Trade-Off Analysis of Moving Average Filter in Light Sensors

Manuscript received February 11, 2026; revised May 16, 2026

Nova Ariyanto
Electrical Engineering Department,
Universitas Negeri Surabaya,
Surabaya, Indonesia
nova.23144@mhs.unesa.ac.id

Farid Baskoro
Electrical Engineering Department,
Universitas Negeri Surabaya,
Surabaya, Indonesia
faridbaskoro@unesa.ac.id

Rifki Firmansyah
Electrical Engineering Department,
Universitas Negeri Surabaya,
Surabaya, Indonesia
rifqifirmansyah@unesa.ac.id

Lilik Anifah
Electrical Engineering Department,
Universitas Negeri Surabaya,
Surabaya, Indonesia
lilikanifah@unesa.ac.id

Tri Wrahatnolo
Electrical Engineering Department,
Universitas Negeri Surabaya,
Surabaya, Indonesia
triwrahatnolo@unesa.ac.id

Abstract*—Light intensity measurements based on sensors often experience signal quality degradation due to noise interference. Although filtering methods are commonly used to reduce noise, improvements in signal stability are frequently accompanied by changes in dynamic response, resulting in a trade-off between accuracy and response speed that has not been extensively analyzed. This study aims to quantitatively evaluate the effect of Moving Average Filter (MAF) parameters on this trade-off in light sensor systems. The proposed method employs a first-order system simulation with a step input signal contaminated by White Gaussian Noise, which is subsequently processed using the MAF with various window sizes (n = 3, 5, 10, 20, and 40). The evaluation is conducted using Root Mean Square Error (RMSE) and rise time as indicators of estimation accuracy and response speed, respectively. The results demonstrate that increasing the window size significantly reduces the RMSE, decreasing from 0.0156 to 0.0072 under step-up conditions and from 0.0132 to 0.0066 under step-down conditions. Optimal performance is observed within the range of n = 10–20. However, this improvement in accuracy is accompanied by an increase in rise time, from 0.1027 s to 0.1175 s for step-up conditions and from 0.1036 s to 0.1191 s for step-down conditions, indicating a slower dynamic response. These findings confirm the existence of a trade-off between signal accuracy and response speed. Therefore, this study provides a quantitative basis for determining optimal filter parameters by considering the balance between measurement accuracy and system responsiveness in light intensity sensing applications.

Keywords—Light Intensity, Moving Average Filter, Noise Reduction, RMSE, Trade-Off

I. INTRODUCTION

Light is the portion of the electromagnetic spectrum detectable by the human visual system and plays a crucial role in various applications, including lighting systems, environmental monitoring, and optical instrumentation [1]. Optical measurement techniques have been widely adopted in various fields because of their high accuracy and broad wavelength range [2]. Light intensity, also referred to as illuminance, represents the amount of light incident on a surface per unit area and is commonly expressed in lux [3]. In practical applications, light intensity is measured using light sensors that employ the photoelectric effect to convert optical signals into electrical outputs [4], [5]. Various types of light sensors have been developed, including Light Dependent Resistors (LDRs), photodiodes, phototransistors, and photomultiplier tubes, each with different sensitivity levels and operational characteristics for detecting changes in light intensity [5], [6]. Among these devices, LDRs are widely used because of their affordability, ease of integration with microcontroller-based systems, and adequate sensitivity to detect changes in light intensity [7].

An LDR sensor operates by changing its resistance in response to the intensity of incident light on its surface [8]. These sensors are commonly used in microcontroller-based monitoring systems and are often integrated with communication networks and Internet of Things (IoT) platforms to enable real-time environmental monitoring [9]. The resistance of an LDR decreases as the incident light intensity increases, and increases as the incident light intensity decreases [10], [11]. This characteristic enables the LDR to function effectively as a sensing element in microcontroller-based light intensity measurement systems [12]. Although widely used, LDR sensors exhibit several limitations. Their measurement accuracy is affected by environmental conditions, variations in sensor characteristics, and the nonlinear relationship between resistance and light intensity [7]. In addition, the use of low-cost sensors tends to produce relatively large measurement deviations, resulting in signals containing fluctuations or noise caused by external disturbances [13]. Consequently, these disturbances can reduce signal stability, leading to measurement results that are less consistent and less representative of actual light intensity conditions [14].

To improve the quality of sensor measurement data, various digital signal processing techniques have been developed. Among these techniques, filtering is one of the most commonly used approaches for noise reduction and signal quality improvement [15], [16]. Several commonly used digital filtering methods include the Kalman filter, Hanning filter, and Moving Average Filter (MAF) [17]. Among these methods, the Moving Average Filter (MAF) is considered one of the simplest and most widely used approaches because of its ease of implementation and effectiveness in smoothing signal fluctuations [18], [19]. This method operates by averaging a series of previous

 EISSN: 2961-872X ●PISSN: 2961-8924●DOI: 10.56741/IISTR.esl.002255

measurement values to produce a smoother and more stable output signal [20]. Furthermore, the Moving Average Filter has been shown to effectively reduce random noise in sensor data and improve measurement stability in various sensor-based monitoring systems [21].

