A Study on Reducing Measurement Fluctuations in Iron-Electrode Salinity Sensor Using Moving Average and Kalman Filters

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Abstract— **Indonesia is recognized as one of the leading shrimp-producing countries globally, with most farms operating on a small scale using traditional methods. This creates a strong demand for low-cost technologies to support aquaculture. One critical component in shrimp farming is water quality monitoring, where salinity is a key parameter affecting shrimp health and growth. Affordable salinity sensors using iron electrodes are increasingly considered. However, they often produce unstable and fluctuating readings, compromising monitoring reliability. This study addresses the issue by applying digital filters to enhance the stability of salinity sensor data. Two filtering methods, Moving Average and Kalman filters were evaluated using salinity ADC data from previous research. The analysis focused on comparing their effectiveness in stabilizing measurements. Results show that the Moving Average filter outperformed the Kalman filter, providing lower standard deviation values (87,09, 65,69, 63,67) and variance values (7,5807E+03, 4,3150E+03, 4,0542E+03), confirming its suitability for improving low-cost salinity sensor performance.**

Keywords: Digital filter, Kalman filter, Moving average filter, Salinity sensor.

I. INTRODUCTION

SHRIMP FARMING is one of the most profitable form of aquaculture, particularly in countries like Indonesia [1]. The country's vast marine territory and tropical climate provide favorable conditions for developing shrimp cultivation [2]. Ensuring high productivity requires proper management practices, especially in maintaining optimal pond water quality. The success of shrimp farming is highly dependent on several water quality parameters, such as temperature, pH, dissolved oxygen (DO), and salinity [3], [4]. Among these, salinity plays a critical role. In shrimp farming, water salinity must be maintained within an optimal range of 15 to 35 ppt to support healthy growth [5], [6]. Continuous monitoring is therefore necessary to ensure that salinity remains within this range, as deviations can negatively affect the entire shrimp growth cycle and reduce overall productivity.

Salinity sensor is a key device used to monitor the salinity levels in aquaculture ponds. This type of sensor is often integrated with other sensors as part of a water quality monitoring system [7]. Several studies have explored the development of salinity sensors [8], [9]. However, the most commonly used type is the salinity sensor with iron electrodes. Iron is frequently chosen due to its good electrical conductivity and low cost, making it suitable for salinity measurements [10], [11], [12]. Previous research has also investigated the use of iron electrodes for salinity detection [13], [14], [15]. For instance, Aldino et al. proposed a system that utilizes iron electrodes in three different signal conditioning schemes: voltage divider, capacitive coupling, and Wheatstone bridge [16]. Despite these efforts, the sensor output still exhibited fluctuations, indicating instability in the measurement data.

To address these limitations, this study explores the application of digital filtering techniques to enhance the stability and reliability of salinity sensor outputs. Specifically, we investigate the effectiveness of the Moving Average filter and the Kalman filter. The Moving Average filter is a well-known smoothing technique widely used in signal processing due to its simplicity and ability to reduce short-term fluctuations in noisy data [17], [18]. On the other hand, the Kalman filter is a recursive estimator that optimally predicts and updates system states by minimizing the mean squared error, and has been successfully applied in various fields including robotics, navigation, and sensor data processing [19], [20], [21]. Both filters have been previously employed in environmental monitoring and IoT-based systems to improve the accuracy and stability of sensor data [22], [23].

However, there has been limited investigation into the use of these filters specifically for low-cost salinity sensors with iron electrodes in aquaculture applications. Therefore, this study aims to evaluate and compare the performance of the Moving Average and Kalman filters in reducing fluctuations in salinity measurement data, as previously observed in the work of Aldino et al. The structure of this manuscript is detailed and systematically organized. Section 1 provides background information on shrimp farming, the importance of effective pond water management, and the rationale behind our focus on digital filtering. Section 2 describes the methodology employed, including the digital filtering scenarios implemented in this study. Section 3 presents our findings and evaluates the performance of the filters based on the tested scenarios. Finally, Section 4 offers our conclusions and outlines potential directions for future development of salinity sensor technologies.

