Design of an IoT System for Machine Learning Calibrated TDS Measurement in Smart Campus

Sai Usha Nagasri Goparaju, SVSLN Surya Suhas Vaddhiparthy, Pradeep C, Anuradha Vattem, Deepak Gangadharan
Smart City Research Centre,International Institute of Information Technology,Hyderabad,India
E mail:{ushasai.g,suhas.vaddhipar,pradeep.c,anuradha.vattem}@research.iiit.ac.in ,deepak.g@iiit.ac.in

2021 IEEE 7th World Forum on Internet of Things (WF-IoT) | 978-1-6654-4431-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/WF-IoT51360.2021.9595057

***Abstract*—This paper focuses on designing a low-cost and robust IoT-based TDS measurement system for the smart campus. The objective of this low-cost design problem is to find a solution that guarantees precise and uninterrupted output data. The dynamic reading of data, storage capacity, and calibration errors of sensors are the major challenges for IoT-based TDS measurement systems. These challenges are combated in the proposed design using a non-invasive mechanism for data collection, wireless connectivity to the data server, and machine learning calibration of sensor nodes. The TDS data of various water stations located inside the campus is used for the experimental study to develop a regression model for temperature compensation and calibration. The value of TDS sensor voltage variation against temperature is analyzed. The evaluation of the model was performed based on the R^2 and the root mean square error. By using 3^{rd} degree polynomial regression, we have obtained an R^2 value of 93.96 % and an RMSE of 27.93.**

***Index Terms*—Smart Campus, IoT, Water Quality, TDS measurement, Temperature Compensation, Machine Learning**

I. Introduction

Many international agencies, including the United Nations, have predicted that nearly 70% of the population will live in the cities by the year 2050. With the rising population in cities coupled with the problem of scarcity of appropriate and suitable resources for comfortable living, it is imperative to use advanced technologies like the Internet of Things (IoT) and Artificial Intelligence (AI) to plan urban areas that can confront many issues in society. The concept of a smart city by utilizing communication and computing technologies for the development and modification of infrastructures in the urban area emerged in the early 1990s. IoT and AI-based innovations and applications for smart cities will bring drastic transformations all around the world. The research and development work related to Smart City falls mainly in the area of sensor-driven data collection, development of powerful analysis, automation, and distribution of a wide range of services. These works are carried out with multiple objectives like optimal use of resources, lowering costs, and tapering ecological impact for better sustainable development.

A. Motivation

There is a massive drive for smart cities in India under the *smart cities mission*, which is an initiative by the Government of India to steer economic growth and improve the quality of life of people by enabling local development and harnessing technology to create innovative outcomes for citizens. The Smart City Research Centre at the International Institute of Information Technology, Hyderabad (IIIT-H) had launched a smart campus project with support from European Union and Indian agencies. The smart campus is created to enhance three value domains: social, economic, and environmental.

The 60-acre campus of IIIT-H situated in the heart of Hyderabad city of Telangana state will be converted into a smart campus as part of the project. The supreme objective of this project is to transform the campus into a platform for learning, experimentation, and showcasing new ideas and approaches. It is essentially a live setup of a building, campus, or facility that gets used for its intended purposes along with being a 'living' testbed for research and innovation. The smart campus would include more than 300 IoT nodes to collect data of different focus areas related to air quality, energy, water quality and quantity, street lighting, etc., as shown in Fig. 1.

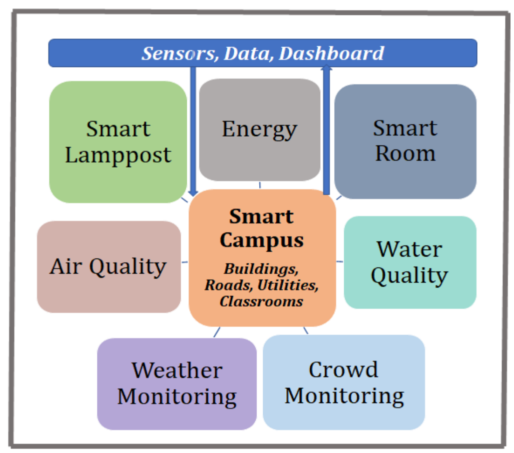

Fig. 1. Smart Campus Verticals

The proposed work presented in this paper is part of water quality monitoring for the smart campus. As the water quality parameters vary with changes in the environmental conditions, it is important to design a robust system to measure live data at an affordable cost. The hardware for the system is planned using low-cost devices by ensuring accuracy and high reliability. The quality of the data is guaranteed by utilizing a machine learning approach which will also reduce unit cost and maintenance cost.