Several previous studies have investigated the application of digital filtering methods to improve sensor measurement quality. The implementation of the Moving Average Filter has been shown to effectively reduce noise and improve signal stability in various sensor systems [20], [21]. Furthermore, comparative studies involving multiple filtering techniques, such as the Kalman Filter and other smoothing methods, indicate that the Moving Average Filter provides a favorable balance between implementation simplicity and filtering performance [17], [18]. Recent studies also indicate that increasing the filter window size improves signal smoothness; however, this improvement is often accompanied by a slower system response due to delays introduced by the filtering process [19], [22]. These findings indicate that the selection of filter parameters plays an important role in determining overall system performance.

Although digital filtering methods have been widely applied to improve sensor measurement quality, most previous studies primarily focus on noise reduction without quantitatively evaluating the influence of filter parameters on system dynamic response. Several studies report improved signal stability through the implementation of the Moving Average Filter; however, the relationship between filter parameters and response characteristics, such as rise time, has not been thoroughly analyzed [17], [21]. Furthermore, studies incorporating dynamic system modeling to investigate the trade-off between noise reduction capability and response speed in LDR-based light sensor systems remain limited.

Therefore, this study proposes a quantitative analysis based on a first-order system simulation to evaluate the effect of Moving Average Filter window size variation on both signal quality and system dynamic response. The primary contribution of this study lies in characterizing the trade-off between accuracy, represented by RMSE, and response speed, represented by rise time, as a basis for determining optimal filter parameters in LDR-based light intensity measurement systems.

II. Research Method

This study employs a quantitative simulation-based approach to analyze the effect of the Moving Average Filter (MAF) on signal quality in a light intensity measurement system using a Light Dependent Resistor (LDR) sensor. The simulation model is used to represent the dynamic characteristics of the sensor in response to changes in light intensity under controlled conditions, as well as to evaluate the effectiveness of the filtering method in reducing noise in sensor signals without being affected by variability in real experimental environments.

A. First-Order Dynamic Model of the Sensor System

In this study, the dynamic characteristics of the sensor are modeled using a first-order system, which is commonly employed to represent the transient response to input changes [23]. The transfer function of the sensor system is expressed as follows.

$$G(s) = \frac{K}{\tau s+1} \quad (1)$$

where:

$G(s)$ is the transfer function of the first-order sensor model,
K is the system gain,
τ is the sensor time constant,
s is the Laplace variable.

This model indicates that the sensor response does not occur instantaneously but requires a certain amount of time to reach a steady-state condition. In the time domain, the model can be represented by the following first-order differential equation [23].

$$\tau \frac{dy(t)}{dt} + y(t) = K\, u(t) \quad (2)$$

where:

$y(t)$ is the sensor output signal,
$u(t)$ is the input light intensity signal,
$dy(t)$ represents the change in the sensor output signal,
dt represents the change in time.

B. Input Signal Generation

To represent sudden changes in light intensity, two input scenarios are considered:

1. A transition from dim to bright conditions (step-up)
2. A transition from bright to dim conditions (step-down)

These scenarios are selected because they represent common operating conditions in light intensity measurement systems, such as transitions between dark and bright environments. The step-up input is modeled as follows [23].

$$u_{up(t)} = \begin{cases} L_1, t < t_0 \\ L_2, t \geq t_0 \end{cases} \quad (3)$$

The step-down input is modeled as follows [23].

$$u_{down(t)} = \begin{cases} L_2, t < t_0 \\ L_1, t \geq t_0 \end{cases} \quad (4)$$

where:

$u_{up(t)}$ represents the step-up input signal,
$u_{down(t)}$ represents the step-down input signal,
L_1 is the initial light intensity (dim),
L_2 is the final light intensity (bright),
t denotes time, and
t_0 is the time at which the change occurs.

The use of these two input types allows the analysis of the system response to both sudden increases and decreases in light intensity.

C. Addition of White Gaussian Noise

The sensor output signal is subsequently corrupted by White Gaussian Noise to simulate real operating conditions in measurement systems. Noise in sensor data may originate from various sources, including environmental disturbances, data acquisition processes, and electronic components in the measurement system [14]. The noisy signal model is expressed as follows [18].

$$y_n(t) = y(t) + n(t) \quad (5)$$

where:

$y_n(t)$ is the noise-contaminated signal,

 EISSN: 2961-872X ●PISSN: 2961-8924●DOI: 10.56741/IISTR.esl.002255

$y(t)$ is the original sensor signal,
$n(t)$ is the Gaussian noise.
The addition of noise is intended to evaluate the effectiveness of the filtering method in improving sensor signal quality.

