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Application of Particle Swarm Optimization in Duty Cycle Adjustment for Optimization of Oxyhydrogen Generator

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ABSTRACT

The duty cycle of pulse width modulation is used to adjust the current of the oxyhydrogen generator with on-off square signals. These signals are essential for an oxyhydrogen gas generator to reduce thermal operation, improve the quality of oxyhydrogen gas, and enhance efficiency. A framework combining particle swarm optimization and regression analysis was proposed to determine the minimum temperature and production time of oxyhydrogen gas while maximizing efficiency using a single input, the duty cycle. The optimization results indicated that the duty cycle for the optimum solution remained within the upper and lower temperature boundaries. In this study, particle swarm optimization successfully provided valuable insights for practical applications in renewable energy technologies.

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1. INTRODUCTION

The Outlook Energy Indonesia 2023 examined the total carbon dioxide (CO_2) emissions across sectors, revealing a 14.8% growth in 2022 compared to emissions in 2021. The emissions calculation focuses on two primary activities: fuel combustion and fugitive emissions. Within the fuel combustion activity, the transportation sector contributed 155.6 million tonnes of CO_2 (22.3%), securing the second position after industrial emissions (Kivevele *et al*., 2020; Waluyo *et al*., 2023). CO_2 emissions contributed to 60% of climate change, causing numerous serious consequences, especially global warming (Pham *et al*., 2016; Krekel *et al*., 2018; Elehinafe *et al*., 2021, Elehinafe *et al*., 2022). There are three potential approaches to mitigate CO_2 levels in the ambient air. Firstly, enhancing the efficiency of combustion processes, such as those in fossil fuel-based power plants or internal combustion engine vehicles, can be employed (Anggono *et al*., 2021; Munahar *et al*., 2021; Ariyanto *et al*., 2023; Raja *et al*., 2023; Veza *et al*., 2023). Secondly, sustainable alternatives replace carbon-intensive processes, such as utilizing renewable energy sources, adopting electric vehicles, or incorporating low-carbon fuels (Hardiyanto & Prawoto, 2023; Maghfiroh, *et al*., 2023; Mohammed *et al*., 2023; Munahar *et al*., 2023; Tambunan *et al*., 2023; Herlambang *et al*., 2024; Santoso *et al*., 2024; Setiawan & Setiyo, 2024). Lastly, advancements in fuel cell technology also present a promising avenue for reducing carbon emissions (Krekel *et al*., 2018; Herlambang *et al*., 2023). The fundamental principle of fuel cell technology involves the electrolysis process, which decomposes water into hydrogen gas (H_2) and oxygen (O_2) products. Water electrolysis provides a reliable solution to address the energy crisis, as the resulting products exhibit clean, efficient, and renewable characteristics of hydrogen (Jalili *et al*., 2021; Yamamoto *et al*., 2021; Adedoja *et al*., 2023; Mukherjee *et al*., 2023).

During electrolysis, a direct current is applied to electrodes and an electrolyte, leading to the generation of hydrogen and oxygen. Hydrogen is produced at the cathode, while oxygen is produced at the anode. The proximity and absence of separation between electrodes in the electrolyte solution contribute to the formation of oxyhydrogen gas (HHO) (Subramanian & Thangavel, 2020). The electrolysis process commonly employs electrolytes in alkaline electrolysis, including KOH, NaOH, and NaCl (Yilmaz *et al*., 2010) solutions chosen for high reactivity. The key factors influencing HHO gas production are electrode surface area, electrolyte concentration, operating pressure, temperature, and power supply (El Kady *et al*., 2020; Subramanian and Thangavel, 2020). The main problem in the HHO gas system is the temperature system rising (Al-Rousan & Sa'ed, 2018; Özgür & Yakaryilmaz, 2018) until 90 °C, high temperature can cause the flow rate of HHO gas production to decrease and affect the quality of gas because the gas produced will be mixed with water vapor (Sudarmanta *et al*., 2016). Mitigating high temperatures within the HHO gas system involves the application of pulse width modulation (PWM) on direct current (Worawat & Aurasopon, 2015). PWM regulates the current input into the HHO gas generator, allowing adjustment by manipulating the duty cycle and frequency. The PWM signal is characterized by the ratio of 'on' times to the entire signal period (Conker, 2019). Employing an IC555 as the central component in the wiring diagram, PWM is utilized to examine duty cycles at 30, 50, and 70% for the HHO gas dry cell type (Pertiwi & Kawano, 2013). The findings indicate that PWM effectively regulates temperature and current stability. Notably, an increase in the duty cycle corresponds to a heightened efficiency in HHO gas production. The utilization of IC555 extends to the HHO gas wet cell type, employing duty cycles of 35, 45, and 55% (Arini & Kawano, 2012). The outcomes align with previous findings, indicating that an elevated duty cycle increases efficiency.

