AFRICAN JOURNAL OF SCIENCE, TECHNOLOGY AND SOCIAL SCIENCES

Journal website: https://journals.must.ac.ke

A Publication of Meru University of Science and Technology

Performance validation for an Internet of Things (IoT)-based Model for Hydro-Electric Monitoring

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ARTICLE INFO

KEY WORDS

Hydro-electric

Internet of Things (IoT)

Performance validation

Latency, Through-put

Metrics

ABSTRACT

Globally, hydro-power has been considered the cheapest renewable source of energy. This form of energy production entirely depends on the water levels which in turn causes a major concern of ensuring that the monitoring systems involved are capable of ensuring monitoring in the prevention of disasters. The disasters involved range from floods and drought conditions that would lead to low power production led by lack of enough water draining in the reservoirs'. Several systems have been implemented towards coming up with a convenient and efficient monitoring system. With the freedom given to software developers in developing the systems, evaluation of the performance of the system must be performed to enable this transformation. Therefore, the study selected n already existing real-time monitoring system using Lora Technology in hydroelectric monitoring to conduct the performance validation. A total of one hundred and twenty readings were taken to be validated with the other models used. Consistency, accuracy, latency, and throughput were the metrics used to validate the IoT-based model's performance. During the performance validation, the study found that the system achieved all the functionalities expected in its assessment. Therefore, IoT-based systems have the potential to inform future hydroelectric monitoring practices

Introduction

Energy can be classified as either renewable [1] or non-renewable [2]. Hydropower is currently the most successful form of renewable energy in Kenya [2]. According to the national energy policy Act 2018, hydro-power is estimated to have a potential of up to 6000 MW as of 2017. Hydropower generation is equally vulnerable to variations in hydrology and climate change leading to the reduction in water levels in the reservoirs [2]. Inadequate storage capacity in the existing power generation plants is also among the challenges present [3].

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https://doi.org/10.58506/ajstss.v2i2.182

Previously models have been used in other areas to monitor the entire process of hydropower generation and management. Barros analyzed the operation of the hydropower generating models observing some of the parameters like water inflow, energy generation and also the water pressure [3]. This monitoring process of the water levels in the

Hydropower Plants were being optimized through the use of nonlinear programming techniques. However, the model also had challenges to detect the probability of an error in the transmission model. Garrido et al. on the other hand, developed a model that made use of a data simulation tool that would be used in the plants for the run-off water in the rivers that fed the reservoirs by adjusting its configuration parameters and achieving good correlation between the two models involved which are the real data and correlation models.

The climate change effect taking place in the world has led to hydropower challenges; a rise in water levels as well as some regions suffering from prolonged droughts or floods[4]. This has led to an increase in the need for a secure and reliable model that can be able to predict the water patterns thus enabling the decision of power consumption in the country that's directly. The government in the need to sustain the power need in the country with the increasing population would therefore put in measures like additional water storage capacity among others.

The current models that monitor hydrological data are aimed at monitoring the water distribution patterns as well as the storage capacity. However, the need to embrace technology that monitors the performance of the technology in place for hydro-power production has not been put in place. IoT (Internet of Things) technology describes the physical objects that are embedded with sensors [5] that can process connect and exchange data with other devices in the models over the internet [1]. This technology is effective as it allows wireless connection of elements that would be used to collect data, visualizes, and store data in models that would enable correct implementation when in decision making. Several IoT technologies have been used in the past including sigfox [6], LoRA WAN (Long Range Wide Area Network) [7], and Narrowband [8] Internet of Things NB IoT. All of them are low-power technologies that could be used in a wide area. LPWAN (Low-Power Wide Area Network) technologies played a crucial role in monitoring hydrological data by enabling long-range and low-power communication between devices. These technologies are designed specifically for applications that require long-range connectivity while operating on low power consumption, making them ideal for monitoring remote areas and transmitting data from various hydrological sensors. They enabled efficient data collection, transmission, and analysis, enabling better decision-making in water resource management, flood prevention, and environmental monitoring.