D. Moving Average Filter

After the sensor signal is corrupted by noise, a filtering process is performed using the Moving Average Filter (MAF). The Moving Average Filter is a digital filtering method that operates in the time domain and is one of the most commonly used techniques in digital signal processing because of its ease of implementation [17]. The fundamental principle of this method is to calculate the average of several consecutive data points to produce a smoother and more stable output signal.
The Moving Average Filter equation is expressed as follows [20], [24].

$$y[i] = \frac{1}{n} \sum_{i=0}^{n} x[i-k] \quad (6)$$

where:
$y[i]$ is the filtered output signal,
n is the filter window size,
i represents the current sample index, and
k denotes the sample offset within the averaging window.
The term x[i-k] represents the previous input samples used in the averaging process. The Moving Average Filter reduces signal fluctuations caused by noise, resulting in a more stable signal.

In addition to noise reduction, the Moving Average Filter also introduces a delay due to the data averaging process. The filter delay is expressed as follows [18], [24].

$$T_d = \frac{n-1}{2} T_s \quad (7)$$

where:
T_d is the filter delay,
T_s is the sampling time.
This equation indicates that increasing the filter window size results in greater system delay, leading to a slower dynamic response.

In this study, several window size variations (n) are evaluated as follows:

$$n = 3, 5, 10, 20, and\ 40.$$

Variations in the parameter n affect both the filter's noise suppression capability and the system's dynamic response. A larger value of n produces a smoother signal; however, it may also result in a slower system response [24].

Fig 1 illustrates the block diagram of the proposed system used to evaluate the performance of the Moving Average Filter. A step signal is applied to a first-order sensor model representing the dynamic behavior of the light sensor system. The resulting sensor output is subsequently contaminated by White Gaussian Noise to simulate real measurement disturbances. The noisy signal is then processed using the Moving Average Filter with various window sizes. Finally, the filtered output is compared with the reference signal to evaluate filtering performance in terms of noise reduction and dynamic response characteristics.

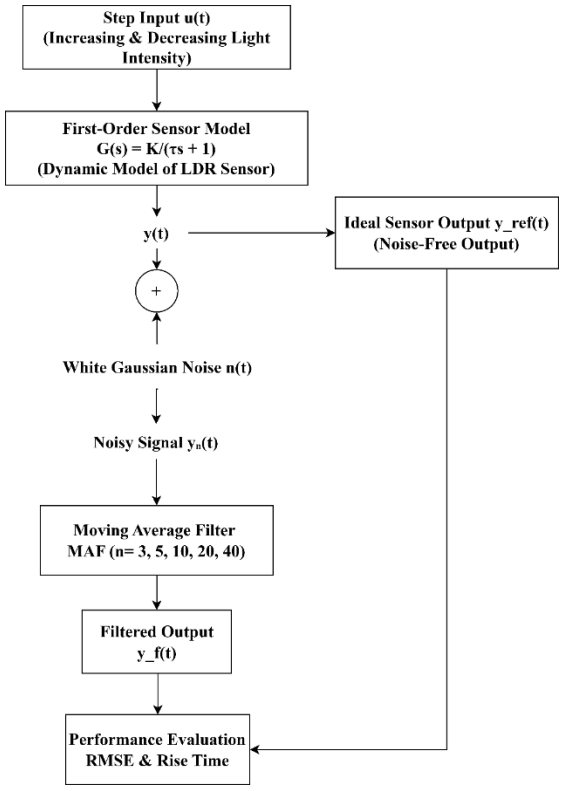


Fig. 1. Block Diagram of the Research System

Fig. 2 illustrates the research methodology employed in this study. The process begins with a literature review to examine the characteristics of light sensors and filtering methods used in sensor signal processing.

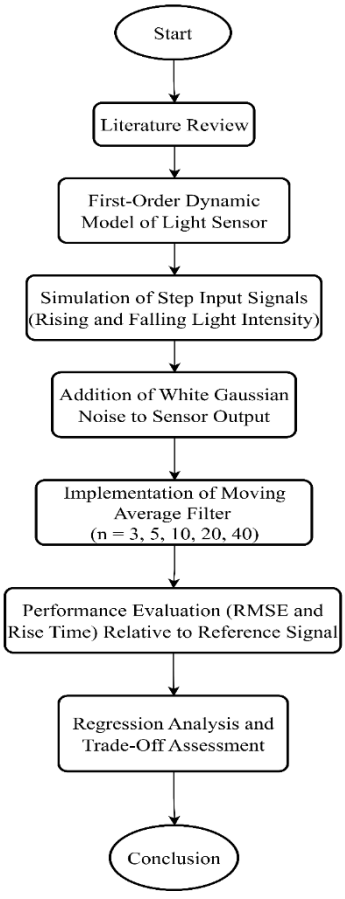


Fig. 2. Flowchart

Subsequently, a first-order sensor system is modeled, followed by the generation of step input signals and the addition of White Gaussian Noise to simulate measurement disturbances. The noisy sensor signal is then processed using the Moving Average Filter with various window size parameters. Finally, the filtered results are evaluated using performance metrics to assess filtering effectiveness in terms of noise reduction and dynamic response characteristics.