II. METHOD

Filters are commonly used to eliminate noise from signals. These filters can be implemented either as analog filters, which consist of electronic circuits, or as digital filters, which are based on mathematical equations. In this study, we used digital filters due to their distinct advantages. Digital filters offer high stability, precision, and ease of implementation [24], [25]. Their flexibility in design and modification through software makes them well-suited for reducing fluctuations in salinity sensor data caused by noise. Although digital filters may introduce slight delays due to computational processes, their overall benefits make them an attractive option for developing salinity sensors with improved performance.

In this study, we employed two digital filtering methods: the Moving Average filter and the Kalman filter. Both filters were applied to the same dataset to evaluate and compare their performance. This approach allows us to determine which filter is more suitable and effective in achieving the objectives of this research.

The Moving Average filter calculates the average of the most recent input values within a defined sample window. In this study, the input data consists of ADC values from salinity measurements obtained in a previous experiment [16]. When a new ADC value is received, the oldest value in the dataset is discarded, and the latest input is added to the window. The filter then recalculates the average of the updated dataset. This averaged value becomes the filtered ADC output. The process is repeated iteratively to generate the complete filtered output corresponding to the full set of input data. The mathematical principle underlying the Moving Average filter is presented in equation (1) [26], [27].

$$y[n] = \frac{1}{N}\sum_{k=0}^{N-1} x[n-k] \tag{1}$$

Here, N denotes the total number of samples. The term $x[n]$ refers to the ADC input data, while $y[n]$ represents the corresponding filtered ADC output.

The Kalman filter method was also applied in this study. This filter operates based on a prediction and correction framework to generate more accurate estimations from noisy data. During the prediction phase, the Kalman filter estimates the ADC value based on previous measurements, along with the associated error covariance. In the correction phase, the predicted ADC value is adjusted using the newly acquired salinity data and the calculated Kalman gain. This process yields the final filtered ADC value. The Kalman filter calculations are presented in equations (2) and (3) for the prediction, and equations (4), (5), and (6) for the correction step [28], [19].

$$x_{t|t-1} = x_{t-1|t-1} \tag{2}$$

$$P_{t-1} = P_{t-1|t-1} + Q_t \tag{3}$$

$$X_{t|t} = x_{t|t-1} + K_t(y_t - x_{t|t-1} \tag{4}$$

$$K_t = P_{t|t-1}(P_{t|t-1} + R)^{-1} \tag{5}$$

$$P_{t|t} = (1 - K_t)P_{t|t-1} \tag{6}$$

In these equations, x represents the estimated ADC value, P is the state variance matrix, Q denotes the process variance matrix, K is the Kalman gain, and R is the measurement variance matrix. The subscripts $t|t$, $t-1|t-1$, and $t|t-1$ refer to the current data, the previous data, and the intermediate prediction step, respectively.

The filtered ADC data obtained from each method is used to evaluate and compare filter performance. These data sets are collected and analyzed based on their standard deviation and variance values, which indicate the variability of the salinity ADC measurements after filtering. Both statistical parameters provide insights into the stability of the sensor measurement data. Higher standard deviation and variance values imply greater variability, indicating that the data are less stable. Conversely, lower values reflect improved stability and therefore suggest better filter performance. The standard deviation is calculated using the formula presented in equation (7) [29].

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{7}$$

Where, s denotes the standard deviation, n represents the total number of samples, x_i is the data point, and $\bar{x}$ is the sample mean. Furthermore, the calculation of variance is presented in equation (8) [29].

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{8}$$

Here, s^2 indicates the variance, n denotes the total number of samples, x_i and $\bar{x}$ refer to the data point and the sample mean.

III. RESULT AND DISCUSSION

The results from previous research [16] are presented in Table I and illustrated in Figure 1. The fluctuations observed in the salinity measurements of salt solutions with concentrations of 10 ppt, 15 ppt, and 25 ppt suggest instability in the sensor readings. To address this issue, digital filtering techniques, such as moving average and Kalman filters, were applied to process the data. These methods were used to reduce data fluctuations and enhance the stability of the salinity sensor.