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The findings mentioned above are substantiated by the studies conducted by Sudarmanta *et al*. (2016), Silaen and Kawano (2014), and Ghiffari and Kawano (2013). The latter research demonstrates that a higher duty cycle and varying frequencies enhance efficiency in HHO gas production. Conversely, contrasting results emerge from the research (Pradipta & Kawano, 2013), where using IC555 with duty cycles of 25, 50, and 75% revealed that a duty cycle of 25% yielded higher efficiency than other duty cycles. Based on the previous study, the PWM technique on HHO gas production is promising in improving combustion by optimizing the necessary current to be drawn (Baltacıoğlu, 2019). The experimentation with different duty cycles aims to determine the optimal setting that can effectively lower the temperature of the HHO gas system. However, it is essential to note that HHO investigations often involve not only a single objective but are frequently characterized by multi-objective scenarios. Consequently, the application of methods supporting multi-objective analysis becomes imperative. In tackling these challenges, different optimization methods, including but not limited to response surface methodology (RSM), genetic algorithm (GA), particle swarm optimization (PSO) (Wilberforce *et al*., 2023), simulated annealing (SA), and predictive approaches like artificial neural network (ANN), have been employed (Secer & Hasanoğlu, 2020; Yahya *et al*., 2021; Munusamy *et al*., 2022; Ahmad & Yadav, 2024).

Metaheuristic is an exploratory technology that emulates natural phenomena through a computational approach to search for optimal solutions or gains iteratively for problems, involving the refinement of solution candidates and the utilization of boundary solutions. Ahmad and Yadav (2024) demonstrated the efficacy of incorporating a metaheuristic approach in their study. The research highlights the effectiveness of integrating RSM, GA, and PSO for precise prediction and optimization of operational parameters in wastewater electrolysis, particularly for green hydrogen production. The identified optimal conditions significantly contribute to improved efficiency and higher hydrogen yield, thereby fostering the progression of sustainable energy systems. Other research compares the metaheuristic technique using a gradient-based optimizer to three proton exchange membrane (PEM) types (Rezk *et al*., 2022) to identify the best parameters of the PEM fuel cell. Duan, *et al*. (2023) also demonstrated the successful utilization of the algorithm, employing the non-dominated sorting genetic algorithm II (NSGA II) to obtain a global solution for ensuring the uniformity of current density and current density distribution in water electrolysis. This coupling was achieved through a model that combines electrochemistry and multiphase flow. The results indicate an average reduction in the variance of current density and a decrease in specific energy consumption. The approach used in this investigation is like that used by other researchers. Zhang *et al*. (2024) investigated multipolar magnesium electrolysis cell, cell voltage, and current density used for NSGA II. The results showed that the relative error of the multipolar magnesium electrolysis cell model is less than 1%. The findings suggest that employing a workflow that integrates the finite element method alongside multi-objective optimization algorithms holds promise for optimizing and scaling up the design of multipolar magnesium electrolysis cells. GA and PSO, or their refined variant, such as NSGA II, remain popular in practical applications (Cui *et al*., 2017; Ramadhani *et al*., 2017).

Therefore, this study employed PSO to achieve multiple objectives in a dry cell-type HHO generator. The duty cycle, as suggested in the literature, was utilized as a single input parameter along with the operation time of the HHO generator to mitigate high temperatures. The main objectives of this study are to minimize temperature, minimize the gas production time of the HHO generator, and maximize its efficiency.

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2. METHODS

2.1. Data HHO generator

This research utilized experimental data from a preceding investigation involving a dry cell-type HHO generator (Pertiwi & Kawano, 2013). A singular input parameter, the duty cycle, was manipulated at three levels: 30, 50, and 70%. The operation persisted until the HHO generator's temperature reached approximately 93°C while powered by a 12-volt accumulator. The specific configuration of the HHO generator employed in this study is depicted in **Figure 1**. Constructed from SS316L electrode plates measuring 120 mm x 120 mm with a thickness of 1 mm, the generator comprises nine plates, each separated by O-rings (diameter = 126 mm, thickness = 3 mm).

