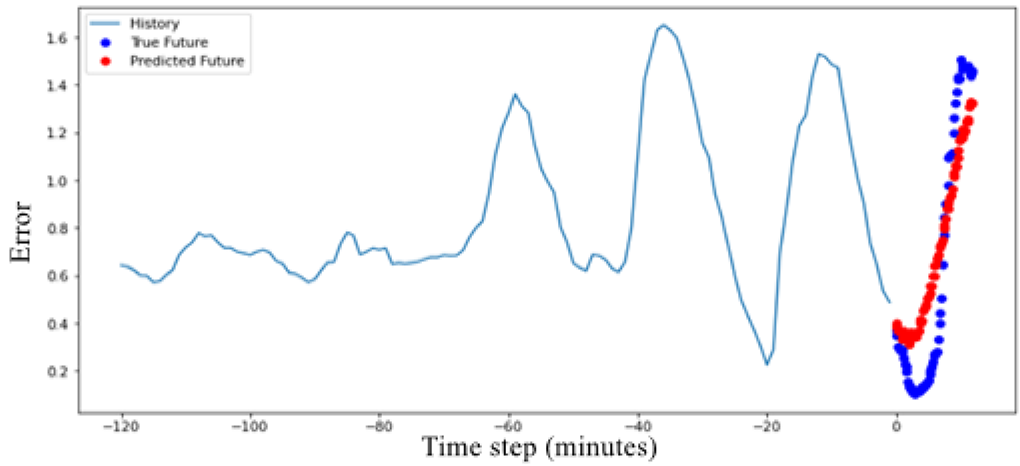
In a multi-step prediction model, based on indoor and outdoor environmental parameters, the RNN-LSTM model learns to predict a range of future values. Thus, unlike a single-step model, where only a single future point is predicted, a multi-step model predicts a sequence of the future. Figure 71 describes the multi-step prediction model results for the fish tank indoor parameters. The multi-step prediction model can predict more accurately and long term environmental parameters for the fish tank. As can be seen from the figure predicted future and actual future values are becoming nearly the same direction.



a) Temperature



b) pH level



c) Water level

Figure 71:The experimental results of the multi-step prediction model results: a) temperature, b) pH level, and c) water level.

Analysis of the one-step forward and multi-step prediction model results for temperature, pH level, conductivity, and water level results are described in Figure 66 and Figure ***71***. However, the difference is not clearly visible in the graphical results; therefore, we conduct a statistical analysis of the prediction results using three different measures. Various statistical indicators are used to summarize these results into a single statistical value for quantitative comparative analysis. Our model produces output for each input or set of inputs so that we can compare this estimate to the actual predicted value. The difference between the actual value and the delay in evaluating the model. We can calculate the delay for each point in the data set, and each of these delays is useful for estimation. These residues play an essential role in evaluating the effectiveness of the proposed model:

Mean Absolute Error(MAE) is the easiest measure of regression error. We just need to take the absolute values of each and calculate the remainder for each data point so that negative and positive residues do not destroy each other. Then all residues are averaged. Indeed, MAE describes a typical degree of residuals.

$$MAE = \frac{1}{n}\sum_{k=0}^{n}\left|P_i - \widehat{P_\iota}\right|$$

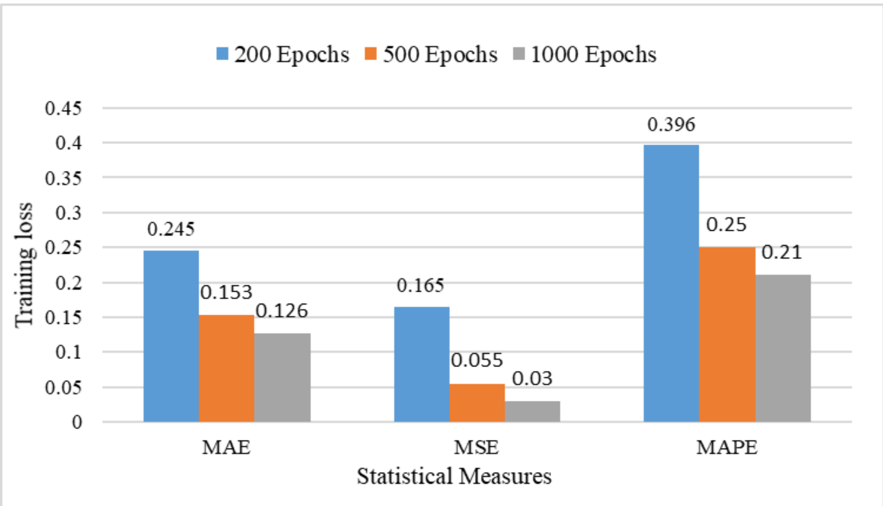
Mean Squared Error (MSE): MSE is considered one of the most commonly used statistics to evaluate the effectiveness of the prediction algorithm. Squared the magnitude of the error not only eliminates the problem of negative and positive errors, but also provides a larger penalty for higher prediction errors compared to lower errors. MSE is calculated using the following formula:

$$MSE = \frac{\sum_{i=1}^{n}\left(P_i - \widehat{P_i}\right)^2}{n}$$

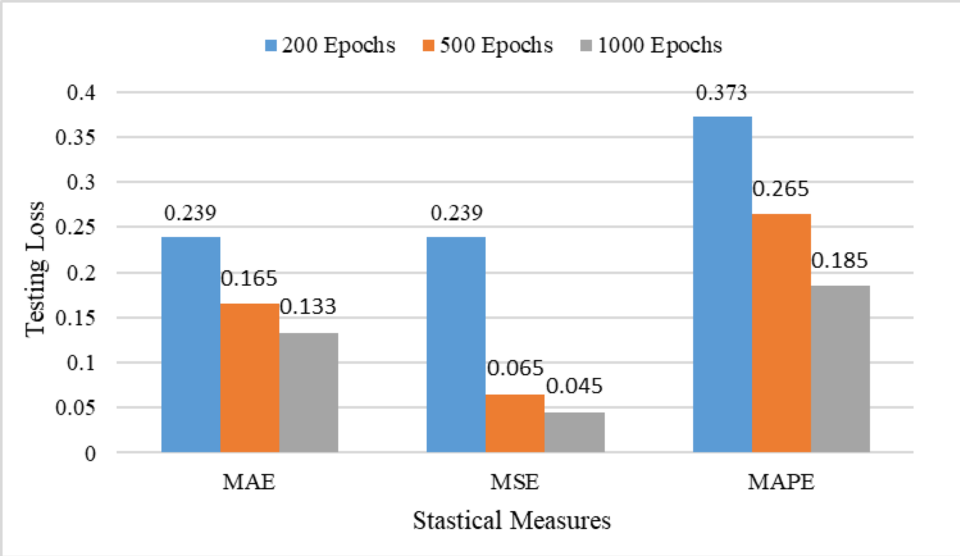
Mean Absolute Percentage Error (MAPE): MAPE is also one of the widely utilized statistics for the evaluation of the prediction algorithms' performance. In this statistic measurement, the average of absolute errors is divided by the actual parameters, and then they multiplied by 100 to turn the results to the percentage parameters.

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{P_i - \widehat{P_i}}{P_i}\right|}{n} \times 100$$

Figure 72 describes the implementation results of the proposed prediction model training and testing loss results based on the three above mentioned error metrics. Training a model simply means learning (determining) good values for all the weights and the bias from llabelled examples. In supervised learning, a machine learning algorithm builds a model by examining many examples and attempting to find a model that minimizes loss; this process is called empirical risk minimization.



a) Training Loss



b) Testing Loss

Figure 72: Training and testing loss of the RNN-LSTM based prediction model a) training loss b) testing loss

Loss is the penalty for a bad prediction. That is, the loss is a number indicating how bad the model's prediction was on a single example. If the model's prediction is perfect, the loss is zero; otherwise, the loss is greater. The goal of training a model is to find a set of weights and biases that have low loss, on average, across all examples. Figure 73 describes that MSE has high accuracy compared with other regression error metrics. For the implementation and experiment, the RNN LSTM models are configured to be 200, 500, 1000 times training epochs to test the prediction performances using Mean Square Error. The number of epochs is a hyperparameter that defines the number times that the learning algorithm will work through the entire training dataset. The number of epochs is traditionally large, often hundreds or thousands, allowing the learning algorithm to run until the error from the model has been sufficiently minimized. It can be clearly seen that in 1000 number of epochs has been minimized error sufficiently. Training an LSTM based Tensorflow model requires various operational duration. Figure f presents the activation duration of the prediction model training based on various error metrics and the number of epochs.

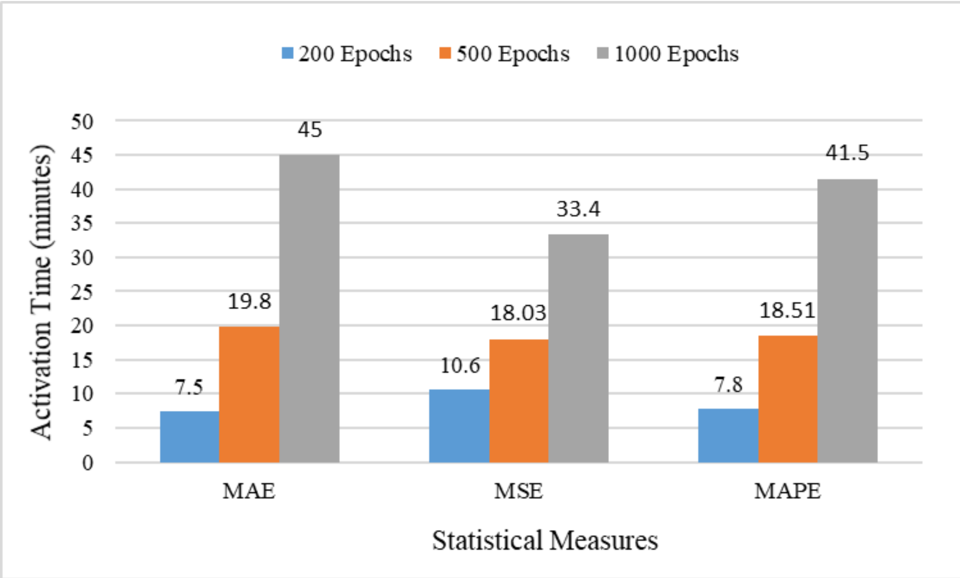


Figure 73: Activation time of the training the prediction model.