Table I
Salinity Measurement Data from sensor

Data	ADC Value		
	10 ppt	15 ppt	25 ppt
1	743	810	766
10	731	853	920
20	777	983	965
30	897	983	1085
40	947	983	1045
50	920	993	1009
60	951	983	1032
70	927	995	1042
80	975	1034	1020
90	1002	1077	1087

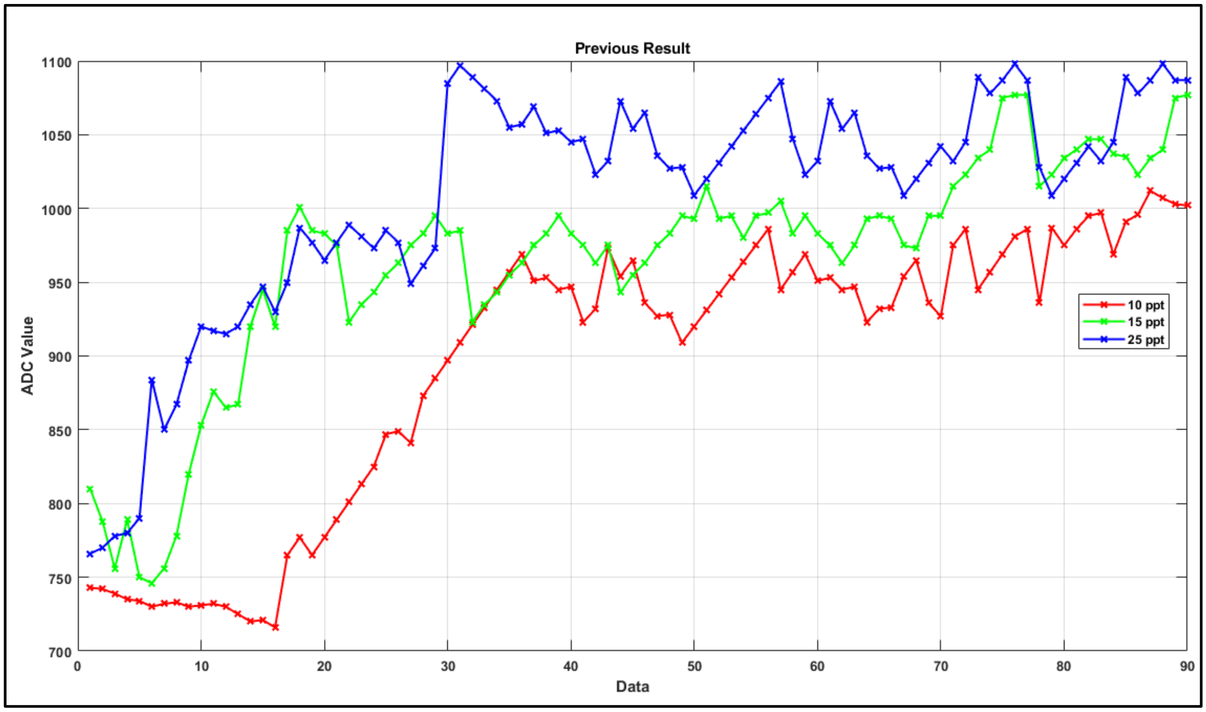

Figure 1. Raw data from salinity sensor

These data were processed using two types of digital filters. First, we used the moving average filter based on (1). This filtering was applied to every set of seven data points. The ADC data for the salinity sensor level of 10 ppt, 15 ppt, and 25 ppt were sequentially processed using the moving average filter. The results of the filtered ADC data from the salinity sensor are presented in Figure 2, Figure 3, and Figure 4. The red line represents the raw data from the salinity sensor, while the green line shows the result after applying the moving average filter. Based on these figures, the fluctuations in the ADC value of salinity sensor are noticeably reduced with the application of the moving average filter. The ADC values for each data point appear more stable than the raw sensor data. However, the ADC values exhibit a consistent upward trend corresponding to the increase observed in the raw data. This suggest that rising pattern in the raw ADC values from the salinity sensor continues to affect the filtered results.