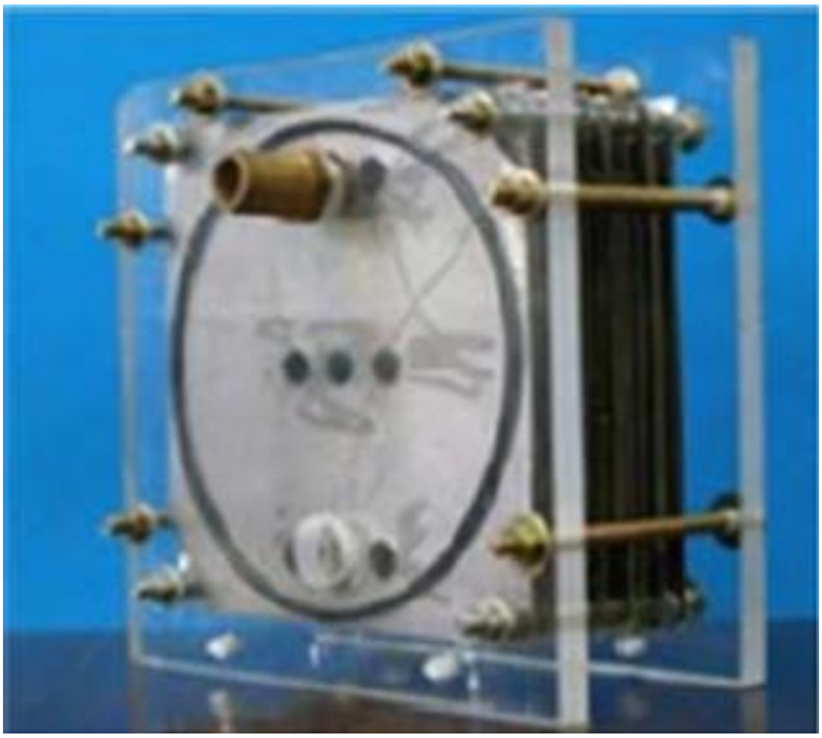

Figure 1. HHO generator dry cell type (Pertiwi & Kawano, 2013).

The HHO generator employed the principle of water electrolysis. This study used 1.4 g potassium hydroxide (KOH) as a catalyst to enhance the electrolysis process, which was then mixed with 750 ml of distilled water. KOH serves the purpose of mitigating corrosion issues typically encountered in acidic electrolytes. Additionally, water electrolysis triggers electrochemical processes at both the anode and cathode in alkaline electrolytes, as described in Equations (1) and (2) (Santos *et al*., 2013). The cumulative reaction in Equations (1) and (2) yields a theoretical cell voltage of -1.23 V.

$$Cathode: 2H_2O + 2e^- \rightarrow H_2 + 2OH^- \;\; (E^0 = -0.83\ V) \tag{1}$$

$$Anodhe: 2OH^- \rightarrow \frac{1}{2}O_2 + H_2O + 2e^- \; (E^0 = 0.40\ V) \tag{2}$$

2.2. PWM

PWM is a control technique utilized to regulate the current input into an HHO gas generator. This method allows for the adjustment of both the duty cycle and frequency of the current input. **Figure 2** illustrates PWM signals exhibiting varying duty cycles. The duty cycle of a PWM signal is characterized by the ratio of on-time to the entire signal period (Conker,

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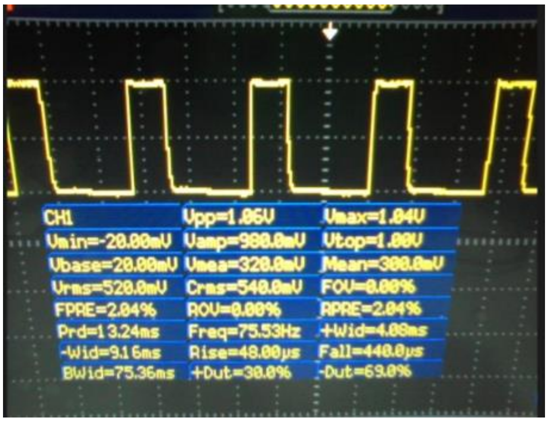
2019). PWM controls the width pulse to period from rectangular signals to reduce the temperature HHO generator (Pradipta & Kawano, 2013) and lower vaporization (Conker, 2019) thereby enhancing the quality.