E. System Performance Evaluation

System performance evaluation is conducted based on two main parameters, namely Root Mean Square Error (RMSE) and rise time.

1) Root Mean Square Error

The RMSE parameter is used to quantify the error between the filtered signal produced by the proposed method and the reference signal. RMSE is mathematically defined as follows [17], [18].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{[i]} - y_{ref[i]}} \quad (8)$$

where:

$y_{[i]}$ is the filtered signal,

$y_{[ref]}$ denotes the reference signal, and

N is the number of samples.

A lower RMSE value indicates a closer agreement between the filtered output and the reference signal.

2) Rise Time

In addition to RMSE, rise time is used to evaluate the speed of the system response to input changes. Rise time is defined as the time required for the system response to increase from 10% to 90% of its steady-state value and is expressed as follows [23].

$$T_r = t_{90}\% - t_{10}\% \quad (9)$$

where:

T_r denotes the rise time,

$t_{90}\%$ is the time at 90% of the steady-state response,

$t_{10}\%$ is the time at 10% of the steady-state response.

This parameter is used to analyze the effect of filter window size on system response speed. Although the Moving Average Filter improves signal quality through noise reduction, it may also reduce system bandwidth, resulting in a slower dynamic response [24].

F. System Trade-off Analysis

The evaluation results of RMSE and rise time are used to analyze the trade-off between signal stability and system response speed. A Moving Average Filter with a larger window size produces a more stable output because noise-induced fluctuations are more effectively suppressed. This behavior is consistent with previous studies indicating that averaging-based filters improve signal smoothness and reduce noise variance [18], [19].

However, the use of an excessively large window size may lead to a slower system response because of the accumulation of previous data during the filtering process. This phenomenon is associated with the inherent delay characteristic of Moving Average Filters, which operate as low-pass filters and introduce lag into the system response [24].

Therefore, this trade-off analysis aims to determine the optimal Moving Average Filter parameter for improving sensor signal quality without causing significant degradation in dynamic performance. The balance between noise reduction and response speed is an important consideration in selecting an appropriate window size, as also reported in previous studies on filtering performance [19].

III. Results and Discussion

The results of this study were obtained through simulations of a light sensor system model as a first-order system subjected to a step input signal. To represent realistic measurement conditions, White Gaussian Noise was added to the sensor output, resulting in sensor signals contaminated by noise. This condition is commonly encountered in sensor-based measurement systems, where acquired signals are often affected by various noise sources, including environmental disturbances, electronic interference, and data acquisition processes [14].

After the addition of noise, the signal was processed using the Moving Average Filter (MAF) to reduce signal fluctuations. The Moving Average Filter is a digital filtering technique that operates by averaging a sequence of data samples, thereby reducing random fluctuations in the signal [17]. This method is widely used in sensor data processing because of its effectiveness in noise reduction and ease of implementation in digital signal processing systems [22].

The evaluation is conducted by varying the window size (n) of the Moving Average Filter to analyze its effects on signal quality and system response characteristics.

Table 1. Performance Evaluation Results of the Moving Average Filter for Various Window Sizes

Window Size *(N)*	RMSE Up	RISE Time Up	RMSE Down	Rise Time Down
3	0.0156	0.1027	0.0132	0.1036
5	0.0123	0.1054	0.0098	0.1083
10	0.0088	0.1111	0.0073	0.1095
20	0.0072	0.1145	0.0066	0.1092
40	0.0101	0.1175	0.0095	0.1191

Based on the simulation results presented in Fig. 3 to Fig. 8, system performance is evaluated in terms of signal behavior, filtering effectiveness, and the trade-off between accuracy and dynamic response under both step-up and step-down conditions using the Moving Average Filter (MAF).

Fig. 3 presents the raw sensor output contaminated by noise in comparison with the ideal first-order response. The noisy signal exhibits significant fluctuations, particularly under steady-state conditions, while still following the general trend of the reference signal. These fluctuations indicate that the sensor output is affected by random disturbances, thereby requiring filtering to improve signal quality.