Based on 200, 500, 1000 times training epochs configuration, we have calculated overall training time for each error metric. As can be seen, less training duration is required based on MAE and MAPE for 200 epochs, 7.5, and 7.8 minutes, respectively. However, MSE spends 18.03 and 33.4 minutes in terms of 500 and 1000 epochs.

Table 15 presents the statistical summary of the prediction results for RNN-LSTM based on various statistical measures and the number of epochs. Comparative analysis shows that MSE with 1000 epochs have high accuracy results outperform the two other statistical measures.

Table 15: The accuracy of the prediction model based on various performance evaluations.

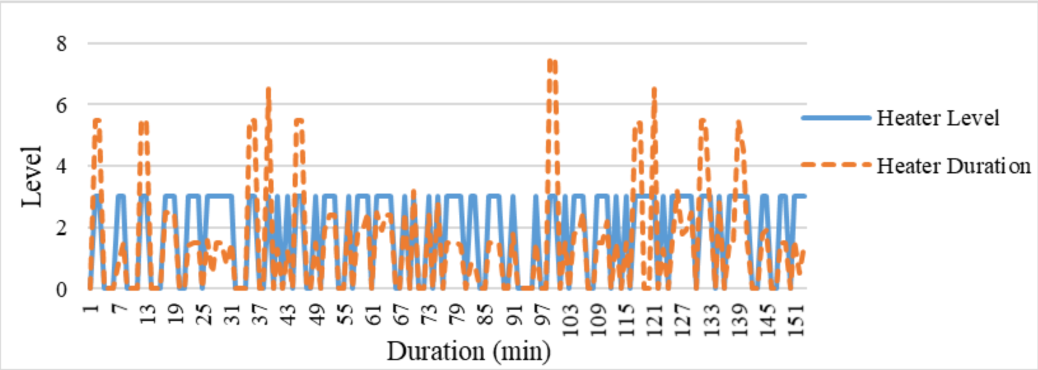
Indoor Parameter	Number of epochs	Statistical Measure		
		MAE	MSE	MAPE
Temperature	200 epochs	0.24	0.23	0.37
	500 epochs	0.16	0.06	0.26
	1000 epochs	**0.13**	**0.05**	**0.18**
pH level	200 epochs	0.25	0.17	0.39
	500 epochs	0.15	0.05	0.25
	1000 epochs	**0.13**	**0.03**	**0.21**
Conductivity	200 epochs	0.26	0.22	0.31
	500 epochs	0.18	0.09	0.19
	1000 epochs	**0.14**	**0.04**	**0.17**
Water Level	200 epochs	0.22	0.19	0.26
	500 epochs	0.18	0.07	0.19
	1000 epochs	**0.1**	**0.03**	**0.14**

After successful training and testing the RNN-LSTM based prediction model, we converted this model to the Tensorflow Lite format to deploy this prediction model to the embedded IoT device in order to predict new environmental parameters for the fish tank based on actual sensing values in real-time. The real-time predicted parameters are forwarded as an input parameter to the Optimization module, which is used to compute the optimal environmental parameters to the fish tank based on user desired settings and the system constraints.

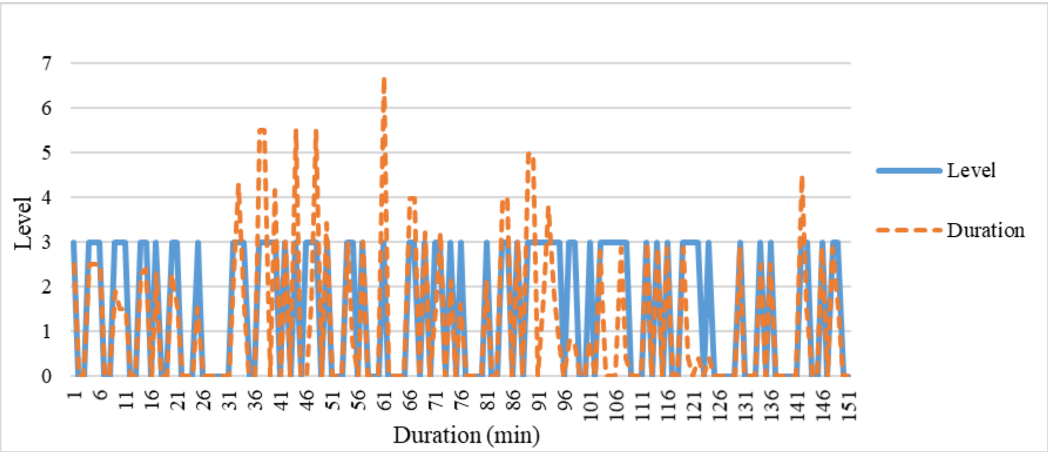
4.8 Performance Results of Embedded Predictive Optimal Control Scheme based on Actuators' Control Parameters

As already explained above, fuzzy logic control is used to analyze predicted and optimized data to determine actuators' operating level and operating time. By providing an optimal environment for the fish tank, an optimal production environment for fish can be designed. Fuzzification, fuzzy inference engine and defuzzification are important components of fuzzy logic system design. Fuzzification is the process by which actual pure values are transformed into linguistic values. The fuzzy inference mechanism is the core unit of the fuzzy logic system for making decisions based on *if-then* rules and is a connector to provide important decision rules. Defuzzification is the process of converting language variables to numeric values. Fuzzy logic describes human preferences and experiences through fuzzy rules and membership features. Each language variable is assigned a confidence value, so each has a unique confidence value. The definition of the language variable is used to describe the membership function diagram. Input values are labelled with very low, low, medium, high, very high, and optimized. We can use fuzzy inference rules to evaluate input values based on IF-THEN conditional statements. This rule tells us the level and duration of the IoT actuators. To determine the operating level and operating time, the reverse purge removal step defines a rule with the exact operating level and minutes of the drive. For example, if the time required by the system is short, the purge logic determines the drive operating time from 3 to 6 minutes. The following subsections detail the purging, inference, and inverse purging elimination processes according to the proposed approach.

A fuzzy knowledge base is a group of knowledge and inference rules for solving specific problems. It is developed to imitate human decision for finding a solution to problems and providing information. Fuzzy inference is the process where the controller analyzes and evaluates input values based on conditional statements. Fuzzy rule evaluation can be performed using Fuzzy Associative Matrix (FAM). FAM table is essential for describing the rule editor into matrix form showing all possible outputs according to all possible inputs. Fuzzy logic control module computes level and activation duration to the actuators based on predicted and optimized sensing values. Figure 74 a and b describe the heater and cooler actuators' working level and activation duration results, respectively. It can be seen that heater and cooler actuators are activated dependently on each other.



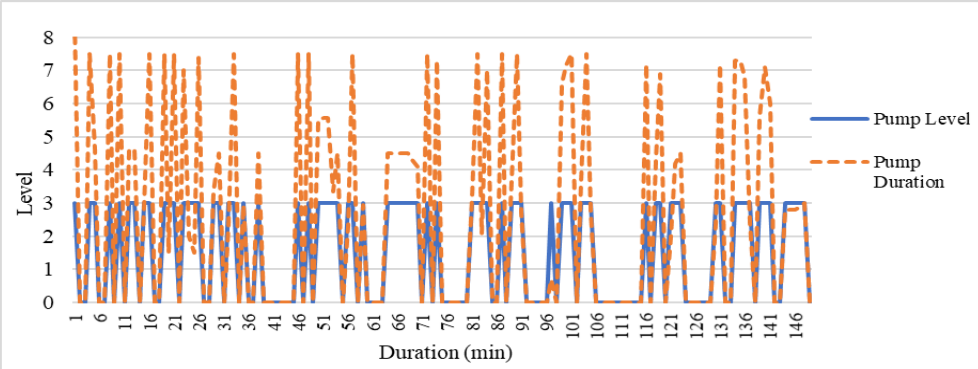
a) Heater



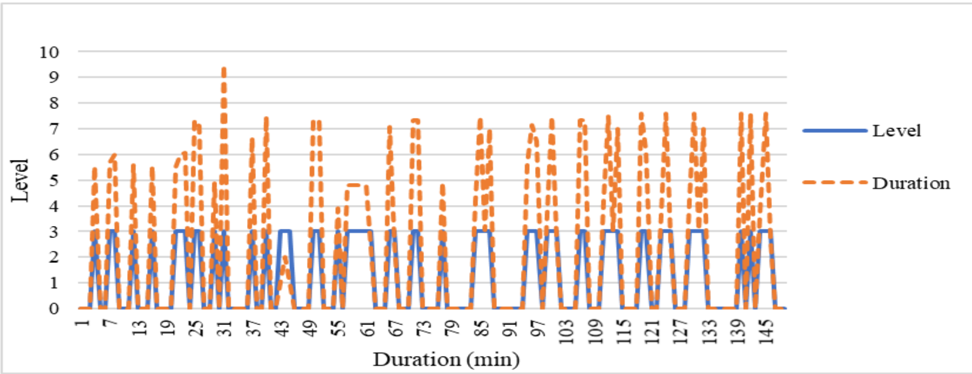
b) Cooler

Figure 74: Fuzzy logic control module results: a) heater b)cooler.