In **Figure 2**, there are two primary types of pulsed operations: voltage pulses and current pulses. In voltage pulses, the voltage modulation from base value (off-time) to peak value (on-time). The total duration of both on-time and off-time constitutes the pulse period. The duty cycle is defined as the ratio between the on-time and off-time pulse periods, while the frequency represents the inverse of the pulse period. The difference between the off-time and the on-time determines the pulse amplitude (Rocha *et al.*, 2021). In this study, PWM control was achieved through analog PWM control employing an integrated circuit (IC) timer 555. The IC timer 555, also known as NE555, is a versatile component capable of PWM control with pulse width management ranging from 0 to 100%.



(a) Duty cycle 30%

(b) Duty cycle 50%

(c) Duty cycle 70%

Figure 2. Oscilloscope PWM signals by varying duty cycles (Pertiwi & Kawano, 2013)

2.3. Regression Equations

In this study, the objective function utilized to evaluate the objectives of the PSO algorithm employed regression equations for each response variable. Minitab 18 was utilized as a tool to facilitate the calculation of these equations. The theory of regression encompasses models with two variables: the response variable (y) and the predictor variable (x). In this context, the predictor variable, referred to as the input, utilized the duty cycle as the sole input parameter.

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The response variables included temperature (°C), HHO gas production time in 500ml (min), and efficiency (%). The dataset used to generate the regression equations is presented in **Table 1**. When both variables are incorporated into a mathematical equation, the regression equations are formulated as shown in Equation (3).

$$y = \beta_0 + \beta_0 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \quad (3)$$

Table 1. Data on HHO gas production (Pertiwi and Kawano, 2013).

Duty Cycle (%)	Temperature (°C)	Production time of 500ml HHO gas (min)	Efficiency (%)	Duty Cycle (%)	Temperature (°C)	Production time of 500ml HHO gas (min)	Efficiency (%)
30	43.0	12.0533	5.71	50	74.5	4.1525	12.22
30	62.5	8.9887	6.41	50	80.0	3.9402	12.34
30	73.0	8.1962	6.69	50	84.0	4.0795	11.84
30	80.0	7.3460	7.15	50	88.0	3.7870	12.36
30	83.5	7.0750	7.36	50	90.5	3.4515	13.29
30	86.0	7.1582	7.18	50	91.5	3.7045	12.24
30	87.5	6.6453	7.73	50	92.0	3.2783	13.83
30	88.5	6.8593	7.49	50	92.0	3.2525	13.94
30	89.5	6.6988	7.67	50	92.5	3.1957	14.19
30	90.5	6.2378	8.24	70	39.5	3.3057	14.24
30	91.0	6.9238	7.42	70	55.0	2.8588	14.95
30	91.0	6.3118	7.82	70	65.0	2.7843	14.65
30	91.5	6.2566	7.70	70	74.0	2.5277	15.37
30	92.0	6.0385	7.95	70	82.0	2.3517	15.66
30	92.0	6.0523	7.94	70	87.5	2.4750	14.39
50	41.0	5.8357	10.34	70	91.5	2.2943	15.12
50	58.0	5.1948	10.63	70	93.0	2.2208	15.20
50	67.5	4.8373	11.08				

The parameter of β_0 represents the response variable value when the predictor variable has zero value. $\beta_{1,}$ $\beta_2, \dots, \beta_k$ are the regression model parameters corresponding to the variables $x_1, x_2, \dots, x_k$. ε in regression denotes the error or residual, representing the discrepancy between the true and predicted values. According to the theoretical framework, this research employs simple linear regression, a calculation method involving a single predictor variable and a single response variable. The mathematical equation utilized is Equation (4).

$$y = \beta_0 + \beta_1 x + \varepsilon \quad (4)$$

Moreover, Equation (4) was generated using Minitab 18 for this study, with the results presented in Equations (5) to (7).