Fig. 4 and Fig. 5 illustrate the filtered responses for the step-up and step-down inputs, respectively. Increasing the window size produces a smoother output signal, indicating improved noise suppression performance. However, larger window sizes also introduce a noticeable delay in tracking the reference signal, particularly during transient conditions. This behavior reflects the inherent characteristic of the Moving Average Filter as a low-pass filter that attenuates high-

 EISSN: 2961-872X ●PISSN: 2961-8924●DOI: 10.56741/IISTR.esl.002255

frequency noise while simultaneously slowing the system response [16].

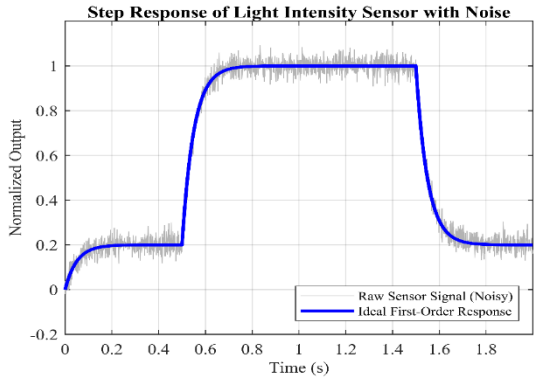


Fig. 3. Time response of a first-order light intensity sensor with noise

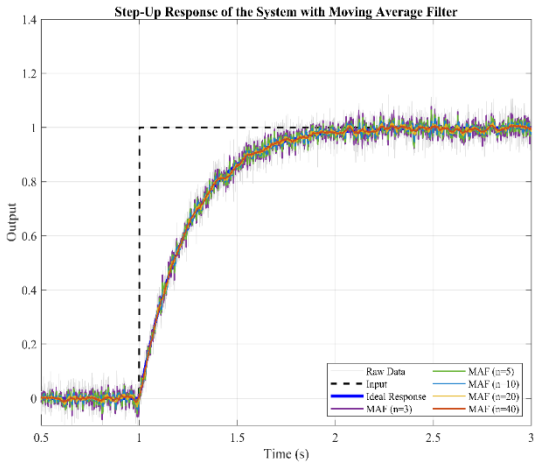


Fig. 4. Step-up time response of the system with MAF for various window sizes

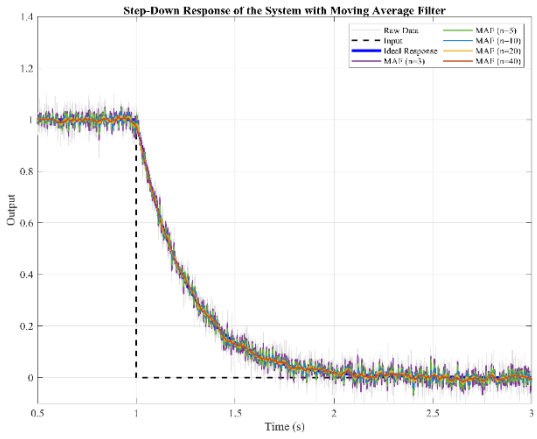


Fig. 5. Step-down time response of the system with MAF for various window sizes

Fig. 6 presents the RMSE performance for different window sizes. For the step-up response, the RMSE decreases from 0.0156 at n = 3 to 0.0123 at n = 5 and 0.0088 at n = 10, reaching a minimum value of 0.0072 at n = 20 before increasing to 0.0101 at n = 40. Similarly, for the step-down response, the RMSE decreases from 0.0132 at n = 3 to 0.0098 at n = 5 and 0.0073 at n = 10, reaching a minimum value of 0.0066 at n = 20 before increasing to 0.0095 at n = 40. These results indicate that increasing the window size effectively reduces noise up to an optimal point, beyond which excessive smoothing degrades estimation accuracy, as also reported in previous studies [17].

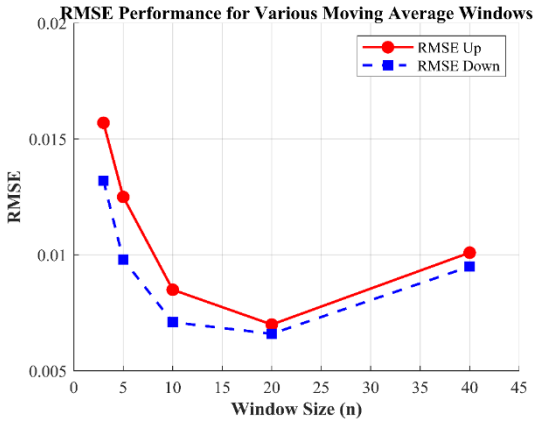


Fig. 6. RMSE comparison for various MAF window sizes under step-up and step-down conditions

The increase in RMSE at larger window sizes ($n > 20$) can be attributed to distortion during the transient phase. When the filter window becomes excessively large relative to rapid signal variations, the averaging process incorporates outdated samples that no longer accurately represent the current signal condition. Consequently, over-smoothing occurs, causing important signal components to be attenuated along with noise. This effect introduces additional delay and increases estimation error, consistent with the fundamental behavior of Moving Average Filters [16]. This behavior is consistent with the filtered responses shown in Figures 4 and 5, where larger window sizes produce smoother outputs but slower tracking of the reference signal. Furthermore, Figure 8 shows that the RMSE curve exhibits a nonlinear U-shaped trend, with the optimal operating region located within the range of n = 10–20 rather than at a single window size.