B. Organization of the paper

The paper is further organized into the following sections. In Section II, we provide an overview of the background and related work on primary topics to be taken into account for the project, namely, the Internet of Things for smart cities and water quality monitoring. In Section III, we explain our approach to hardware design, software development, and packaging for this water quality monitoring system. Section IV provides a detailed experimental procedure, data pre-processing, training, and testing of the model for the temperature compensation and calibration of the Total Dissolved Solids (TDS) sensor. In Section V we draw the results, and a discussion based on it, followed by the conclusion and future work in Section VI.

II. Background and related work

A. Internet of Things

The far and comprehensive utilization of present-day sensor advancements has made the leap from the laboratory to the natural environment through the careful design of professional scientists [1]. A comprehensive survey of the enabling technologies, protocols, and architecture for an urban IoT is presented in [2]. A summary of the major smart city challenges to give a broader insight into possible fields of action is presented in [3]. A discussion on problems and solutions in the area of smart city technologies and IoT, including development, implementation, strategies, and policies are presented in [4]–[6]. IoT-based data acquisition systems connected to cloud storage are appropriate for research and development related to smart cities by sharing a platform based on open data. The application of the IoT concept to an urban perspective is adopted by many national governments for managing public affairs [7]. Cloud computing which has unlimited capability in terms of storage and processing power together with advancements in IoT, is expected to provide solutions for the current and future research in the Smart City domain [8].

B. Water Quality Monitoring

Water is one of the basic needs of the citizens, but now the world is facing challenges in protecting less than 0.5% of available usable water. As mentioned in [9], the pollution of water is due to many factors making it even more difficult to find a unique solution. A robust water environment monitoring system is necessary for the highly populated areas to understand the problems associated with water pollution and prevent excessive water usage since water pollution has increasingly become a serious issue due to the rapid urbanization in some places [10]. The need for water management procedures to control water shortage and the idea of a smart water grid for the conservation of water and the challenges in its implementation is discussed in [11], and a review of studies that deal with smart water techniques and approaches for the building of the smart water system is presented in [12]. As mentioned in [13], conventional water quality measurement is carried out by taking water samples manually to the laboratories for analysis. This approach is not widely accepted in AI-related research of water quality due to the requirement of trained persons & specific apparatus, delay in getting results, high cost, and lack of extensive data analysis. So there is a need to monitor and protect the water with a real-time water quality monitoring system.

The latest AI techniques, along with the development of the IoT and cloud computing, provide new chances and methodologies for water environment monitoring to be used for water quality improvement [14]. The need and scope of a real-time water quality monitoring system by using the IoT and AI techniques for faster processing and intelligent forecasting to reduce contamination are also discussed in this literature. The specific issues in sensors of IoT node for water quality monitoring, especially nonlinear drift in the output voltage, can only be solved by frequent calibration of the sensors with the help of trained persons, which is expensive. The mathematical drift correction methods are used commonly, but sometimes it shows unexpected behavior such as drift and deviations due to unknown reasons. As a solution to this problem, a regression calibration method implemented by the machine learning approach is described in [15] to extend calibration lifetime, and the method showed superior performance over the existing methods. However, the collection of real-time data and validation with the ML model is out of the scope of this article.

The effectiveness of temperature drift compensation for pH sensors using various ML techniques like multi-layer perceptron, support vector regression, random forests, linear regression, and decision trees are investigated [16]. From the insightful results presented in the above work, it is evident that the ML-based methods are cost-efficient and more accurate for the compensation and calibration of sensor nodes. However, the impact of applying the approaches with TDS sensors based on the electrical conductivity principle in a real-time environment is to be studied separately, which is proposed in this paper. The authors have also reviewed the methods for short-term prediction of water quality parameters using Deep learning methods and traditional ML principles in [17], [18]. As the deep learning models need high computing power and memory storage, a low-cost memory-efficient model proposed in this research becomes more relevant.