$$y_1 = 89.87 - 0.227\ duty\ cycle\ (\%) \quad (5)$$

$$y_2 = 10.670 - 0.1212\ duty\ cycle\ (\%) \quad (6)$$

$$y_3 = 1.782 + 0.1962\ duty\ cycle\ (\%) \quad (7)$$

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In this context, y_1 represents the temperature response, y_2 denotes HHO gas production time, and y_3 signifies efficiency. The three equations serve as the objective function for PSO, as outlined in Equation (8).

$$Obejctive\ function = minimize\ (y_1 + y_2) - maximize\ (y_3) \tag{8}$$

$$30\% \leq duty\ cycle \leq 70\% \tag{9}$$

2.4. PSO Algorithm

The PSO algorithm operates based on the swarm principle observed in nature, such as the collective behavior seen in schools of fish or flocks of birds. This principle mimics how a swarm collectively searches for food, adjusting its velocity and position accordingly. In PSO, the swarm refers to a population comprising solution candidates, also known as particles. These particles navigate through a search space, guided by their velocity and position, in pursuit of an optimal solution. Each particle's movement influences the entire search area, continually updating as the search progresses. This study utilized the Matlab R2021b academic version to compute Equations (5) to (7) and search for the optimal solution. The PSO algorithm implemented in the Matlab R2021b academic version adheres to the fundamental principles (Marini & Walczak, 2015) outlined in **Figure 3**.

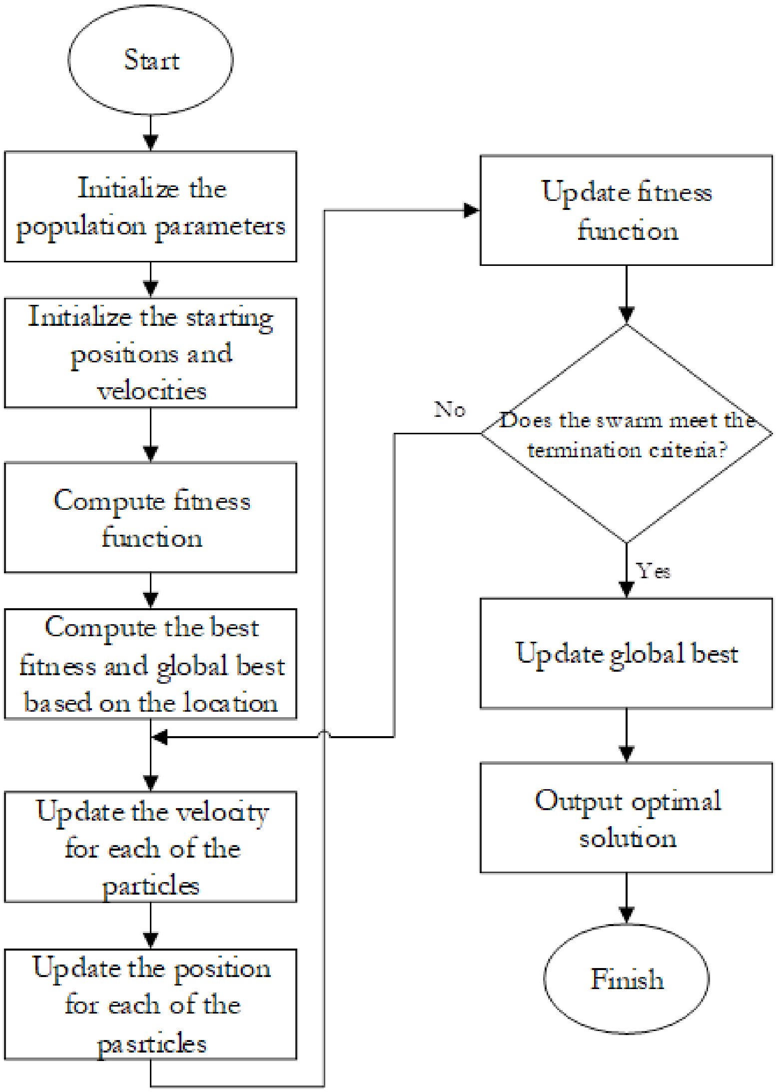

Figure 3. PSO algorithm flowchart.