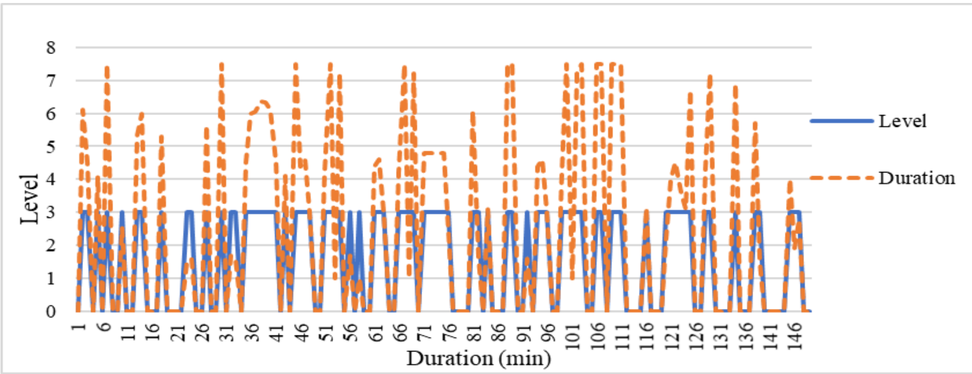
This means if the predicted temperature is higher than the optimal temperature, then the cooler actuator is activated automatically. If the predicted temperature is lower than optimal temperature, then the heater is activated automatically and increases the temperature level of the fish tank. Afterwards, heater and cooler are operated after certain intervals when indoor temperature drops below the desired minimum level, and temperature increases above the maximum desired limit. Figure 75 describes the water pump, fish feeder, and pH controller working level and operational duration results. If the predicted temperature is higher than the optimal temperature, then the cooler actuator is activated automatically.



a) Water Pump



b) Fish feeder



c) pH Controller

Figure 75: Fuzzy logic control module results a) pump b) fish feeder c) pH controller.

If the predicted water level is lower than the optimal water level, then we activate the water pump. Then the water pump increases the water level of the fish tank. As the water level reaches the optimal level, then the water pump is deactivated water level automatically and activation duration become 0.

4.9 Performance Results of Embedded Predictive Optimal Control Scheme based on Power Policy

In this subsection, we describe the power policy results of the proposed embedded predictive optimal control scheme. For the calculation of the power policy we consider 1 kWh electricity cost 129 won on average for a typical spring day in Jeju, South Korea. As we mentioned above the optimal power policy can be achieved with controlling the actuators with an optimal way. Actuators can be activated with minimum, medium, and maximum working level, and they require various activation duration based on these working levels. Various working level and operational duration consumes different energy consumption and power policy. If actuators are activated with a minimum working level, then they require long time activation. If actuators are run with a maximum working level, then they require a short time activation period. Figure 76 presents the power policy results of the proposed embedded predictive control scheme results based on actuators working levels. It can be seen in order to achieve optimal power policy fish feeder and heater are needed to activate with minimum working level. Fish feeder requires 20446.5 won, 31401 won and 30948 won, with activating the actuator minimum, medium, and maximum levels, respectively. Maximum level activation requires the least pricy policy in terms of pH controller, water pump, and cooler actuators; these actuators spend 14476, 41229.6, and 26545.4 won power policy, respectively.

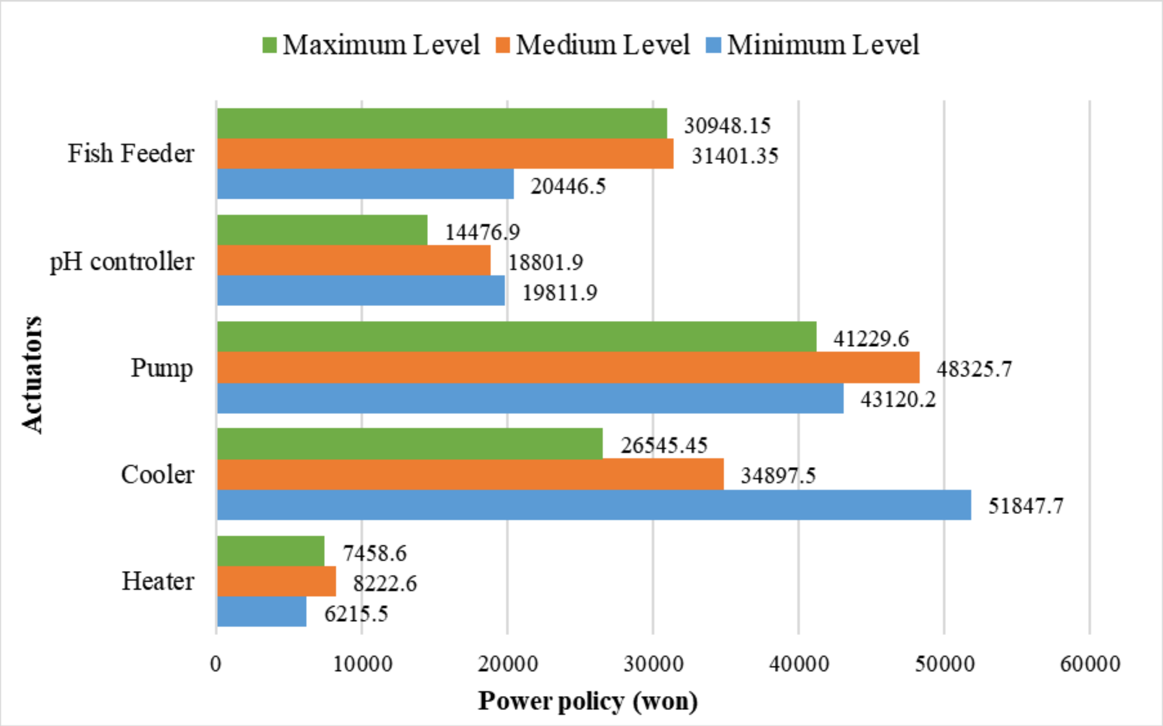


Figure 76: Power Policy results of the proposed embedded predictive control.

5. Performance and Comparison Analysis

In this chapter, we present a detailed discussion of the comparison and performance analysis results. For a clear explanation, we describe our performance analysis in four phases. Firstly, we will discuss the optimization module results along with other necessary system parameters and settings. The second phase presents the actuators' control module results. In the third phase, we present a comparative analysis of energy consumption results. Lastly, optimization of power policy results is described based on optimization and without optimization schemes in order to evaluate the advantages of the proposed system.

5.1 Comparison and Performance Analysis of Optimization Scheme

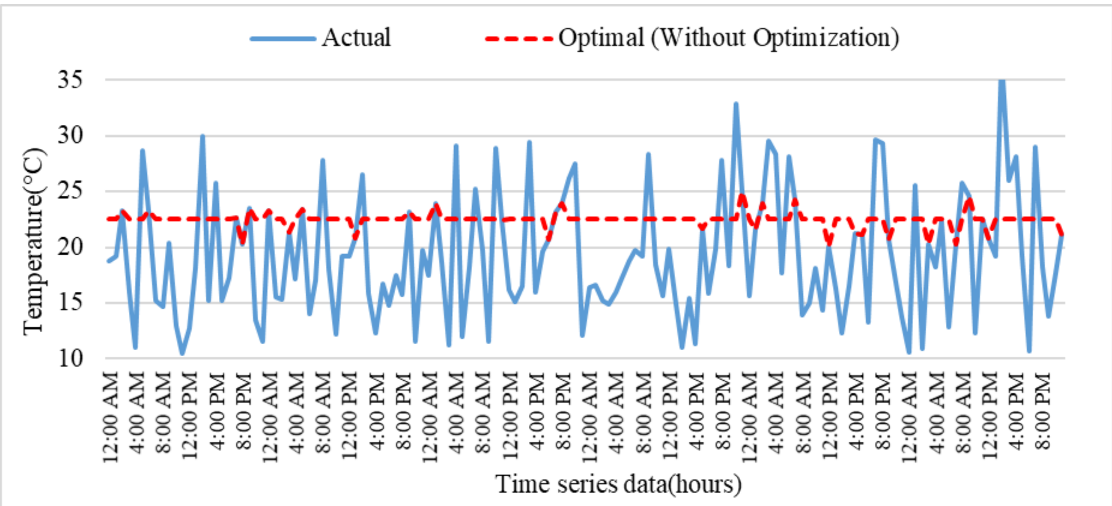
This section presents the analysis of the optimization module results. For analysis of the effectiveness of the proposed optimization module, we have conducted numerous experiments and based on actual sensing values and predicted values. In addition, we have tested the proposed system effectiveness the optimization module by comparing the with and without optimization module results. The optimization scheme is based on a mathematical formula, which is described in detail in Chapter 3.2; this objective function can calculate the optimal temperature, water level, conductivity and water level parameters with efficient energy consumption to the fish tank based on user-desired parameters and the system constraints. Without optimization, module does not have any optimization formulations, and it is based on the selection of the midpoint of the user-specified range for each parameter. If the predicted sensing values are outside of the user desired ranges, then the system automatically considers the optimal values as a midpoint of the user-desired minimum and maximum values. Table 4 describes the fish farm environmental values, available and optimal ranges. As we mentioned already, this work considers four environmental parameters of the fish tank environment, namely, temperature, pH level, conductivity and water level. The available ranges describe overall cases for each parameter in general, whereas, an optimal range provides the most acceptable values to the fish farm. Fish farm related researches describe that the available value ranges for the first three parameters are 10-40°C, 0-14 acid, and 10-2000 µS/cm, respectively, while optimal ranges are 20-25 °C, 6.5-8.0 acid, and 300-500 µS/cm.

Table 16 presents the objective function weights and alpha parameters which are performed for these experiments. In the simulation process, we mention the time interval of and fish tank sensor data collection in every 15 minutes; then, the objective function is activated in the required period. Actuators operational level is divided into three levels, namely, minimum, medium, and maximum.