III. Materials and Methods

A. Hardware Platform Design

The main challenges addressed by the hardware part of this project are the design, deployment, testing, and validation of low-cost and robust IoT nodes for measuring TDS values without disturbing the normal operation of the water supply and post the data to the OM2M data server [19]. As an initial step, five IoT nodes were designed to read TDS of various water stations named RO-I, RO-II, RO-III, RO-IV, and UG-I. The first four are the Reverse Osmosis(RO) based water filtering stations located in the Vindhya building, and the fifth one is the underground water tank near the main gate of the campus. The proposed system consists of a TDS sensor, temperature sensor, and an ultrasonic sensor. These sensors are interfaced with the ESP32-WROOM-32D micro-controller, as shown in Fig. 2. A brief explanation of the functions of each component of the hardware is presented here.

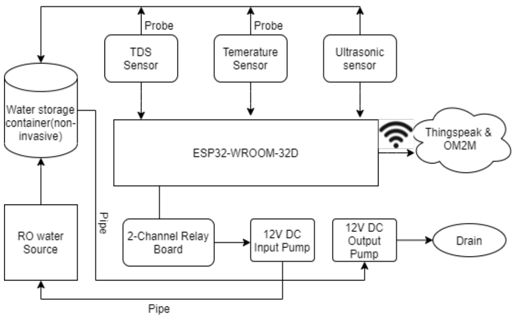

Fig. 2. Block Diagram

1) Microcontroller: ESP32-WROOM-32D is a low-cost, powerful and generic module with WiFi, and Low energy Bluetooth(BLE) connectivity, and many other peripherals [20]. This board is selected for this work since it is designed to be scalable and adaptive. The chip also has a low-power co-processor and 520 KB of on-chip SRAM, which are suitable for the deployment of ML models [21].

2) TDS sensor: The DFRobot SEN0244 gravity analog TDS sensor based on the principle of conductivity is a low-cost TDS sensor. The supply voltage required is in the range of 3.3 V to 5.5 V, and the output is of the range 0 to 2.3 V. It allows the measurement of TDS value from 0 to 1000 ppm. The TDS probe is water-resistant and designed for immersion into the water for a longer duration [22].

3) Temperature Sensor: The gravity DS18B20 temperature sensor is used to measure the temperature of the water. The supply voltage required is 3.3 V to 5 V and it can measure the temperature from -55°C to 125°C. The 12-bit serial output makes the output resolution of the sensor is 0.5°C [23].

4) Ultrasonic Sensor: The Ultrasonic sensor HC-SR04 is used for controlling the water level of the container used for the collection of water samples [24].

The sensor nodes are deployed without disturbing the existing water stations available on the campus by using a non-invasive mechanism that is developed in such a way that the water from water stations is diverted into a small water storage container, which is filled and drained at regular intervals. The probes from the TDS and temperature sensors immersed in the container produce an output voltage variation corresponding to the TDS and temperature values of water present in the container. The controller reads the data from the sensors and posts it to the server at predefined intervals through the wireless network on the campus.

To the best of the knowledge, this is the first system that can be deployed anywhere irrespective of the structure and location of water stations. As the probes are made up of plastic, it may degrade into water over time if it is directly immersed into the water. Earlier studies have proven that consuming water that is in contact with a plastic material creates a lot of health problems in the long run. Bisphenol-A and other plastic toxins can then make their way into the bloodstream of the human body, which can cause various cancers as well as liver and kidney damage. So, the non-invasive mechanism proposed in this work turns out to be more relevant for the smart campus project. In this method, the water sample is collected into the container and drained out at every four-hour interval using 12V DC pumps. The process is designed to measure and post TDS values continuously on to the data server. The deployment of the entire mechanism is shown in Fig. 3.

Fig. 3. Hardware Implementation

B. Software Development

The software development for the IoT node and OM2M data server is carried out separately. The Eclipse Integrated Development Environment is used for coding and debugging of the controller. A robust code is developed in such a way that in case of any power failures or network issues, the data is stored in a buffer, and it will be posted to the server as soon as the network is connected. The data is posted to the OM2M server using one of the IoT protocols called HTTP. OM2M is an open-source implementation of the oneM2M standard, which is an IoT middleware. A separate OM2M server is hosted and managed by the institute, is used in this work.