The use of open source platforms has allowed monitoring of big data [9] projects at reasonable rates and as a result Several applications of open source monitoring models have been developed including the hydrological smart irrigating models, smart parking, smart light detectors as well as water quality monitoring models using the Arduino MKR WAN 1310 technology. In this research, LoRA technology was embraced. It is a low-power wide-area technology developed that enables a wide range of new IoT devices. It also improves the power consumption of the user devices, model capacity, and spectrum frequency. It has a long battery life going for up to about 10 years. The technology can co-exist well with 2G, 3G, and 4G networks. Looking at the nature of the research the environment

to place the devices that act as the sensors does not support the usage of Wi-Fi network [10] or the Ethernet. Wi-Fi networks and Wi-Fi-based appliances lose their connection to the various sites due to password changes or router changes thus not very reliable. The model will require a measuring and signal transmission device that can be used without power and thus adopting the LoRA. The model is a real–time that considers close monitoring of the parameters being observed. Once the correct data reading is collected and passed to the cloud the sites to be streamed data were essential to allow data visualization as well as the process of real-time monitoring. The success of the monitoring model led to the development of the data sites where in this research we used to use The Things Network [11]. Several sites are available including the things speak however; this site supports only the LoRA WAN technology. Using the wireless internet mode of communication data was appropriately sent to TTN. Several studies have shown regular data transmission over shorter distances using manual technology and none supported the long-range wireless transmission of data for over 80kilometers distance over an uninterrupted medium. Therefore the early system of monitoring contributed significantly to the efficiency of data transmission. Validation [12] is an activity usually done by researchers after the data collection process

To show the effectiveness of one model over the others based on some specific performance metrics. According to [13], during the model evaluation, the evaluation goals must be well defined, have specific user interface evaluation features, and have clearly defined usability metrics. The need to validate the performance of the models has increased because of the need to establish efficiency and effectiveness at the places of model usage. According to [13], validation of the model's performance means assessing the achievements in hardware, software, computer networks, data, and human resource upgrade and improving the quality of performance. The performance validation method is used based on analysis of the resource consumption as well as its influence on the hardware application. According to [14], metrics are criteria used to compare performance. The metrics that were used in the real monitoring model were; Accuracy, consistency, latency, and

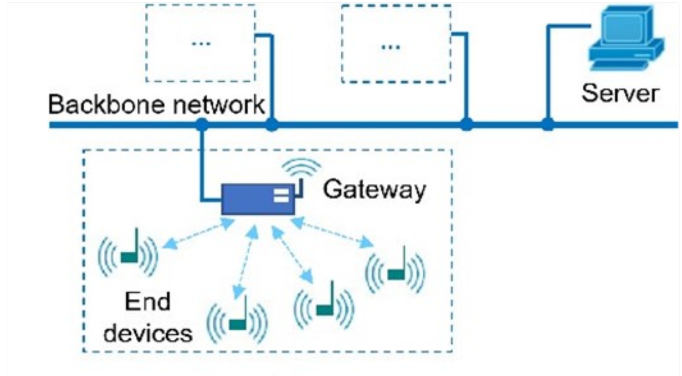

Figure 1: *A Real-Time Monitoring Lora Model Architecture[21]*

throughput of the data. The study aimed at validating the performance of the real-time monitoring hydroelectric model that had been developed. This monitoring model of the hydroelectric enabled collection of the data readings that would be validated as well as obtaining secondary data from the dataset developed in the model too.

Previous studies have validated the performance acceptance [15] and usability validation [16] of IoT technologies, especially in short-range operations. These studies have examined whether the validated models have worked as expected in complete usefulness and user satisfaction. However, there is a need to validate the performance of the Lora technology in real-time monitoring of the hydropower plants. These led to the author's motivation to begin the research work related to performance validation of the real-time monitoring due to cases of data loss and system break down thus leading to a lack of proper data monitoring methods during transmission and storage especially when there is an interrupt. The article is organized in the following structure. The material and methods section includes the performance validation conducted on the IoT-based model for real-time monitoring of the hydroelectric plant. The results present the outcomes of the validation. The discussion section describes the significance of the results obtained and the conclusion section gives a summary of the work.

Materials and Methods

Performance validation of IoT models is an essential task in research to enable one to justify the importance and significance of using fast-growing IoT technology to solve real-life issues. Therefore, embedded software [17] developers need to understand the LoRA IoT technology applications' performance after developing them. Using a real-time monitoring model in hydroelectric power plants, the study conducted performance validation to confirm that the model developed worked as expected to satisfy the user needs which in this case was the hydro-electric power monitoring. The study was carried out in Kenya in Murang'a County at Wanjii station which is part of the small hydro-power plants registered under the KenGen. Two rivers monitored that feed the water in the wanjii station reservoir namely river Mathioya and river Maragua. The choice of selecting this hydro-power station was because the researcher needed to deploy devices to a closer location for monitoring and also to save on operational costs of having to travel long distances to capture and observe data. During data collection, systems had real-time data being captured but for purposes of future analysis, secondary data was held and stored in cloud storage. During data collection, readings from the sensors were transmitted at an interval of five minutes per reading. This means that within one hour a total of twelve readings were supposed to have been transmitted to the TTN application server from the sensors, and later stored as secondary data in the cloud storage.