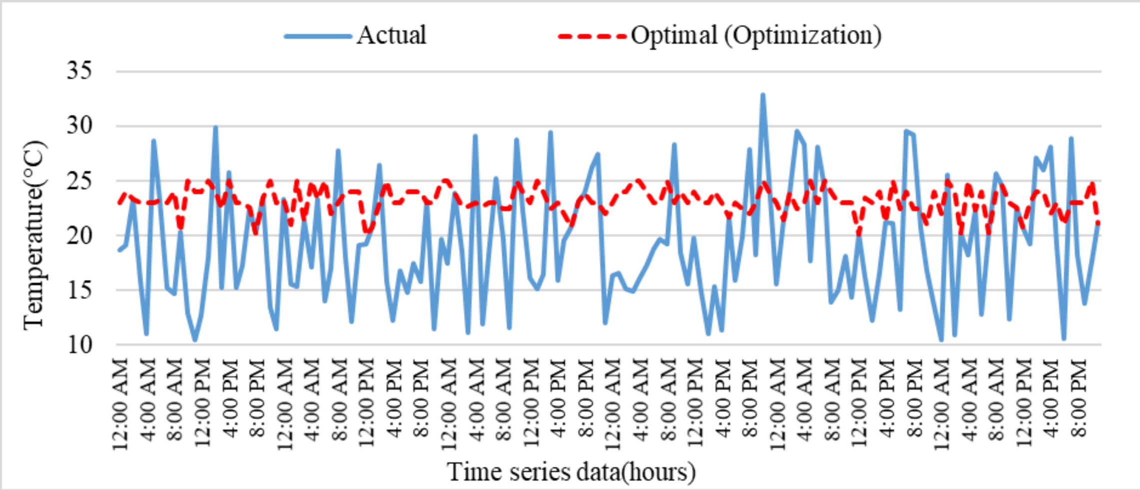
Table 16: Parameter settings for the optimization algorithm.

Parameter	Value Ranges
α_{EC}	0.5
α_{OE}	0.5
T^{min}	20
T^{max}	25
pH^{min}	6.5
pH^{max}	8.0
C^{min}	300
C^{max}	500
W^{min}	280
W^{max}	320

Figure 77 describes the temperature optimization module results based on optimization and without optimization schemes using actual sensing values. It can be seen that the actual temperature parameters are between 10-40 °C in the fish tank. Using an optimization algorithm, the system calculates the optimal temperature values to the environment between user desired maximum and minimum values. Baseline scheme based optimization calculates the midpoint of the user maximum and minimum values.



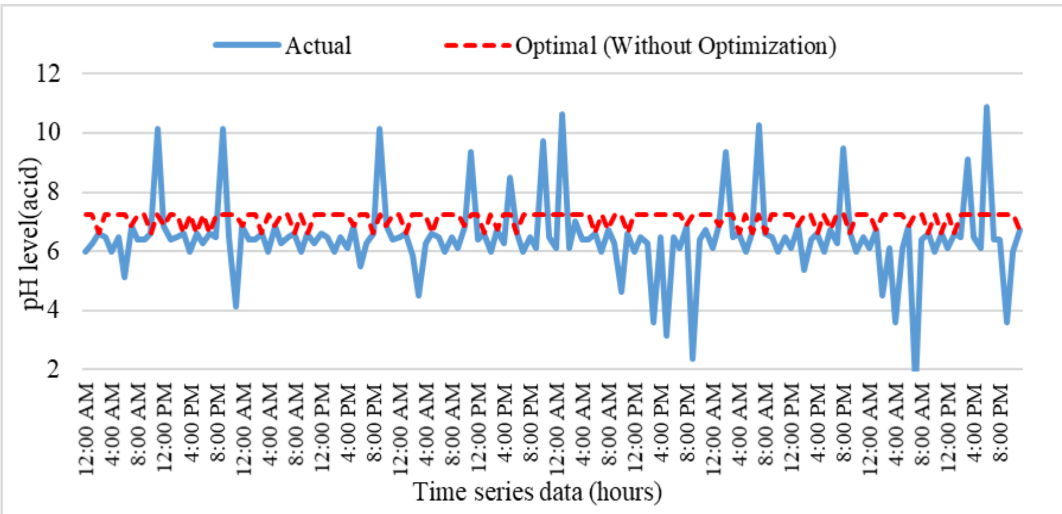
a)



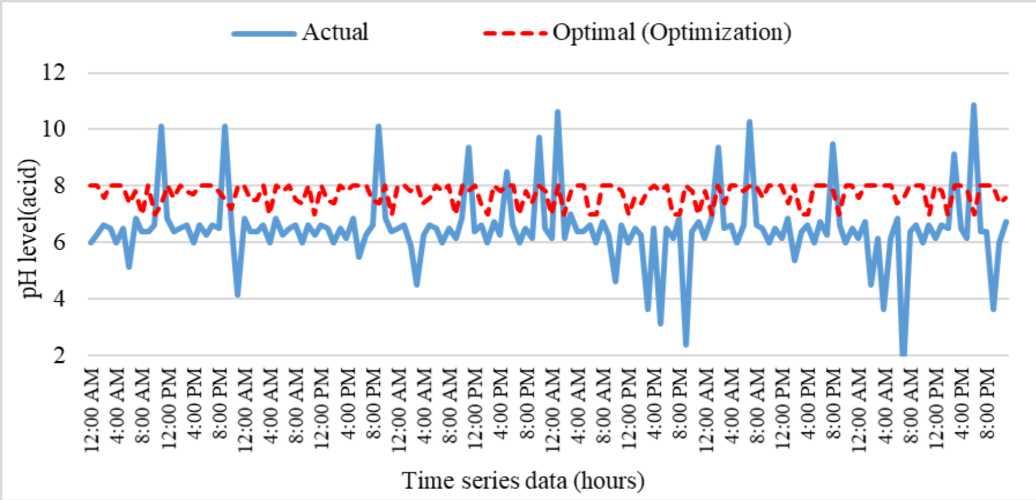
b)

Figure 77: Analysis of temperature level optimization module results without predicted values a) without optimization b) with optimization.

Figure 78 presents the pH level optimization module results based on optimization and baseline scheme. It can be seen that the actual pH level parameters are between 0-14 acid in fish tank. With using an optimization algorithm, the system calculates the optimal pH level values to the environment between user desired maximum and minimum values. Baseline scheme based optimization calculates the midpoint of the user maximum and minimum values. If the actual pH level is outside from 6.5-8 values then the system automatically takes (6.5+8)/2 = 7.25. Optimization scheme is based on an objective function which calculates the optimal pH level values based on that formulation.



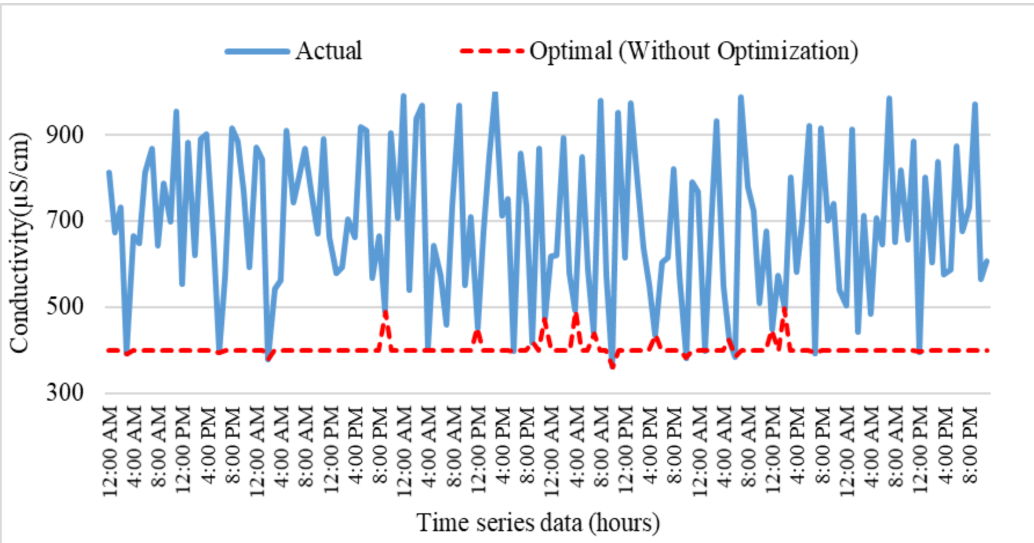
a)



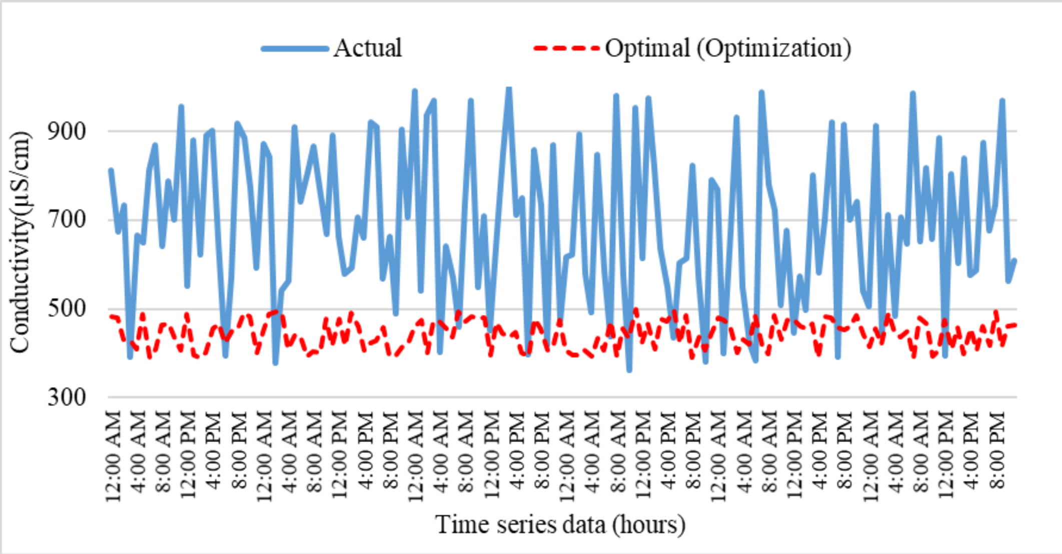
b)

Figure 78: Analysis of pH level optimization module results without predicted values a) without optimization b) with optimization.