Fig. 7 presents the rise time variation as a function of window size. For the step-up response, the rise time increases from 0.1027 s at n = 3 to 0.1054 s at n = 5 and 0.1111 s at n = 10, further increasing to 0.1145 s at n = 20 and reaching 0.1175 s at n = 40. A similar trend is observed for the step-down response, where the rise time increases from 0.1036 s at n = 3 to 0.1083 s at n = 5 and 0.1095 s at n = 10, slightly decreasing to 0.1092 s at n = 20 before increasing to 0.1191 s at n = 40. These results indicate that increasing the window size generally slows the dynamic response of the system because of the averaging process, commonly referred to as smoothing-induced delay [16].

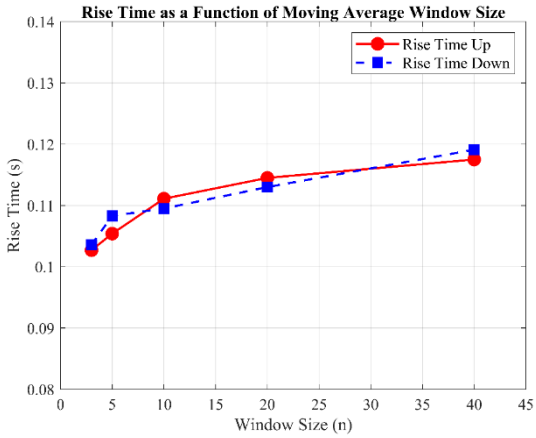


Fig. 7. Effect of MAF window size on rise time for step-up and step-down responses

Fig. 8 illustrates the trade-off between RMSE and rise time for different Moving Average Filter window sizes. The

optimal operating region is observed within the range of n = 10–20, where the RMSE values are significantly reduced while the increase in rise time remains relatively moderate. For the step-up response, the RMSE decreases from 0.0156 at n = 3 to 0.0072 at n = 20, whereas the rise time increases from 0.1027 s to 0.1145 s. Similarly, for the step-down response, the RMSE decreases from 0.0132 at n = 3 to 0.0066 at n = 20, while the rise time increases from 0.1036 s to 0.1092 s. These results indicate that moderate window sizes provide a balanced compromise between noise suppression capability and dynamic response performance.

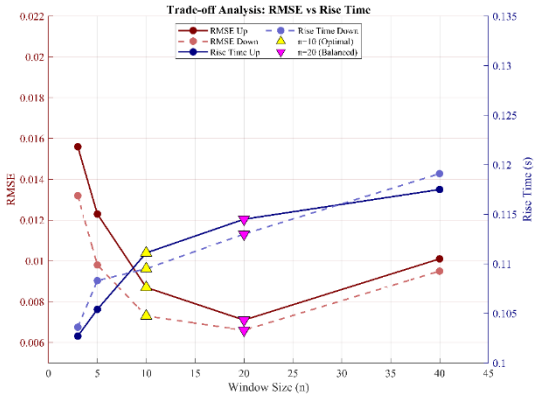


Fig. 8. RMSE–rise time trade-off for various Moving Average Filter window sizes

However, when the window size is increased to n = 40, both RMSE and rise time increase noticeably. The step-up RMSE rises to 0.0101 with a corresponding rise time of 0.1175 s, whereas the step-down RMSE increases to 0.0095 with a rise time of 0.1191 s. This behavior is directly related to the filter delay characteristic of the Moving Average Filter, as described in Equation $Td = \frac{n-1}{2} T_s$ (*7*), in which the delay increases proportionally with the window size. According to the equation $Td = \frac{n-1}{2} T_s$ (*7*), increasing the window size from n = 20 to n = 40 approximately doubles the filter delay, contributing to the noticeable increase in both rise time and RMSE. As the value of n increases, a larger number of previous samples are incorporated into the averaging process, thereby increasing the effective filter delay during transient conditions. Consequently, the temporal mismatch between the filtered output and the reference signal becomes larger, increasing the RMSE value. This effect becomes more pronounced at n = 40, where the additional delay introduced by the averaging process outweighs the benefit of noise reduction. Although a larger window size produces a smoother signal, the slower transient response reduces the filter's ability to accurately track rapid signal variations. As a result, both rise time and estimation error increase simultaneously, indicating degradation in both dynamic response and estimation performance. Similar behavior has been reported in previous studies, where increasing the Moving Average Filter window size improves noise suppression performance but also introduces greater response delay and reduced dynamic accuracy [19], [22], [24]. These findings quantitatively confirm the existence of a trade-off between noise suppression capability and dynamic response in Moving Average Filter implementation.