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3. RESULTS AND DISCUSSION

3.1. Analysis model

3.1.1 ANOVA

The data in **Table 1** was analyzed using Minitab 18 to model the relationship between input and response parameters. Before performing the regression analysis, an analysis of variance (ANOVA) was conducted on this model. Anova is used to determine whether there are significant effects between the parameters and to assess the influence of one or more factors (Sharma *et al*., 2023). The ANOVA results for data listed in **Table 1** are presented as follows: the temperature results are shown in **Table 2**, the production time of HHO gas in 500 ml is detailed in **Table 3**, and the efficiency of the HHO generator is displayed in **Table 4**.

Table 2. Results of ANOVA for temperature.

Source	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	P-Value
Duty Cycle (%)	2	454.5	227.3	0.89	0.419
Error	32	8144.4	254.5		
Total	34	8598.9			

Table 3. Results of ANOVA for a production time of HHO gas in 500ml.

Source	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	P-Value
Duty Cycle (%)	2	132.64	66.320	50.14	0.000
Error	32	42.33	1.323		
Total	34	174.97			

Table 4. Results of ANOVA for Efficiency.

Source	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	P-Value
Duty Cycle (%)	2	343.77	171.885	213.34	0.000
Error	32	25.78	0.806		
Total	34	369.55			

The results in **Tables 2-4** display the *P-value* used to evaluate the statistical hypotheses. The *P-value* indicates whether the input parameters significantly affect the responses. If the *P-value* is greater than the magnitude of the *significant level* (α), the null hypothesis (H_0) fails to be rejected; otherwise, H_0 is rejected. The hypothesis tested in Anova is represented by Equations (10) and (11).

$$H_0 = \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_k \qquad with\ k = 1, 2, 3, 4, \ldots, k \tag{10}$$

$$H_1 = at\ least\ a\ pair\ of\ \mu_k\ is\ not\ the\ same \tag{11}$$

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Equations (10) and (11) dictate that if H_0 is rejected, it signifies that the input parameters have a significant effect on the responses. Conversely, if H_0 fails to reject, it indicates that the input parameters do not have significant effects and that there is no interaction between the input and responses. In **Tables 2-4**, only the temperature (**Table 2**) exhibits the magnitude of *P-value* greater than the magnitude of *significant level* (α=0.05), contrasting with the other responses (production time of HHO gas in 500ml and efficiency). The results suggest, in statistical terms, that the duty cycle has no significant effect on temperature. Regardless of the duty cycle's value, there are no discernible effects on the temperature in the HHO gas generator.

However, experimental results diverge from this statistical theory. PWM (used to control the current for HHO) has been shown to optimize temperature during HHO gas operation due to the electrolysis process (Kumar & Kumar, 2015). This optimization enhances the quality of HHO gas production because PWM-generated pulses have a square waveform with an *on-off* principle. A higher duty cycle value implies that the voltage used in the HHO generator is applied for a more extended period than usual, enhancing the current in the electrolysis process. The current is a thermal source in the electrolysis cell due to the internal resistance in water alkaline and electrodes, producing heat proportional to the electric current as per Joule's law. Additionally, resistive heating occurring in the electrolysis cell can lead to high temperatures in alkaline water and electrodes, potentially decreasing of water electrolysis process. Despite this theoretical understanding of statistics, this study investigates the temperature response to address its multi-objective aims.

3.1.2 Residual Assumption Test

In regression analysis, residuals are expected to be independent of each other, have a mean equal to zero, exhibit constant variance (homoscedasticity), and be normally distributed. Therefore, model assumptions must be analyzed with assumption tests to verify that the residuals meet these characteristics. This study used a normality distribution test to identify the characteristics of the residuals for the three response variables. The normality distribution test was conducted using the Kolmogorov-Smirnov test. The hypotheses for this test are represented by Equations (12) and (13), and the results are shown in **Figure 4**.

$$H_0 = \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_k \qquad with\ k = 1, 2, 3, 4, \ldots, k \tag{12}$$

$$H_1 = at\ least\ a\ pair\ of\ \mu_k\ is\ not\ the\ same \tag{13}$$

The decision regarding the hypotheses used the *P-value*, similar to the ANOVA test, with a *significant level* of 5% (α=0.05). **Figures 4a** and **4b** show that if the *P-value* is smaller than α, the decision is to reject H_0, indicating that the residuals are not normally distributed. In contrast, **Figure 4c** shows a *P-value* greater than α, meaning the residuals are normally distributed. The unique characteristic of the residual data, based on the mean and standard deviation values, shows that the mean and standard deviation are close to zero for all these residuals. The results suggest that the residuals are normally distributed. The normal distribution of residuals based on the mean value indicates that the model has no systematic tendency to predict consistently higher or lower values, thereby minimizing bias.