Figure 79 illustrates the conductivity level optimization module results based on optimization and baseline scheme. It can be seen that the actual conductivity level parameters are between 10-2000 in the fish tank. Using an optimization algorithm, the system calculates the optimal conductivity level values to the environment between user desired maximum and minimum values. Baseline scheme based optimization calculates the midpoint of the user maximum and minimum values. If the actual conductivity level is outside from 300-500 values, then the system automatically takes (300+500)/2 = 400.



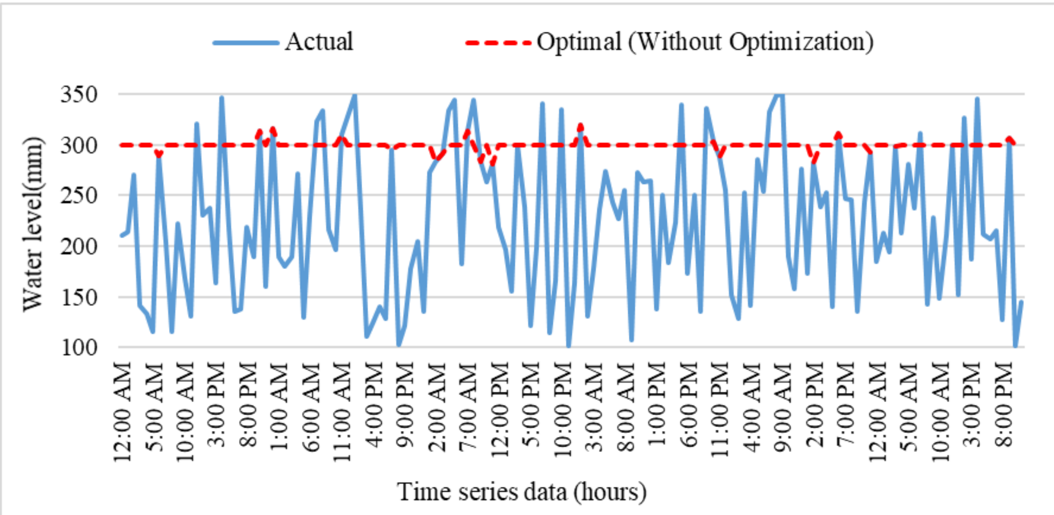
a)



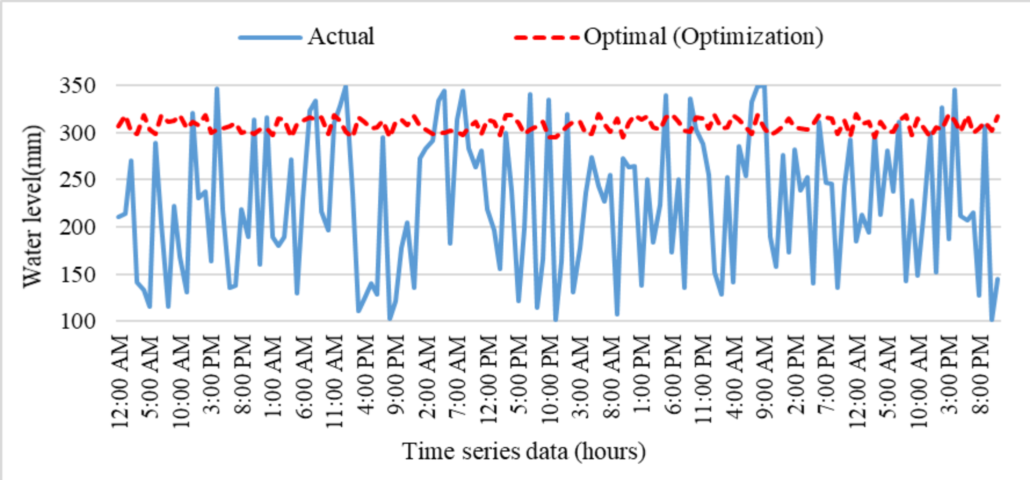
b)

Figure 79: Analysis of conductivity optimization module results without predicted values a) without optimization b) with optimization.

Figure 80 shows the water level optimization module results based on optimization and baseline scheme. It can be seen that the actual water level parameters are between 0-350 mm in fish tank. Using an optimization algorithm, the system calculates the optimal water level values to the environment between user desired maximum and minimum values. Baseline scheme based optimization calculates the midpoint of the user maximum and minimum values.



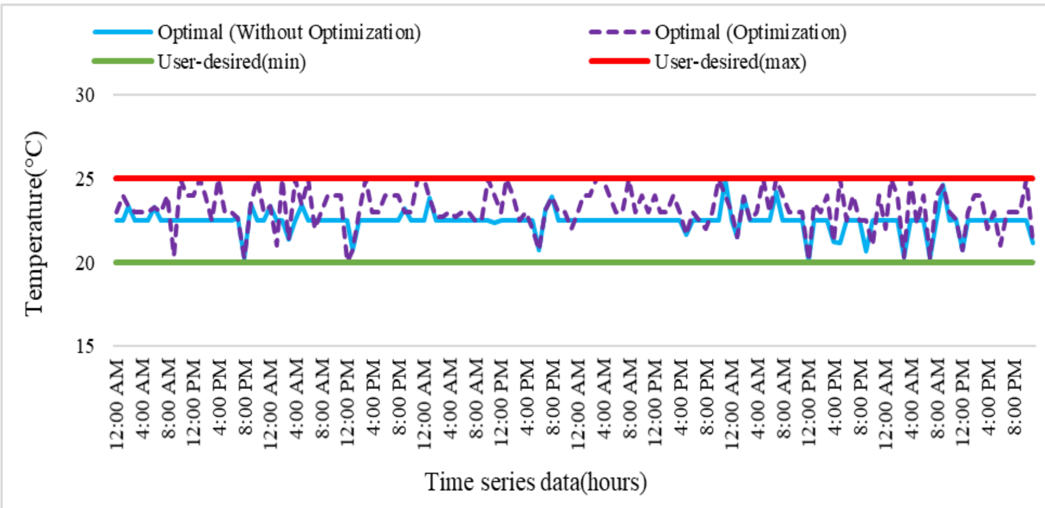
a)



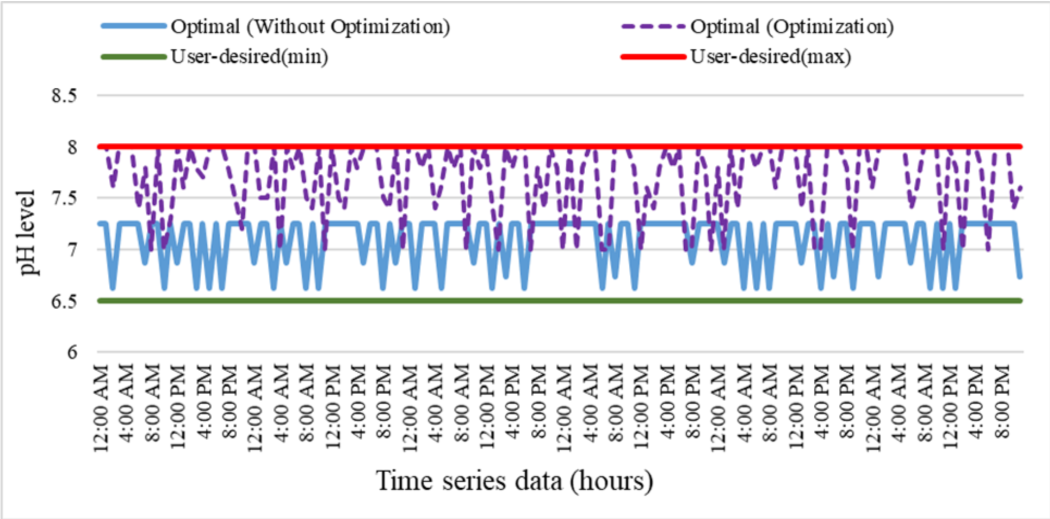
b)

Figure 80: Analysis of conductivity optimization module results without predicted values a) without optimization b) with optimization.

Figure 81 compares the optimization and without optimization scheme based optimization module results with user-desired set points. It can be clearly seen that in both cases the optimization scheme based optimal temperature and pH level results are more optimal with comparing without optimization schemes. Also, it is important to note that during the mentioned period, temperature and pH level values are between the user-desired minimum and maximum set-points, which means the optimization module is working accurately.