Therefore while performing the validation of this study a total of twelve readings at different intervals each were captured meaning that validation was done in hourly data collection readings. The arduino micro-controller [18] [19], the gateway [20], the Sensors and the TTN application server together with the cloud server were all interconnected to enable collect the readings that showed the results of the validated data from the IoT model for monitoring hydro-electric production.

The model's consistency [13] was measured by taking two water level and temperature readings from the same points to see the variations between the two readings collected from both parameters monitored.

While the consistency indicator [14] was being measured, we took a total of twelve readings within an hour. The readings were taken twice one after the other from the sensors capturing temperature and water level. The latency performance indicator was used to monitor the delay time it took from when the data was collected and readings are taken and when the readings got to the TTN application server. A total of ten readings were used to compute the latency observed from the research model.

The model's accuracy performance indicator was tested by observing the readings obtained by capturing the parameters of water level, temperature, and humidity using the manual devices and other separate readings taken using the IoT model devices that used the LoRA technology. A total of twenty-four readings were captured to test the accuracy. The performance indicator for accuracy computed the percentage error rate that was produced during the readings capturing process.

Results

The study towards validating the performance of the model used the following indicators, latency [22] , throughput [23] , accuracy[24] , and consistency. Each of the metrics was analyzed as follows:

A) Consistency

The model's consistency was observed and monitored by taking the manual temperature readings, water level readings, and humidity readings within the specified timeline over one hour at an interval of five minutes for the next reading to be taken. This means that within an hour an estimated total of twelve readings were captured.

Pair	N	Metric	Mean	Significance	95% Confidence interval		t	df	Sig.2 tailed
					Lower	Upper			
Sample 1	12	humidity	45	.000	1	1	-2.232	14	0
		Temperature	22.4	.000	1	1	-2.271	14	.557
		Water level	1.465	.000	1	-2.48	-2.268	14	.442
Sample 2	12	humidity	46.08	.000	1	1	-2.232	14	0
		Temperature	23.5	.000	-.391	1	-2.271	14	.557
		Water level	2.176	.000	-2.48	1	-2.268	14	.442

Table-1: *Consistency performance test*

Two separate one-hour readings were taken giving a total of twenty-four readings captured on an hourly basis. The two separate hourly readings were meant to observe the variations of the readings to capture the metric of consistency.

It was found that readings 1 and readings 2 for water level, and temperature readings were strongly and positively correlated with the data collected from the same point at different time frames using the same devices. They correlated at ($r=0.906, p<0.000$) (table 1). On the same parameters readings for readings 1 and readings 2 on the LoRA technology IoT devices, there was no significant average difference between the two readings ($t12= -2.232$ for the water level parameter and ($t12 = -2.27$ for the temperature parameter readings, and ($t12 = -2.268$ for the water level readings). The test seemed logical because the two water levels and temperature readings were similar. On average, the confidence level between the two pairs of data the difference observed was very minimal as from the table above. From the temperature readings, the difference observed was (1 to -0.391) while the humidity readings (1 to 1) and the water level readings ranged (1 to -0.248). This indicated that the confidence level in the readings and the difference between the tests was extremely minimal and thus the LoRa model produced consistent results. On average the readings on test 1 for humidity were more than those of test 2 by (1.08), the temperature difference between test 1 and test 2 was (1.1) and the water level readings difference between test 1 and test 2 was (0.611), if you keenly observe the difference between the average readings from the two test readings you realize it is very minimal and that confirms that the model we used using the LoRA technology produced consistent results.

B) Latency

The performance metric latency showed the delay time taken in the model between when the data readings were sent from the sensors and the time it took for the next reading to be observed from the TTN which is the application server where live readings of data real-time monitoring was taking place.

N from the table below indicated the total number of readings that were used to validate the latency metric. A total of ten data readings were used to calculate the delay time. From the table below it was observed that the minimum time taken for data transmission from the sensors to the gateway for transmission to the database for live storage and live data capturing was six micro-seconds while the maximum time taken was eight micro-seconds.