Overall, the results demonstrate that the Moving Average Filter introduces a trade-off between noise reduction and dynamic response. A moderate window size within the range of n = 10–20 provides the most favorable trade-off by achieving low RMSE values for both step-up and step-down responses while maintaining relatively fast response times. These findings confirm that optimal filter design requires a balanced consideration of both filtering accuracy and response speed.

IV. Conclusion

This study demonstrates that the window size of the Moving Average Filter (MAF) is a critical parameter governing the trade-off between signal accuracy and dynamic response in an LDR-based light intensity measurement system modeled as a first-order system. The results indicate that increasing the window size effectively reduces noise up to an optimal operating range of n = 10–20, where the RMSE reaches minimum values of 0.0088–0.0072 for the step-up response and 0.0073–0.0066 for the step-down response while maintaining relatively moderate dynamic response characteristics. Beyond this range, particularly at n = 40, excessive smoothing and increased filter delay introduce transient mismatch and higher estimation error, resulting in degraded dynamic performance. These findings quantitatively confirm the existence of a trade-off between noise suppression capability and system responsiveness, in which improved signal smoothness is inherently accompanied by a slower transient response. Furthermore, this study provides a quantitative basis for selecting Moving Average Filter parameters by emphasizing that optimal filtering performance is achieved through a balanced consideration of both estimation accuracy and response speed rather than solely minimizing RMSE.

However, this study is limited to simulations based on a first-order system model under White Gaussian Noise assumptions, which may not fully represent real-world sensor environments. Therefore, future work should focus on real-time implementation and the development of adaptive filtering strategies to maintain optimal performance under varying and non-ideal operating conditions.

References

[1] M. Pamungkas, Hafiddudin, and Y. S. Rohmah, "Perancangan dan Realisasi Alat Pengukur Intensitas Cahaya," *J. ELKOMIKA*, vol. 3, no. 2, pp. 120–132, 2015, doi: 10.26760/elkomika.v3i2.120.

[2] Y. Wu, K. Ma, Z. Wu, and W. Zhang, "Intensity Noise Suppression in Photonic Detector Systems for Spectroscopic Applications," *Sensors*, vol. 25, pp. 1–14, 2025, doi: 10.3390/s25226932.

[3] T. B. Bano *et al.*, "Perancangan Alat Ukur Intensitas Cahaya menggunakan Sensor BH1750 Berbasis Mikrokontroler ATMega328P," *Kappa J.*, vol. 8, no. 1, pp. 95–101, 2024, doi: 10.29408/kpj.v8i1.24917.

[4] N. Nasution, A. Supriyanto, and S. W. Suciyati, "Implementasi Sensor Fotodioda sebagai Pendeteksi Serapan Sinar Infra Merah pada Kaca," *J. Teor. dan Apl. Fis.*, vol. 03, no. 02, pp. 111–116, 2015.

[5] N. Shi, J. Yang, Z. Cao, and X. Jin, "A Programmable Ambient Light Sensor with Dark Current Compensation and Wide Dynamic Range," *Sensors*, vol. 24, pp. 1–10, 2024, doi: 10.3390/s24113396.

[6] J. A. Nava-Pintor *et al.*, "Development and Evaluation of Solar Radiation Sensor Using Cost-Effective Light Sensors and Machine Learning Techniques," *Technologies*, pp. 1–31, 2025, doi: 10.3390/technologies13050182.

[7] Heriansyah and F. B. Gultom, "Evaluasi Kinerja Berbagai Jenis Sensor LDR," *J. Kumparan Fis.*, vol. 8, no. 3, pp. 87–94, 2025, doi: 10.33369/jkf.8.3.87-94.

[8] A. A. Syukron and I. L. Elviyanti, "Pembuatan Sensor Cahaya dengan Memanfaatkan LED dan LDR Berbasis Arduino Uno," *J. Kridatama Sains dan Teknol.*, vol. 03, no. 02, pp. 161–169, 2021, doi: 10.53863/kst.v3i02.435.

 EISSN: 2961-872X ●PISSN: 2961-8924●DOI: 10.56741/IISTR.esl.002255

[9] A. Fahmi and I. Kurniawan, "Studi Kinerja Transmisi Data Menggunakan ESP32 dan Raspberry Pi Pico Berbasis Simulasi Wokwi," *Zetroem*, vol. 07, no. 01, pp. 80–87, 2025, doi: 10.36526/ztr.v7i1.5102.