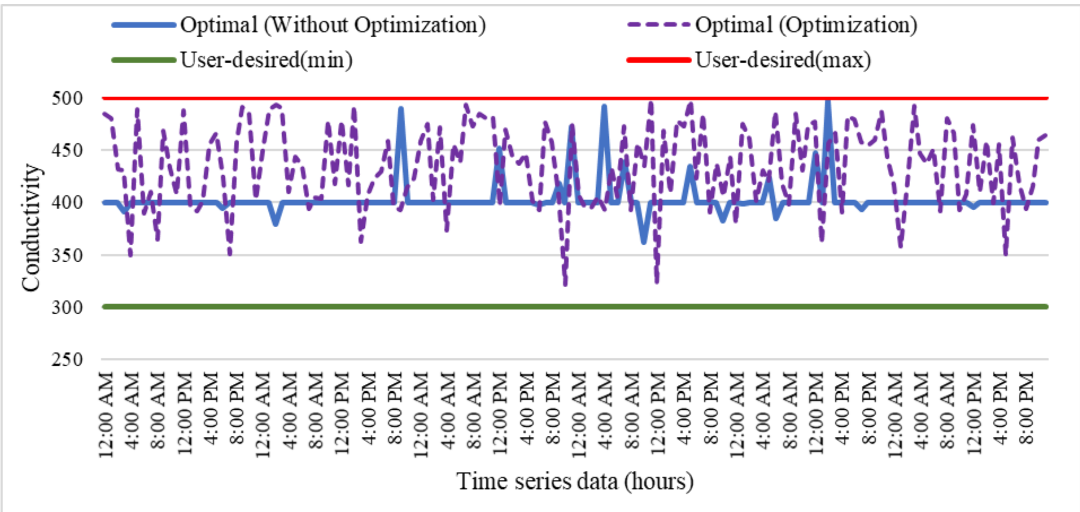
a) Temperature



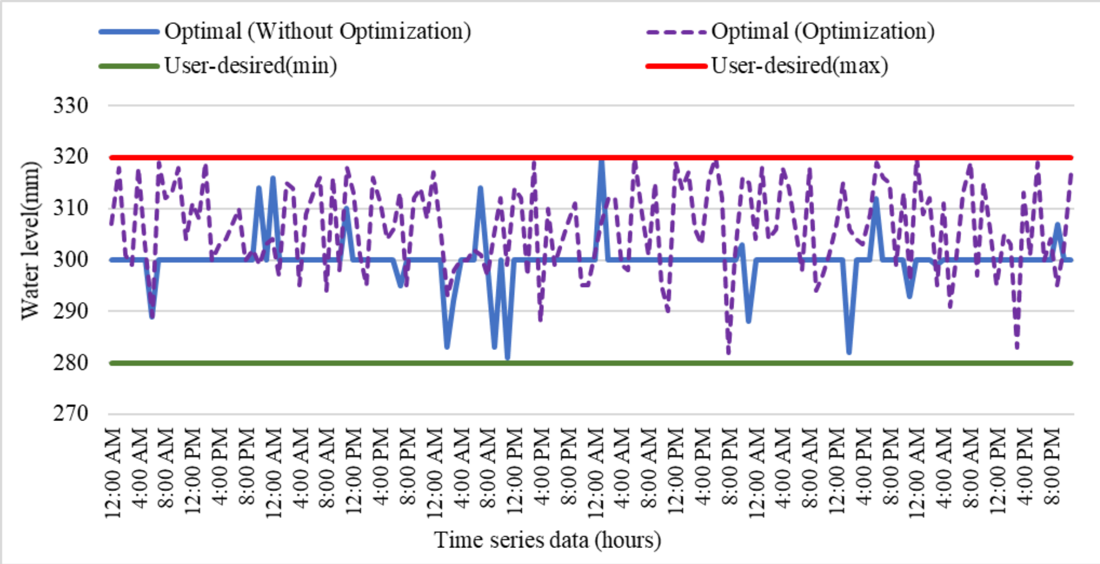
b) pH level

Figure 81: Comparisons of Optimization and without optimization module results a) temperature b) pH level

Figure 82 compares the optimization and baseline scheme based optimization module results with user-desired set points. It can be clearly seen that in both cases, the optimization scheme based optimal conductivity and water level level results are more optimal with comparing baseline scheme based optimization. Also, it is essential to note that during the mentioned period, temperature and pH level values are between the user-desired minimum and maximum set-points, which means the optimization module is working accurately.



a) Conductivity



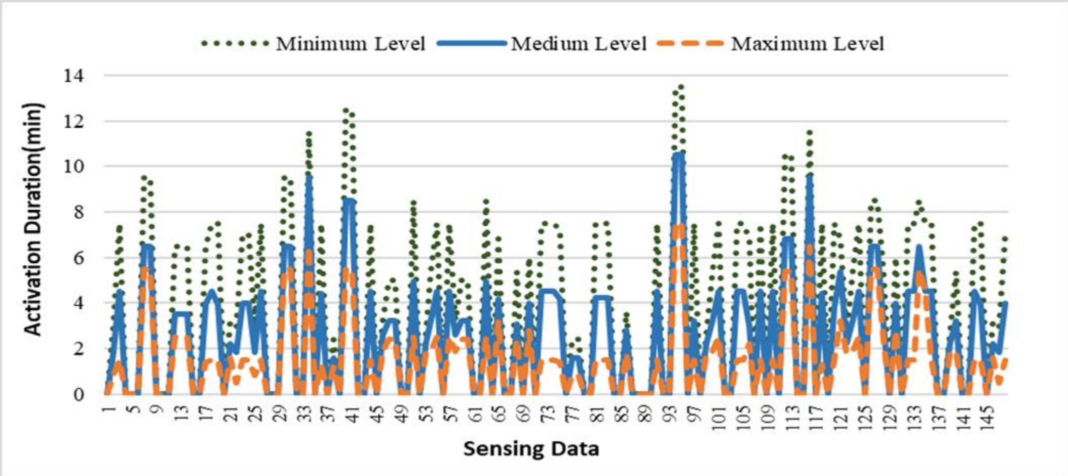
b) Water level

Figure 82:Comparisons of Optimization, and without optimization module results a) conductivity b) water level.

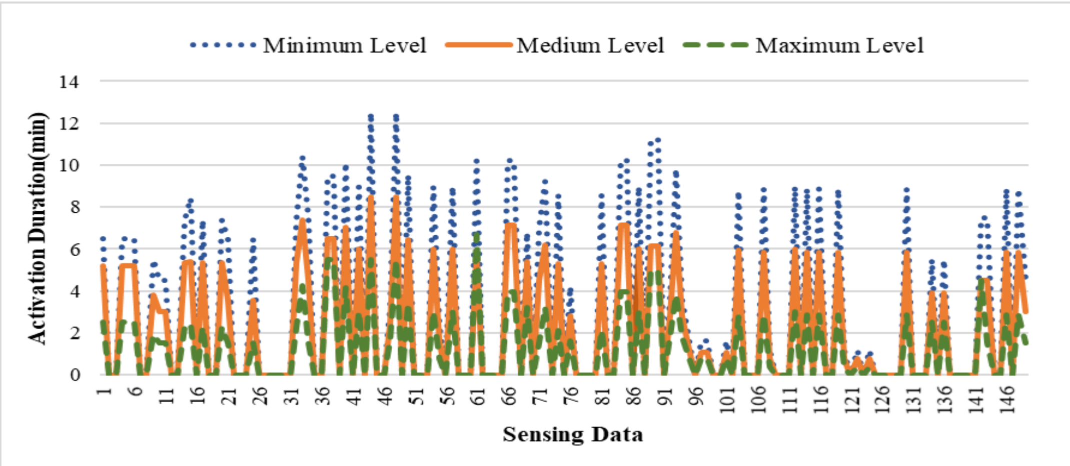
Optimization scheme results represent that optimized sensing values always come inside of the user desired minimum and maximum values. Furthermore, the optimization scheme based results are more optimal compared to without optimization scheme results.

5.2 Comparison and Performance Analysis of Actuator Control

Generally, fixed and variable working-level heater, cooler, water pumps, pH control, and fish feeder are utilized in real-life solutions. The fixed working-level actuators operate with a specific speed and consume the same amount of energy for each task. On the other hand, the variable speed or working level devices can operate with various working levels to produce different temperature, water, ph or feeding level according to the user demand. A high working level requires more energy as compared to the lower working levels. In the fish farm or the greenhouse environment, the power consumption of the actuators can be minimized by decreasing the working level, but it requires to operate actuators with extra time. Figure 83 illustrates the heater and cooler working level and activation duration results in the first 150 sensing data instances. Heater and Cooler system work dependently. If the predicted temperature level is lower than the optimal temperature level, then the heater is activated for reaching the optimal temperature level. If the predicted temperature level is higher than the optimal temperature level, the cooler operates for decreasing the predicted temperature to the optimal temperature level. When actuators are working with a different level, they require different time for achieving the optimal point. For instance, in the first sensing data, the water pump is spending 4.5, 7.5, and 10.5 minutes with the minimum, medium, and maximum working levels, respectively.



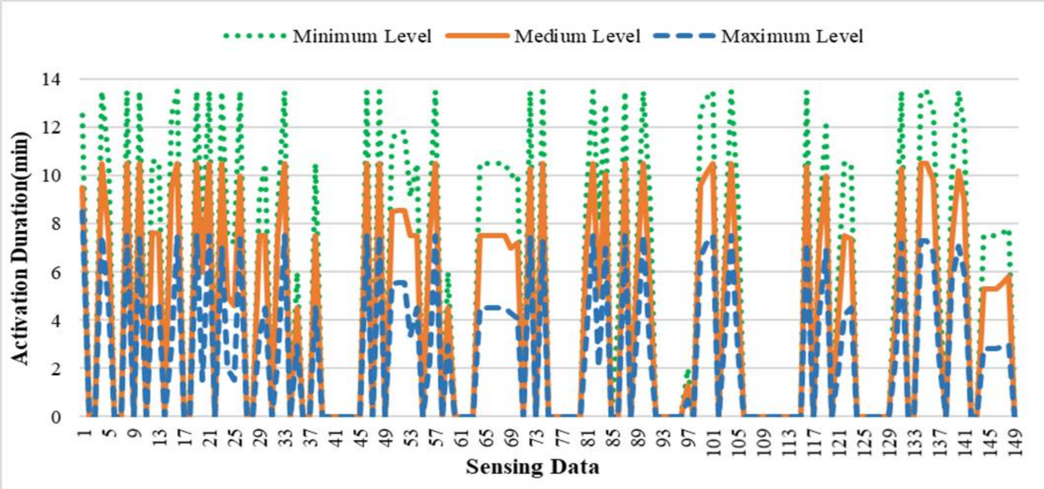
a) Heater



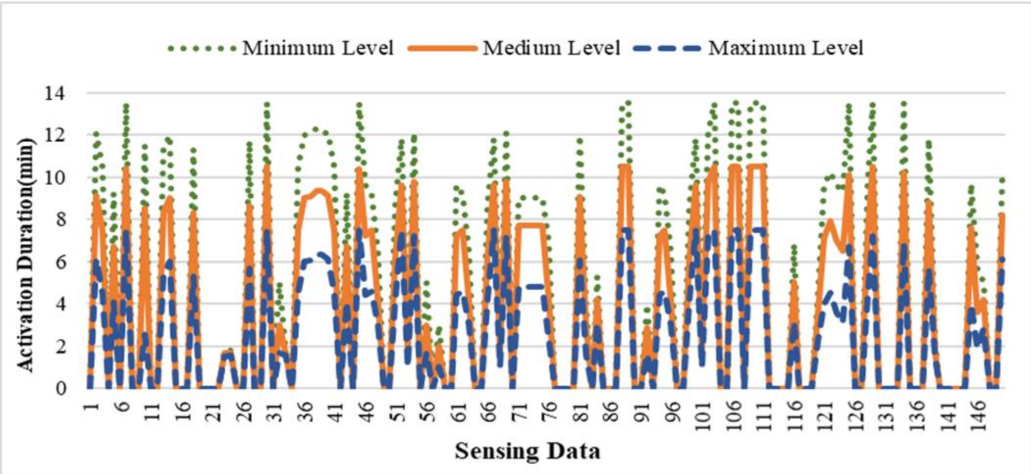
b) Cooler

Figure 83:Activation duration results based on different working levels for the Heater and Cooler.