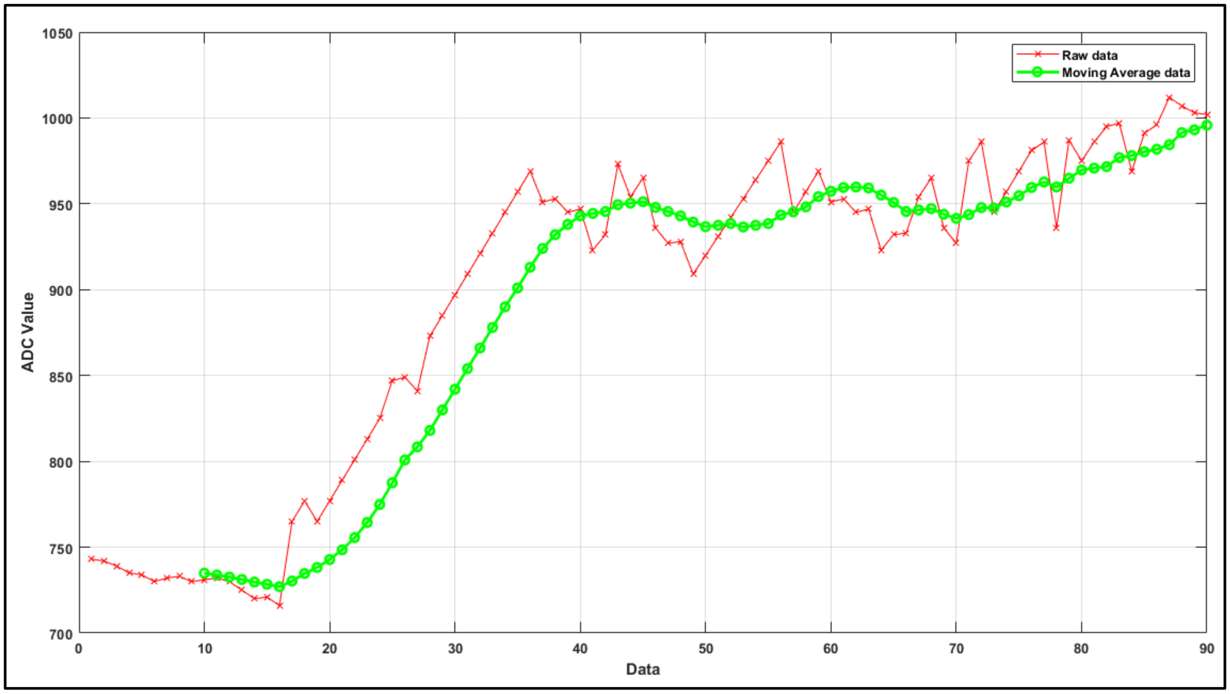

Figure 2. Moving average data result from 10 ppt salinity

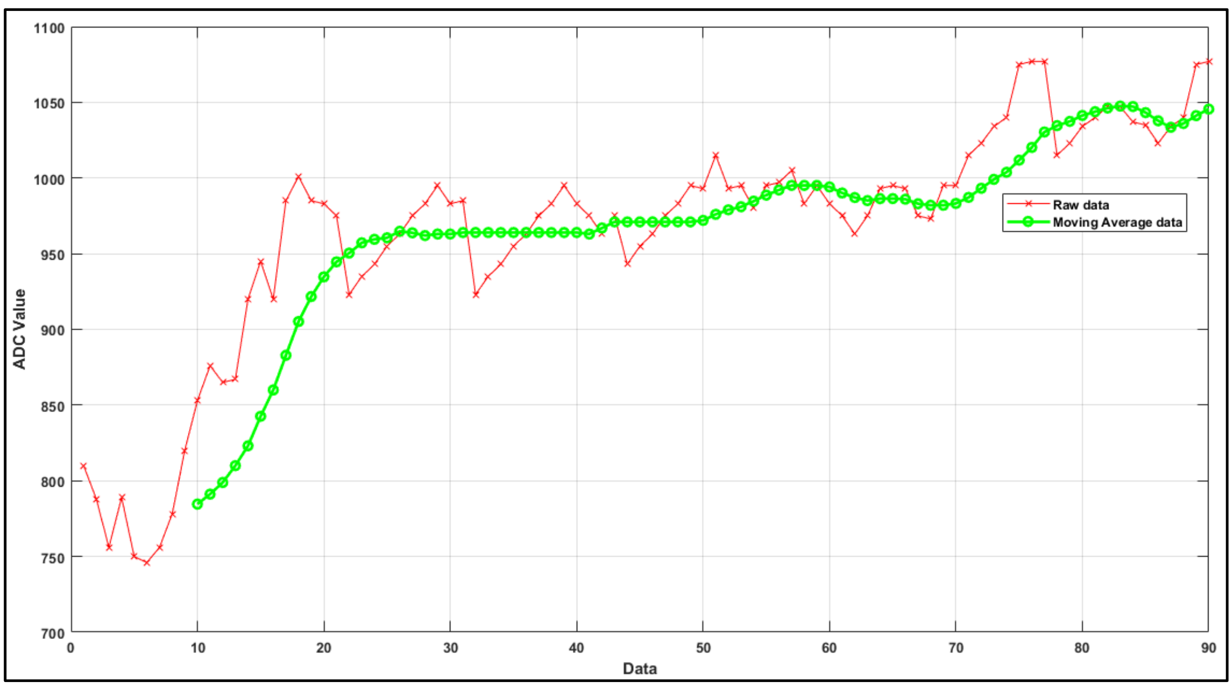

Figure 3. Moving average data result from 15 ppt salinity

The Kalman filter was also implemented to process the raw ADC data obtained from the salinity sensor. The calculations were based on (2) – (6). The parameters set with R = 7 and Q = 1, taking into account the output response to variations in the input values. Figure 5, Figure 6, and Figure 7 present the filtered result of the salinity sensor for salt solutions with concentration of 10 ppt, 15 ppt, and 25 ppt. The fluctuations in the ADC data from salinity sensor in red line were reduced by applying the Kalman filter (in green line). Similar to the results obtained with the moving average filter exhibited an upward trend corresponding to the increase in the raw ADC data. Additionally, a more significant gap was observed between the raw ADC data and the filtered data using the Kalman Filter, compared to the result produced by the moving average filter. This observation suggest that the moving average filter is more suitable for reducing fluctuations in the raw ADC data obtained from salinity sensor.