The average time taken out of the ten data readings was 0.72 micro-seconds and the standard deviation stood at 0.539. This illustrated that despite the long-range mode of data transmission being used on the IoT technology, the delay time was very minimal or almost insignificant as it was actually below ten seconds. Therefore it showed that the latency experienced with the model was not significant and thus the model performed efficiently with less to insignificant delay time.

	N	Maximum	Minimum	Mean	Std. Deviation
Time Difference Valid N (List Wise)	10	00:00:08	00:00:06	0.72 Seconds	0.539 Seconds

Table-2: *Descriptive statistics for latency*

C) Accuracy

The accuracy metric was used to test the comparison between temperature readings and the water level readings observed from the Lora model and was closely compared to those obtained from the manual water level meter reader for the height of the water level and the normal thermometer used to capture the temperature.

The table below showed data analyzed for paired sample T-Test. It was found that the water level and temperature readings from the LoRa module had a high correlation and were positively and strongly correlated ($r=0.903, p<0.000$) while the manual devices readings had a ($r=0.889, p<0.000$), This implies that the measurements were both consistent and the two devices were logical and consistent.

On the reading for Manual devices, there was no significant average difference between the two readings ($t_{12}= -2.271$, $p<0.557$). On Temperature and water level for LoRa devices, there was no significant average difference between the two readings ($t_{12}=-2.268$, $p<0.442$). This implies that the two devices gave almost the same readings which seemed logical.

On average, the manual Devices readings were less than the Lora module by 0.762 readings (95% CI [-2.377, 0.853] in addition, the manual devices readings were more than the LoRa module by 0. 952 readings (95% CI [-0.331, 2.236].

In conclusion, the study illustrated that the difference between the manual devices used and the IoT technology LoRa model used was extremely minimal and thus the LoRa IoT model is also accurate when compared to the manual device.

Pair	N	Metric	Mean	Significance	95% Confidence interval		t	df	Sig.2 tailed
					Lower	Upper			
Manual readings	12	Temperature	22.4	.000	-2.377	1	-2.271	14	.557
		Water level	1.465	.000	-1.77	-2.48	-2.268	14	.442
Lora module	12	Temperature	23.5	.000	-.391	1	-2.271	14	.557
		Water level	2.176	.000	-2.48	1	-2.268	14	.442

Table-3: *Accuracy paired sample data*

D) Throughput

Throughput is an indicator of the total amount of data that is transmitted within a given amount of time. With the study, readings were set to be captured at an interval of 5 minutes; this means that within an hour which is 60 minutes, 12 readings were supposed to be captured. The table below illustrates the actual total readings captured 100% as expected, and therefore the model produced the required output as required and operated as expected with zero error in transmission

Reading notification	Expected readings In 1 hour	Received readings	Accuracy %
Water Level readings	12	12	100
Temperature readings	12	12	100
Humidity readings	12	12	100

Table-4: *Throughput table*

Discussion

This section of our research study was used to validate the performance of the IoT-based model for hydroelectric power generation monitoring in Kenya, Wanjii station situated in Murang'a County. This is a critical activity in this research as it justifies how much better our model is as compared to the other models in the aspects of performance. The two things that determined the performance of the model were the interface and the applications used on the end nodes to collect the data. In the validation of the performance metrics [14], the following were used; latency, throughput, consistency, and lastly accuracy.

In the validation, the LoRa model for hydroelectric monitoring resulted to produce consistent results where the readings were taken from the same point of sensor data collection at alternate periods and the difference between the two test readings was extremely minimal and thus it illustrated that the Lora model was effective as it produced consistent results. The model's latency was extremely minimal and thus showing that its response time was very high. The average time taken out of the ten data sample readings was 0.72 seconds and the standard deviation was 0.539 seconds; Thus there was no prolonged delay in the data transmission. The device was also accurate compared to the manual devices used previously in the hydro-plants. The parameters measured were all closely related and showed to be accurate. The manual gadgets and devices used acted as control devices to be compared to the IoT model developed to validate the accuracy metric. Therefore, the study found the IoT LoRa model to be very reliable with an actual error rate insignificant.

Conclusion

The IoT-based model for hydroelectric monitoring has shown a great need for the hydroelectric production sector to adopt a reliable monitoring model to be well prepared for disaster management whether it's floods or drought. In future work, the research could be improved to come up with a model that can monitor the entire system including the turbine and valve operations and monitor the performance as well as faults and leakages. This great impedance would be very well adopted especially in developing countries as it illustrated a high response rate, accuracy, consistency, and hundred percentages in throughput. In short, the model can inform very critical decisions regarding the hydro-power plants' policies and future predictions in the monitoring model.

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