Figure 84 (a) and (b) describes the working level and duration results of the water level and pH values. For instance, for the 3-4 sensing data, the water pump is spending about 12.5, 9.5, and 8.6 minutes with the minimum, medium, and maximum working level, respectively. We make a group of the results according to the actuators working level. However, the proposed fuzzy logic control module selects the optimal working level and duration to the actuators according to the predicted and optimal data. Controlling actuators not only helps the optimal utilization of resources but also provides automation of the fish farm.



a) Water Pump



b) pH Controller

Figure 84: Activation duration results based on different working levels for the Water Pump and pH controller.

Figure 85 describes the fish feeders' operational duration according to the various working levels. The feeding process is based on the data, which is collected in the historical feeding process. With activating the fish feeder with various working-level, we can achieve various energy consumption then we can find out the minimum energy consumption level based on the various working level and operational duration.

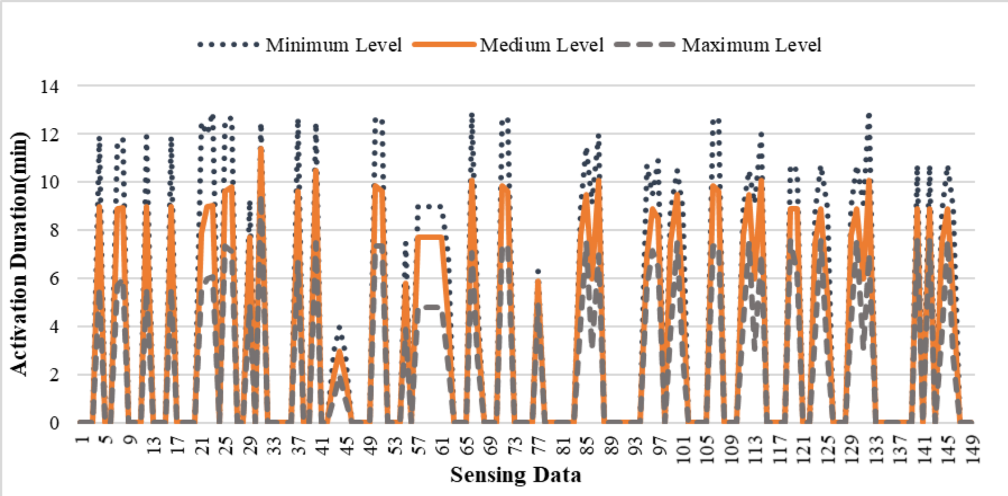


Figure 85: Fish feeder actuator’s activation duration with various working level.

Based on the working-level level and activation duration, we can calculate the overall activation duration for each actuator, namely, heater, cooler, pump, pH controller, fish feeder. Computing the activation period of the actuators based on different working-level helps us to calculate energy consumption for each level as shown in Figure 86.

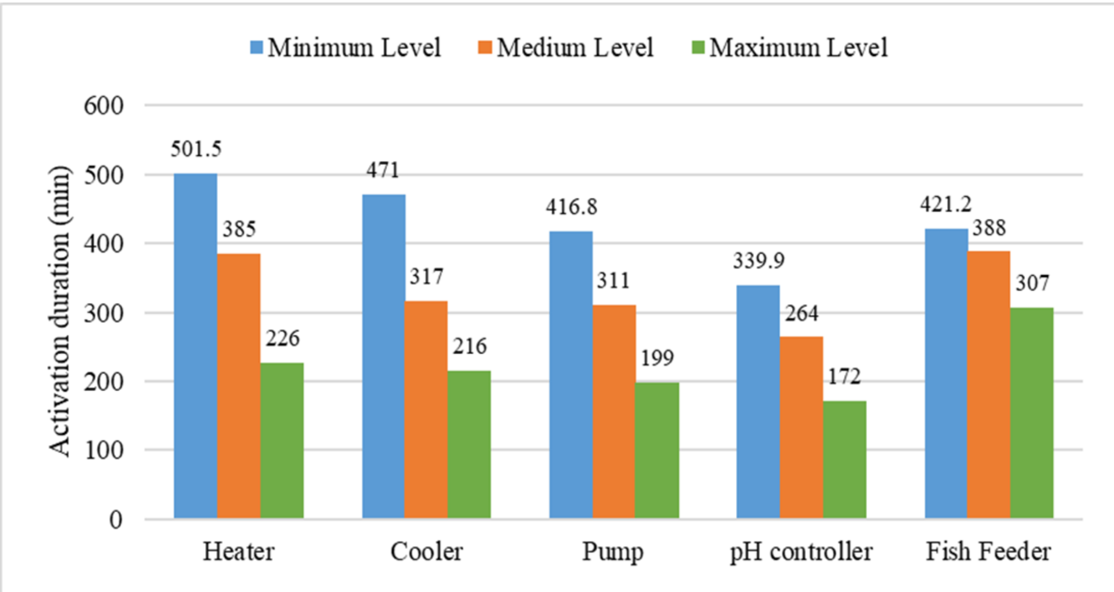


Figure 86: Comparative analysis of actuators operational duration results based on different working levels.

With activating the actuators with various working levels, actuators require various activation duration. As can be seen, if we activate the heater actuator with minimum working level then actuator requires 501.5 minutes to achieving the optimal temperature for the 1-week data.

5.3 Comparison and Performance Analysis of Energy Consumption

To calculate energy consumption analysis, we have selected power ratings as in Table 16. For every actuator, we assume three working-level operations with different energy consumption. When the water pump is activated with maximum working level, 1400-1800 watts energy is needed with little operational duration. For module simplicity, we have taken the mid-point of the power rating ranges of the working levels. For instance, with the minimum, medium, and maximum working level, the water pump requires 800, 1200, and 1600 watts, respectively. Figure 87 illustrates the actuators' energy consumption results in kWh according to the different working levels. As can be seen from the graphs, power consumption by the water pump is dominating comparing with other actuators. The water pump is spending 333, 373.2, and 318.3 kWh with activating minimum, medium, and the maximum level, respectively.

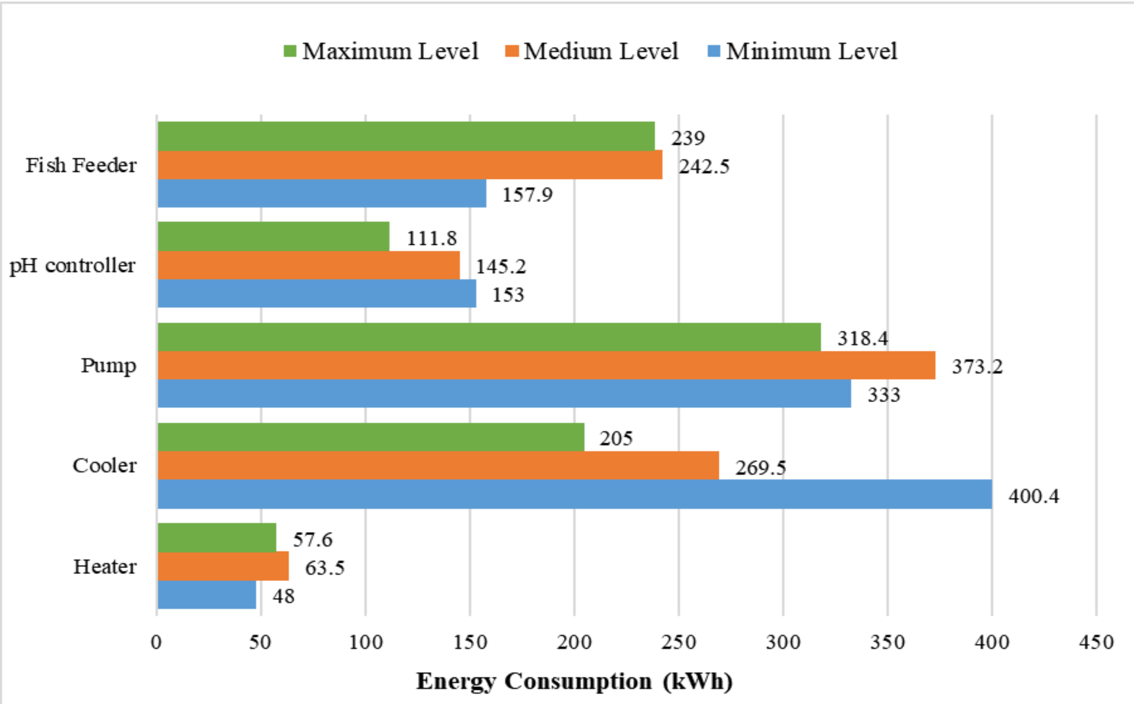


Figure 87: Comparative analysis of energy consumption of the actuators.

If the water pump is activated with maximum working level, then it consumes less energy, and when it works with the medium working level, it spends the most power compared to other working levels. For decreasing the energy consumption results, we need to activate the fish feeder and heater actuators with a minimum working level. However, the rest of the actuators, namely, pH controller, water pump, and cooler, needs to be activated with a maximum working level.