[10] M. A. Annas, A. Widodo, M. C. Aisiyah, I. E. Ningrum, and D. Makrufah, "Karakterisasi Sensor Cahaya Light Dependent Resistor (LDR)," *Pendidik. dan sains*, vol. 2, no. 4, pp. 612–622, 2022, doi: 10.58578/masaliq.v2i4.516.

[11] M. F. Lathifah and A. Doyan, "Arduino-Based Light Intensity Measurement," *J. Sci. Technol. Inov.*, vol. 1, no. 1, pp. 1–3, 2022, doi: 10.56566/amplitudo.v1i1.5.

[12] C. H. Pardosi, M. Siregar, and L. W. Pandjaitan, "Design and implementation of a dual-axis solar tracking system using Arduino Uno microcontroller," *J. ELTIKOM*, vol. 8, no. 1, pp. 44–56, 2024, doi: 10.31961/eltikom.v8i1.1105.

[13] N. Rinanto, A. P. A. Wuri, R. Y. Adhitya, and H. Ismail, "Comparative Simulation of Kalman Filter and Moving Average on Siemens S7-1200 PLC-Based Loadcell Sensor Readings," *Sustain. Energy Control Optim.*, vol. 1, no. 2, pp. 67–76, 2025, doi: 10.62762/seco.2025.538779.

[14] M. M. Ardestani and H. Yan, "Noise Reduction in Human Motion-Captured Signals for Computer Animation based on B-Spline Filtering," *Sensors*, vol. 22, pp. 1–15, 2022, doi: 10.3390/ s22124629.

[15] A. S. Fiddariani and B. Sumanto, "Studi Penerapan Filter Digital pada Sistem Pemantau Parameter di Kolam Ikan," *J. List. Instrumentasi, dan Elektron. Terap.*, vol. 5, no. 1, pp. 30–38, 2024, doi: 10.22146/juliet.v5i1.87377.

[16] J. Tong, Y. Zhang, H. Huang, J. Xiong, and Y. Luo, "Composite filter-based detection of rock joints from drilling parameters," *Sci. Rep.*, vol. 15, pp. 1–16, 2025, doi: 10.1038/s41598-025-26233-4 1.

[17] E. P. Rodrigues, D. S. dos Santos, and F. Buiochi, "Comparison of Three Linear Digital Filters Applied to Improve the Quality of the Measured Acoustic Field," *eng*, vol. 4, pp. 2582–2600, 2023, doi: 10.3390/eng4040148.

[18] L. Türkler and L. Ö. Akkan, "Noise Reduction Techniques for Sensor Data : Comparative Analysis of Kalman, Butterworth , Savitzky-Golay , Median , and Moving Average Filters for UWB-Based Position Estimation," *Celal Bayar Univ. J. Sci.*, vol. 21, no. 4, pp. 146–159, 2025, doi: 10.18466/cbayarfbe.1682594.

[19] F. Baskoro, M. Rohman, D. Arya, and A. P. Nurdiansyah, "Optimizing Stability of Ultrasonic Sensor Readings : Study on Moving Average Filter Parameter Selection," *Zetroem*, vol. 07, no. 01, pp. 59–65, 2025, doi: 10.36526/ztr.v7i1.3603.

[20] M. R. Fauzi, S. Pramono, and G. Wibisono, "Implementasi Moving Average Filter untuk Sensor Arus pada Sistem Pemantauan Penerangan Jalan Umum," *J. Teknol. Rekayasa*, vol. 8, no. 1, pp. 1–8, 2023, doi: 10.31544/jtera.v8.i1.2023.1-8.

[21] S. Pramono, J. B. Tarihoran, and G. Wibisono, "Implementasi Moving Average Filter untuk Sensor Tegangan Pada Sistem Kontrol Dan Monitoring Lampu Jalan," *Din. Rekayasa*, vol. 19, no. 1, pp. 37–44, 2023, doi: 10.20884/1.dr.2023.19.1.536.

[22] F. Baskoro, I. G. P. Asto, M. Rohman, D. A. Soeadyfa, and A. P. Nurdiansyah, "Impact of Sample Size Variation on Moving Average Filter Performance for Stability and Accuracy in Ultrasonic Sensor Measurements," *TEM J.*, vol. 14, no. 2, pp. 1681–1688, 2025, doi: 10.18421/TEM142.

[23] K. Ogata, *Modern Control Engineering*, 5th ed. Upper Saddle River, NJ, USA: Prentice Hall, 2010. ISBN: 978-0-13-615673-4.

[24] C. Liu, J. Jiang, J. Jiang, and Z. Zhou, "Enhanced Grid-Connected Phase-Locked Loop Based on a Moving Average Filter," *IEEE Access*, vol. 8, pp. 5308–5315, 2020, doi: 10.1109/ACCESS.2019.2963362.