IV. TEMPERATURE COMPENSATION AND CALIBRATION FOR TDS SENSOR

To ensure the accuracy of the data collected by the IoT system, a proper compensation and calibration mechanism needs to be incorporated in the system. As the TDS sensor used in this design functions based on the principle of *conductivity*, the TDS value varies with temperature. The amount of total dissolved solids and conductivity are positively correlated to each other as per (1), and the TDS is the measure of the total dissolved concentration of organic and inorganic solids in a liquid. As temperature increases, mobility of the dissolved ions increases, which increases the conductivity of water.

$$TDS(mg/L) = k * EC(\mu S/cm) \tag{1}$$

Here,

EC is the electrical conductivity.

k is a proportionality constant.

The relationship between conductivity and TDS is not directly linear even though the value of k increases with the rise of ions in water [25].

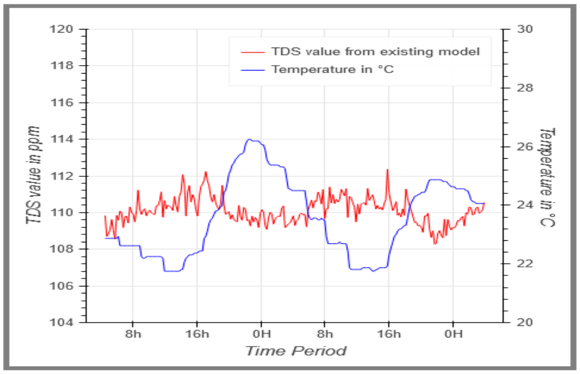

Fig. 4. Temperature and TDS variation of RO-I

In the initial phase of this work, the authors have used the temperature compensation mechanism suggested by the manufacturer of the TDS sensor. The posted data in the server from these IoT nodes are observed and analyzed. The Fig. 4 shows the variation of TDS values and temperature of RO-I for two days. It can be inferred from the figure that the TDS value has an unusual negative correlation with the temperature i.e., as the temperature increases, there is a decrease in TDS value. The issue is taken for further investigation by using manual experimentation.

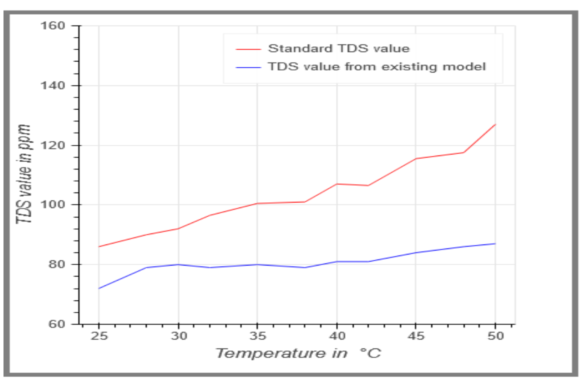

Fig. 5. Standard TDS value and TDS values from existing model with Temperature

To identify the exact reason for the unexpected variation of TDS value, a water sample of known TDS value is considered for the study. TDS values of these water samples are collected using SEN0244 TDS sensor and a HI 99300 standard TDS meter at the same time. From Fig. 5, we can notice that there is a notable offset between the obtained TDS value and the true value. To achieve a unified mechanism for minimizing the offset as well as for better temperature compensation, regression method has been used in [26]. The authors have used various regression models for experimentation, and the details are presented below.

A. Experimental setup

As shown in Fig. 6, the experimental setup consists of a test node, a standard TDS meter, a water bath, and different water samples of TDS values ranging from 0 to 400 ppm as the TDS values of water sources lie in this range. The test node is a replica of the deployed nodes, and to identify the exact temperature dependency, the values are measured by varying temperature. A water bath is used for controlling the temperature of these water samples. A reference meter (HI 99300) from Hanna Instruments is used as the standard TDS meter.

B. Preparation of Dataset and Pre-processing

As a proper dataset is essential for applying any machine learning model, water samples of different concentrations are mixed in various proportions such that many samples of different TDS values are obtained. The procedure is fairly straightforward, the temperature of these water samples is varied between 20°C to 50°C, as the temperature of the locality falls in this range. Both the sensor and the reference meter are immersed in the water sample simultaneously, and the corresponding values from the standard meter and the sensor are recorded. The same procedure is continued with other water samples to generate a balanced dataset.