As we have mentioned above, the optimization module provides the optimal temperature, pH level, conductivity, and water levels to the environment based on user-desired settings and constraints. According to the optimal level, the predicted values of the environment can be increased with controlling actuators. For the development of without optimization scheme, we have used the baseline scheme, which is relatively simple. The without optimization scheme is based on the selection of the midpoint of user-desired ranges for each parameter. For instance, if user desired maximum and minimum ranges water level ranges are equal to 280 mm and 320 mm, respectively. Optimal water level becomes equal to 300 mm ((280+320)/2 = 300 mm). The water pump is needed to activate for increasing or decreasing the predicted water level for achieving the optimal point. From the above-mentioned user-desired mid-point level selection, temperature, water level, pH level, and conductivity level optimal levels become 22.5°C, 300 mm, 7.25 acid, 400 μS/cm, respectively. Our target is controlling the actuators for reaching the current levels for these levels. The maximum working level, operational durations, and fuzzy logic rules are also applied to the for all four cases. Figure 88 describes the comparative analysis of the energy consumption results based on various cases of the relations between without prediction, prediction, without optimization and optimization cases. As expected, the proposed prediction-optimization based system has less energy consumption. It can be seen that without prediction-without optimization case heater, cooler, pump, pH controller, and fish feed have spent 10.8, 34.6, 50.7, 22.7, and 32.8 kW energy, respectively, for one day. In the prediction-optimization case, these actuators have spent 6.8, 29.3, 42.5, 14.9, and 22.5 kW energy for the same task. If we take the heater actuator as an example, the prediction-optimization based system has 37.2%, 33.3%, and 8.1% energy efficiency compared to without prediction-without optimization, with prediction-without optimization, without prediction, and with optimization results.

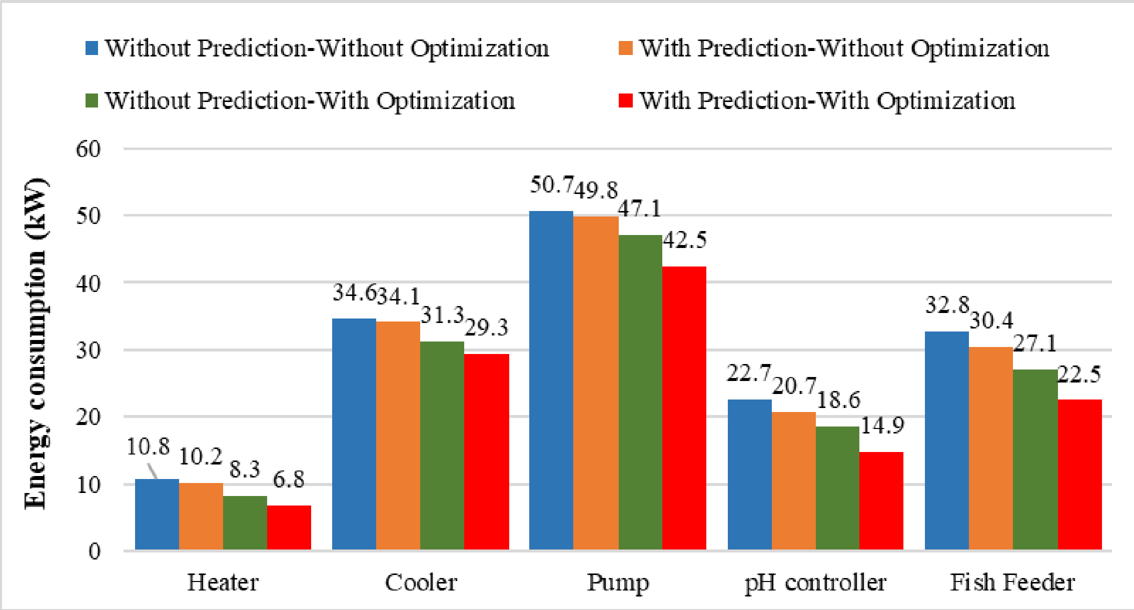


Figure 88: Comparative analysis of energy consumption results based on various cases.

Overall, the proposed prediction-optimization based environment control energy consumption is 27%, 23.6%, and 11.8% effective in energy consumption compared with without prediction-without optimization, with prediction-without optimization, without prediction, and with optimization results, respectively.

5.4 Comparison and Performance Analysis of Power Policy

In order to conduct cost and power consumption analysis, we have to assign power ratings to the 1 kWh electricity costs 129 won on average for a typical spring day in Jeju, South Korea. According to the actuators' overall energy consumption, we can calculate the overall pricy policy to each actuators' working level. Figure 89 illustrates the power policy results of the proposed system. Power policy results show that fish feeder and heater minimum level activation requires the least payment compared with other activation levels. However, the pH controller, water pump, and cooler actuators spend less price with activating the maximum level. The diagram compares how much money is spent on fish tank actuators in four different cases. Overall, more money is spent on water pump activation than any other product. Also, without prediction-without optimization case is required the highest amount among the compared other cases, while the lowest spending levels are attributed to proposed with prediction-with optimization case. In overall, the proposed system spends 918 krw, 753 krw, and 423 krw less money compared to without prediction-without optimization, without prediction-with optimization, with prediction-With Optimization cases.

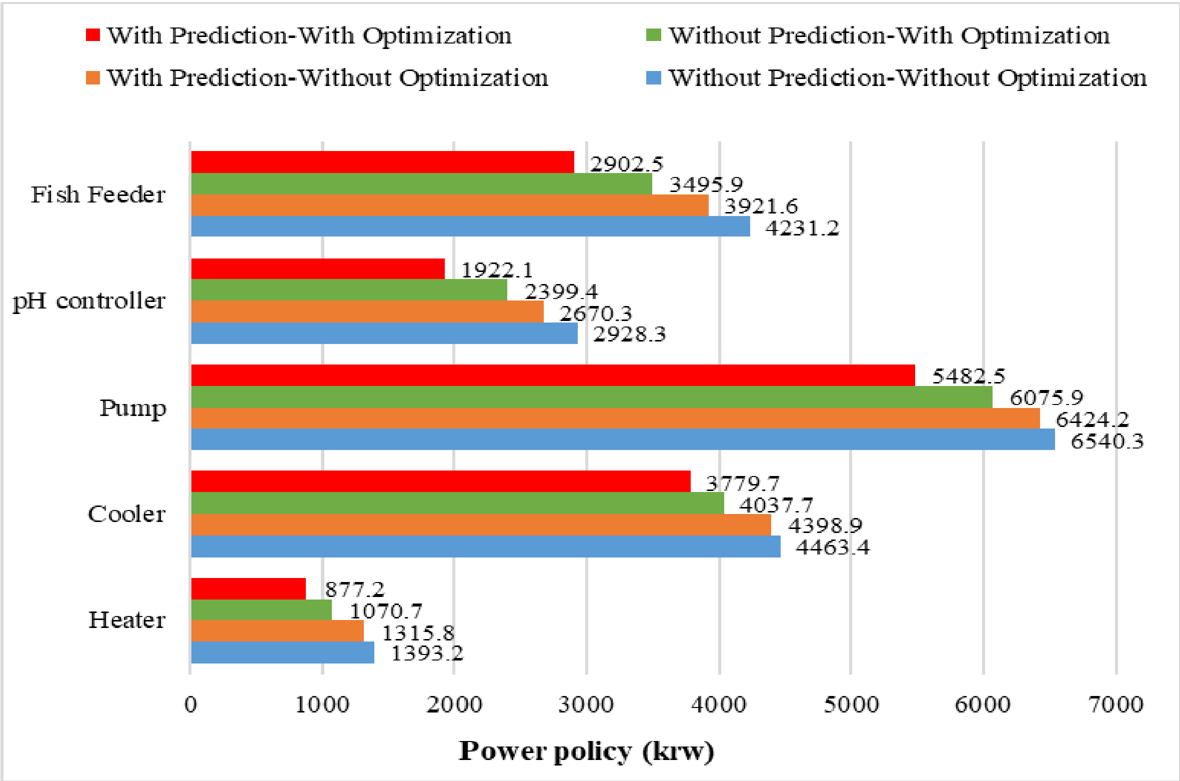


Figure 89: Comparative analysis of power policy results of the actuators.

6. Conclusion and Future Directions

In this thesis, we have proposed an embedded machine learning technologies based optimal embedded control platform for efficient energy consumption and fish growth in the fish tank. The contribution of the proposed embedded solution is as followed. Firstly we installed temperature, pH level, conductivity, and water level sensors, and various actuators to the fish tank and collected real-time sensing values from the environment. Secondly, we trained RNN-LSTM based prediction model using internal and external environmental parameters to predict temperature, pH, conductivity, and water level parameters. As well as we converted this model to the Tensorflow Lite format. Thirdly, we have formulated the objective function for the optimization to calculate the most desirable environmental parameters for fish growth with efficient energy consumption. Fourthly, the development of the fuzzy logic-based control module which sets up working level and operational duration to the actuators using predicted and optimal values. Lastly and the most important, the deployment of the overall platform to the Embedded Device. Power policy results show that fish feeder and heater minimum level activation requires the least payment compared with other activation levels. However, pH controller, water pump, and cooler actuators spend less price with activating the maximum level. If the water pump is activated with maximum working level, then it consumes less energy, and when it works with the medium working level, it spends the most power compared to other working levels. For decreasing the energy consumption results, we need to activate the fish feeder and heater actuators with a minimum working level. However, the rest of the actuators, namely, pH controller, water pump, and cooler, needs to be activated with a maximum working level. Energy consumption results show that through an optimization scheme, we can achieve a significant reduction (22.8%) in energy consumption. The proposed prediction-optimization based environment control energy consumption is 27%, 23.6%, and 11.8% effective in energy consumption compared with without prediction-without optimization, with prediction-without optimization, without prediction, and with optimization results. Also it spends 918 krw, 753 krw, and 423 krw less money compared to without prediction-without optimization, without prediction-with optimization, with prediction-With Optimization cases.

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