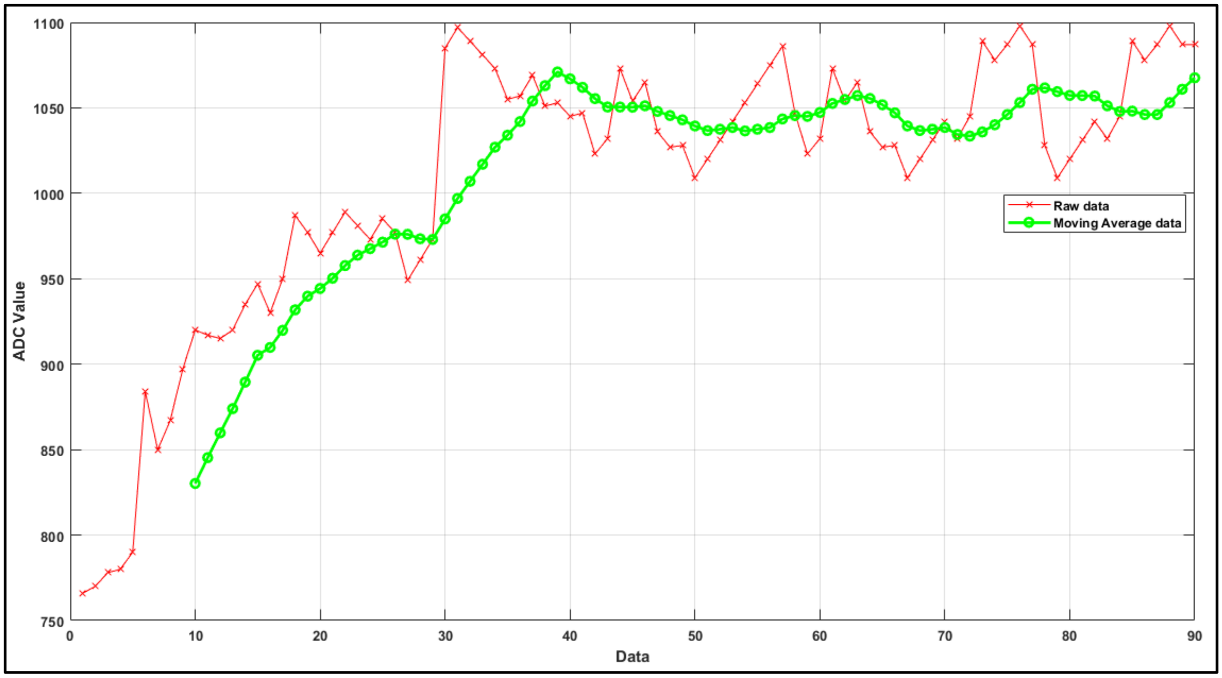

Figure 4. Moving average data result from 25 ppt salinity

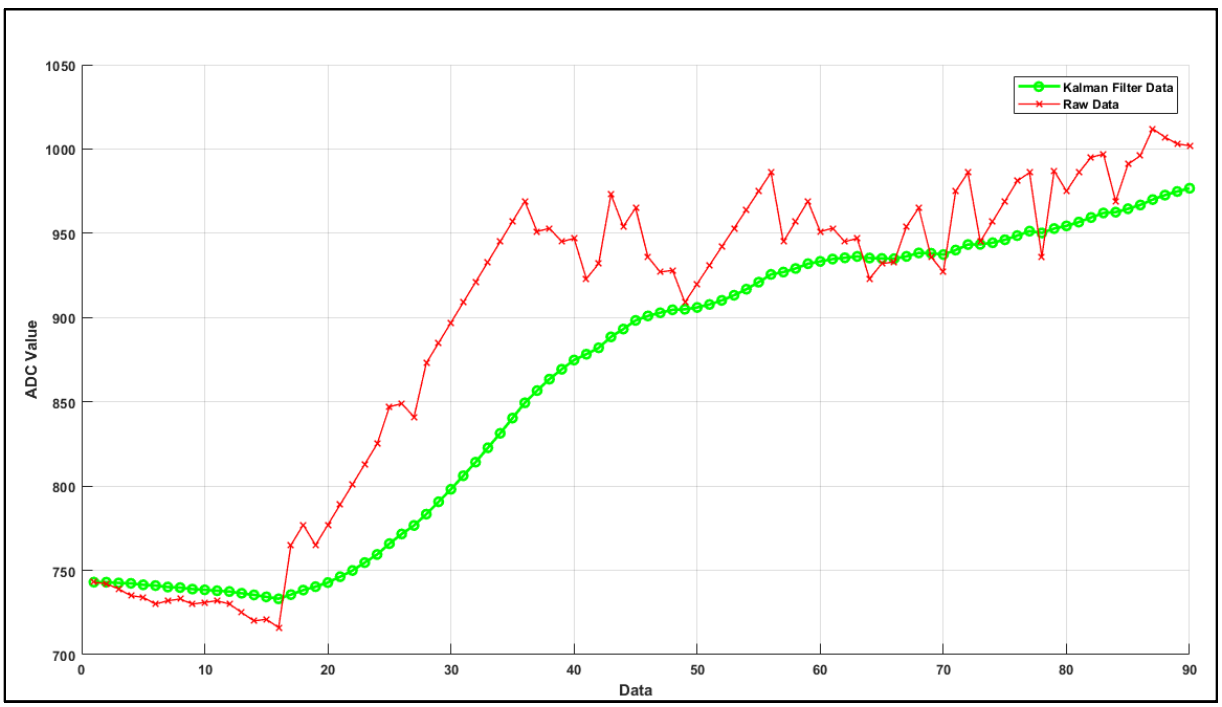

Figure 5. Kalman filter data result from 10 ppt salinity

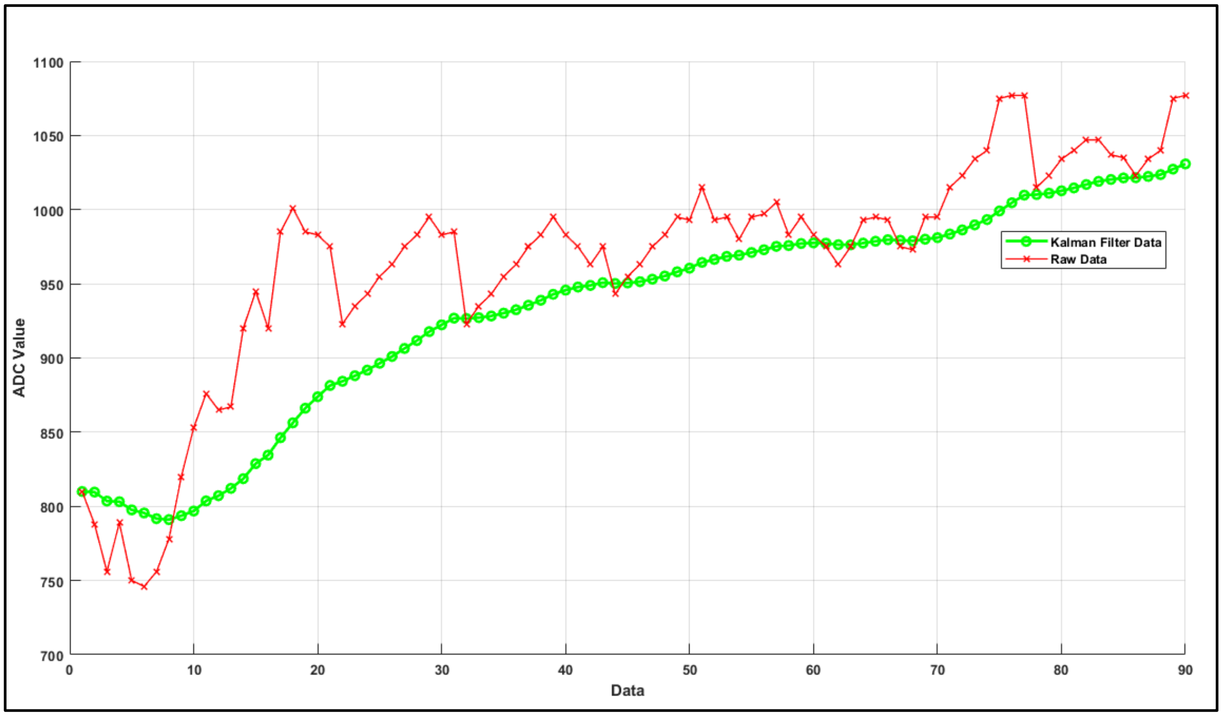

Figure 6. Kalman filter data result from 15 ppt salinity

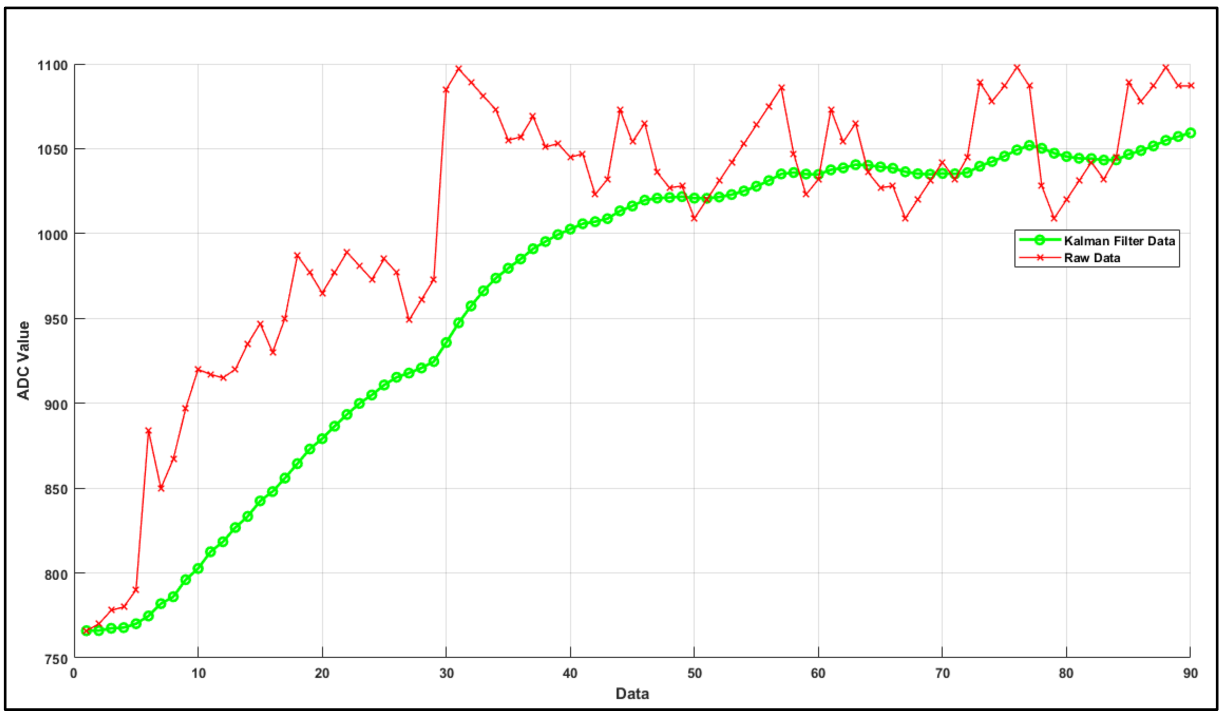

Figure 7. Kalman filter data result from 25 ppt salinity

Table II shows a comparison between the raw data, the Moving Average, and the Kalman filter. This conducted based on standard deviation and variance values. Both filters were able to reduce the fluctuations present in the raw salinity measurement data. The Moving Average filter consistently produced lower standard deviation and variance values across all salinity level compared to the Kalman filter. Therefore, this study hypothesizes the Moving Average filter is more appropriate for reducing fluctuations in salinity sensor to achieve stable reading. This attributed to the random nature of the fluctuations in the ADC data from salinity sensor, which makes the Moving Average filter more effective in this context [30].