Fig. 6. Experimental Setup

C. Machine Learning Approach

The machine learning approach is widely used to minimize the non-linear offset [15], [16] between the sensor TDS value and the standard meter TDS value, simultaneously performing the temperature compensation. The prediction model is developed by considering standard TDS meter value as a dependent variable while temperature and sensor voltage are independent variables. The details and mathematical representation for different regression models applied in this work are discussed below.

1) Multivariate Linear Regression : Multivariate linear regression denoted by (2) is a supervised machine learning algorithm involving multiple variables for analyzing the data, which is an extension of multiple regression with one dependent variable and multiple independent variables [27].

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \quad (2)$$

The generalized equation for the multivariate regression model is represented by (3)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \cdots + \beta_n x_n \quad (3)$$

Where n represents the total number of independent variables, $\beta_0 \cdots \beta_n$ represents the coefficients and $x_1 \cdots x_n$ are the independent variables.

2) Polynomial Regression: Polynomial regression is a form of regression analysis in which the relationship between the independent variable x and the dependent variable y is modelled as an n^{th} degree polynomial in x. A polynomial regression can be applied to a single independent variable called simple polynomial regression or on multiple independent variables called multivariate polynomial regression (4) .

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 + \epsilon \quad (4)$$

Here,

β_1, β_2 are called linear effect parameters,
β_{11}, β_{22} are called quadratic effect parameters,
β_{12} is called interaction effect parameters,
ϵ is error value.

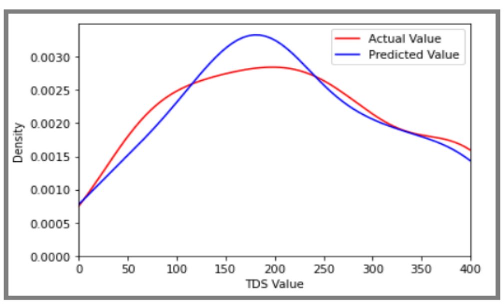

Fig. 7. Distribution Curve of Standard TDS values and estimated TDS values

Fig. 7 is a kernal density estimate of 3^{rd} degree multivariate polynomial regression, which compares the distribution of the standard meter TDS value and the TDS value from the prediction model. It can be inferred that they are reasonably close to each other with an R^2 value of 93.96.

V. Results and Discussion

The regression models are developed using Python 3.8 in Jupyter Lab IDE. To train the model, out of the 560 data samples in the dataset 80% is used for training and 20% for validation. To minimize under-fitting and over-fitting, the polynomial features of the model are increased. It can be inferred from Table I that the 3^{rd} degree Multivariate Polynomial Regression model has better R^2 and RMSE with improved prediction capabilities.

One of the main motives of the experiment is to reduce the deviation of IoT measured TDS value to the standard value. The prediction model has been applied to real-time data of RO-I and the results are tabulated in Table II. The 'Predicted TDS' column is obtained after applying the model whereas, the 'Existing TDS' column refers to the readings before applying regression.

TABLE I
Error values of Machine learning Models

SL.No	Model	R^2	RMSE
1	*Multivariate Linear Regression*	91.27	33.60
2	*Second Degree Multivariate Polynomial Regression*	92.11	31.94
3	*Third Degree Multivariate Polynomial Regression*	93.96	27.93

TABLE II
Deviation of TDS values

SL.No	Standard TDS	Existing TDS	Predicted TDS	Deviation with existing model	Deviation with prediction model
0	145.66	178.1	156.52	-32.43	-10.85
1	145.5	174.97	159.42	-29.47	-13.92
2	145.33	174.11	156.11	-28.77	-10.78
3	145.16	172.11	158.44	-26.94	-13.27
4	145	168.4	157.05	-23.4	-12.05
5	144.83	164.39	156.76	-19.55	-11.93
6	144.66	159.5	152.09	-14.83	-7.42
7	144.5	157.19	154.13	-12.69	-9.63
8	144.33	155.17	152.68	-10.83	-8.35
9	144.16	151.41	152.08	-7.24	-7.91
10	144	149.09	151.26	-5.09	-7.26

It can be observed that the deviation between predicted and standard values is reduced compared to that of existing values. Although the model is performing as expected most of the time, there are few outlier cases where the deviation is slightly higher than the standard value. Even though RMSE values are high, the model has superior performance over the existing method. This better prediction is achieved through the best possible model fitting [28].