Table II. Comparison of filter results

Method	Raw Data			Moving Average			Kalman		
	10 ppt	15 ppt	25 ppt	10 ppt	15 ppt	25 ppt	10 ppt	15 ppt	25 ppt
Standar Deviasi	95.20	80.19	77.15	87.09	65.69	63.67	87.79	94.27	71.86
Variansi	9.0628E+03	6.4301E+03	5.9521E+03	7.5807E+03	4.3150E+03	4.0542E+03	7.7065E+03	8.8862E+03	5.1650E+03

In this study, we conclude that the moving average filter is the most effective method for reducing fluctuations in salinity measurement. However, the observed increase in salinity sensor readings requires further investigation. This phenomenon may be attributed to the oxidation process between the iron-base electrodes and the saline solution, which can lead to electrode corrosion. Such corrosion may affect the accuracy and consistency of sensor readings. Furthermore, the implementation of a more advance signal conditioning circuit could potentially enhance the stability of the salinity sensor reading.

IV. CONCLUSION

This study evaluated the use of digital filtering techniques specifically the Moving Average and the Kalman filters to improve the stability of salinity sensor readings using iron electrodes. Both filters were effective in reducing fluctuations in the raw sensor data. However, the Moving Average filter demonstrated superior performance, as evidenced by lower standard deviation and variance values. This finding suggests that simple filtering methods can significantly enhance data reliability in low-cost salinity sensor technology. Despite these promising results, the study has several limitations. The analysis was conducted using previously collected data, and no real-time or field testing was performed, which may limit the generalizability of the results to dynamic environmental conditions. Future work should address these limitations by implementing the filters in real-time embedded systems, conducting in-field validation, and evaluating alternative electrode materials and signal conditioning circuits for improved performance in practical aquaculture applications.

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