To understand the TDS variation with temperature, a two-day data of RO-I and RO-II has been studied. The TDS value obtained after applying the model is in synchronization with the temperature variation of those particular days. It can be observed from Fig. 8 and Fig. 9 that as the temperature increased, the corresponding TDS value also increased. Hence the prediction model yields a positive correlation between TDS value and temperature.

VI. Conclusion and Future work

In this study, a cost-efficient and robust TDS measurement IoT node with a non-invasive design is developed for water quality measurement in the campus using ML principles. We have used a set of low-cost solutions throughout the design and development of the system, and we have shown that the entire system can be used as a guideline for TDS measurement for water quality analysis and prediction. The design was made

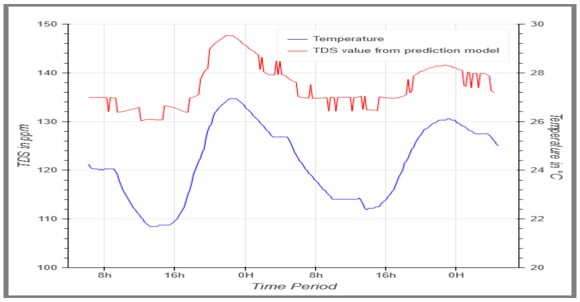

Fig. 8. Temperature vs TDS variation RO-I after prediction

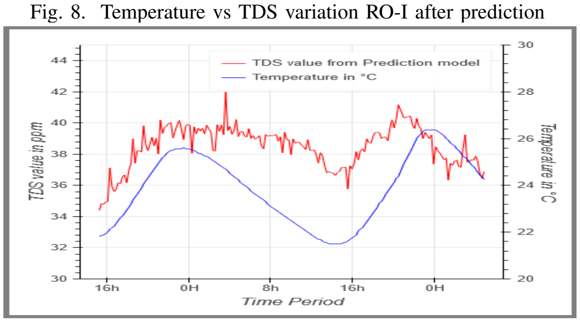

Fig. 9. Temperature vs TDS variation RO-II after prediction

to guarantee a lesser cost and higher robustness, and adequate features. In the recent past, machine learning algorithms are widely used instead of conventional statistical methods, the reason being, the statistical methods involve larger human intervention and are not economical when it comes to multi-sensor networks. The experimental study conducted has proved that Multivariate Linear and Polynomial regression method is effective for temperature compensation and calibration. This method exhibited acceptable performance in the temperature range of 20°C–50°C and can be used to design other IoT nodes for measuring water quality parameters. The machine learning technique of temperature compensation and calibration can be used for designing low-cost, reliable, and robust IoT nodes for measuring water quality parameters in smart cities and related research. The other challenges were power and network coverage to the nodes deployed at the underground tanks. Although the model was tested successfully in the currently deployed five nodes, the system needs to be tested exhaustively using a bigger set of data in a larger multi-sensor network which can be done as future work. Also, in future research, the ML classification can be used to classify the input source water according to various environmental conditions.

References

[1] D. Cuff, M. Hansen, and J. Kang, "Urban sensing: out of the woods," *Communications of the ACM*, vol. 51, no. 3, pp. 24–33, 2008.

[2] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," *Computer networks*, vol. 54, no. 15, pp. 2787–2805, 2010.

[3] L. Belli, A. Cilfone, L. Davoli, G. Ferrari, P. Adorni, F. Di Nocera, A. Dall'Olio, C. Pellegrini, M. Mordacci, and E. Bertolotti, "Iot-enabled smart sustainable cities: Challenges and approaches,"

[4] K.-D. Chang, C.-Y. Chen, J.-L. Chen, and H.-C. Chao, "Internet of things and cloud computing for future internet," in *International Conference on Security-Enriched Urban Computing and Smart Grid*, pp. 1–10, Springer, 2011.

[5] T.-h. Kim, C. Ramos, and S. Mohammed, "Smart city and iot," 2017.

[6] H. Samih, "Smart cities and internet of things," *Journal of Information Technology Case and Application Research*, vol. 21, no. 1, pp. 3–12, 2019.

[7] H. Schaffers, N. Komninos, M. Pallot, B. Trousse, M. Nilsson, and A. Oliveira, "Smart cities and the future internet: Towards cooperation frameworks for open innovation," in *The future internet assembly*, pp. 431–446, Springer, Berlin, Heidelberg, 2011.

[8] J. Zhou, T. Leppanen, E. Harjula, M. Ylianttila, T. Ojala, C. Yu, H. Jin, and L. T. Yang, "Cloudthings: A common architecture for integrating the internet of things with cloud computing," in *Proceedings of the 2013 IEEE 17th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pp. 651–657, IEEE, 2013.

[9] N. Sasakova, G. Gregova, D. Takacova, J. Mojzisova, I. Papajova, J. Venglovsky, T. Szaboova, and S. Kovacova, "Pollution of surface and ground water by sources related to agricultural activities," *Frontiers in Sustainable Food Systems*, vol. 2, p. 42, 2018.

[10] E. B. Tirkolaee, A. A. R. Hosseinabadi, M. Soltani, A. K. Sangaiah, and J. Wang, "A hybrid genetic algorithm for multi-trip green capacitated arc routing problem in the scope of urban services," *Sustainability*, vol. 10, no. 5, p. 1366, 2018.

[11] M. Fatima, S. Jain, A. Chikara, and M. Luthra, "Review on implementing smart water grid for smart cities in india: Challenges and solutions," in *2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS)*, pp. 216–219, IEEE, 2019.

[12] J. Li, X. Yang, and R. Sitzenfrei, "Rethinking the framework of smart water system: A review," *Water*, vol. 12, no. 2, p. 412, 2020.

[13] Y. Chen and D. Han, "Water quality monitoring in smart city: A pilot project," *Automation in Construction*, vol. 89, pp. 307–316, 2018.

[14] V. Radhakrishnan and W. Wu, "Iot technology for smart water system," in *2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, pp. 1491–1496, IEEE, 2018.

[15] P. Khatri, K. K. Gupta, and R. K. Gupta, "Drift compensation of commercial water quality sensors using machine learning to extend the calibration lifetime," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–9, 2020.

[16] S. Sinha, R. Bhardwaj, N. Sahu, H. Ahuja, R. Sharma, and R. Mukhiya, "Temperature and temporal drift compensation for al2o3-gate isfet-based ph sensor using machine learning techniques," *Microelectronics Journal*, vol. 97, p. 104710, 2020.

[17] R. Barzegar, M. T. Aalami, and J. Adamowski, "Short-term water quality variable prediction using a hybrid cnn–lstm deep learning model," *Stochastic Environmental Research and Risk Assessment*, pp. 1–19, 2020.

[18] P. Liu, J. Wang, A. K. Sangaiah, Y. Xie, and X. Yin, "Analysis and prediction of water quality using lstm deep neural networks in iot environment," *Sustainability*, vol. 11, no. 7, p. 2058, 2019.

[19] "OM2M Data server." https://www.eclipse.org/om2m.

[20] "ESP32 Data sheet." https://www.espressif.com.

[21] K. Dokic, "Microcontrollers on the edge–is esp32 with camera ready for machine learning?," in *International Conference on Image and Signal Processing*, pp. 213–220, Springer, 2020.

[22] "DFROBOT TDS sensor." https://wiki.dfrobot.com.

[23] "DFROBOT Temperature sensor." https://wiki.dfrobot.com.

[24] "Ultrasonic sensor." https://cdn.sparkfun.com/datasheets.

[25] A. F. Rusydi, "Correlation between conductivity and total dissolved solid in various type of water: A review," in *IOP Conference Series: Earth and Environmental Science*, vol. 118, p. 012019, IOP Publishing, 2018.

[26] L. Kleiboer and P. Havinga, "Calibration of sensors in sensor networks," in *2005 IEEE Conference on Emerging Technologies and Factory Automation*, vol. 2, pp. 8–pp, IEEE, 2005.

[27] E. C. Alexopoulos, "Introduction to multivariate regression analysis," *Hippokratia*, vol. 14, no. Suppl 1, p. 23, 2010.

[28] J. Xie and Q. Wang, "Benchmarking machine learning algorithms on blood glucose prediction for type i diabetes in comparison with classical time-series models," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 11, pp. 3101–3124, 2020.