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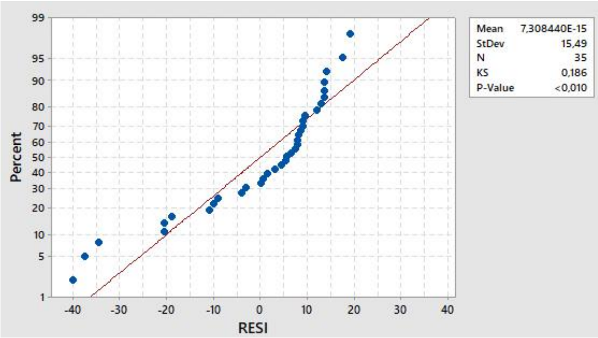
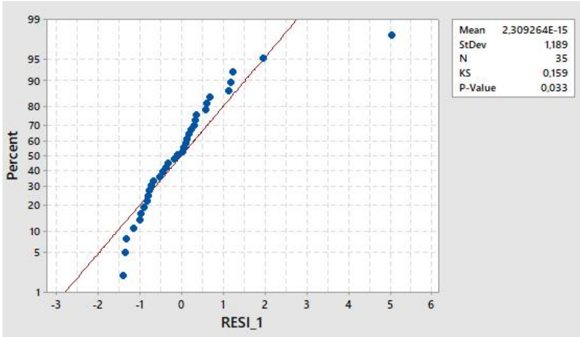
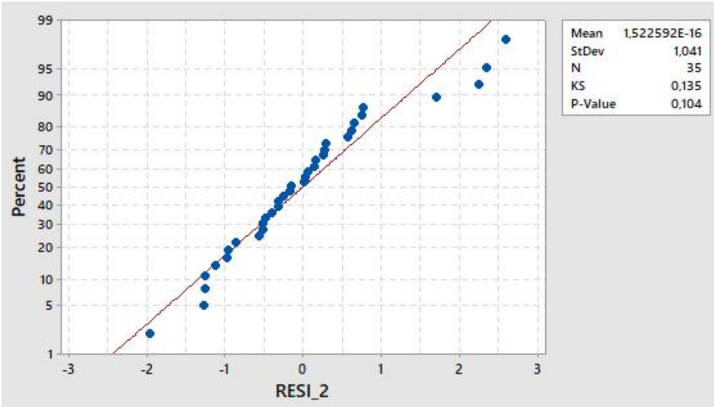


(a) Normally distributed plot for temperature



(b) Normally distributed plot for time production of HHO gas



(c) Normally distributed plot for efficiency

Figure 4. Results of normally distributed test

3.2. PSO analysis

PSO is a natural-inspired optimization method widely recognized alongside GA. PSO generates solutions using inertia, social, and cognitive components. In each iteration, PSO adjusts the gap between current and previous solutions, which enhances the algorithm's diversity compared to GA. This characteristic supports the observation that PSO converges faster than GA in this application. This study did not perform experimental confirmation to compare the simulation results with experimental outcomes. However, the discussion is based on previous literature and a scientific approach. Figure 5 illustrates the convergence curve from the PSO simulation, where the best cost achieved was 60.65%. This value represents the duty cycle suggested by PSO within the constraints specified in Equation 9. This simulation was run ten times, consistently yielding the same results (60.65% for the duty cycle). This duty cycle was identified as the best compromise between various performance metrics, namely temperature and efficiency.

Furthermore, the corresponding response results are presented in **Table 5**. At the optimized duty cycle of 60.65%, the HHO generator achieved a temperature approximately of 76 °C. This temperature is a critical parameter in the operation of HHO generators, as it directly affects the production rate of HHO gas and the system's stability. The elevated temperature indicates a higher gas production rate due to increased energy input, consistent with the expected behavior under optimal operational settings. However, maintaining a temperature of 76 °C requires careful thermal management to prevent overheating and ensure the long-term durability of the system components. The efficiency of the HHO generator at the optimized duty cycle was 13%. This metric is pivotal for assessing the generator's overall performance and viability. While an efficiency of 13% might seem modest,

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it represents a significant improvement over baseline configurations where duty cycles were not optimized.

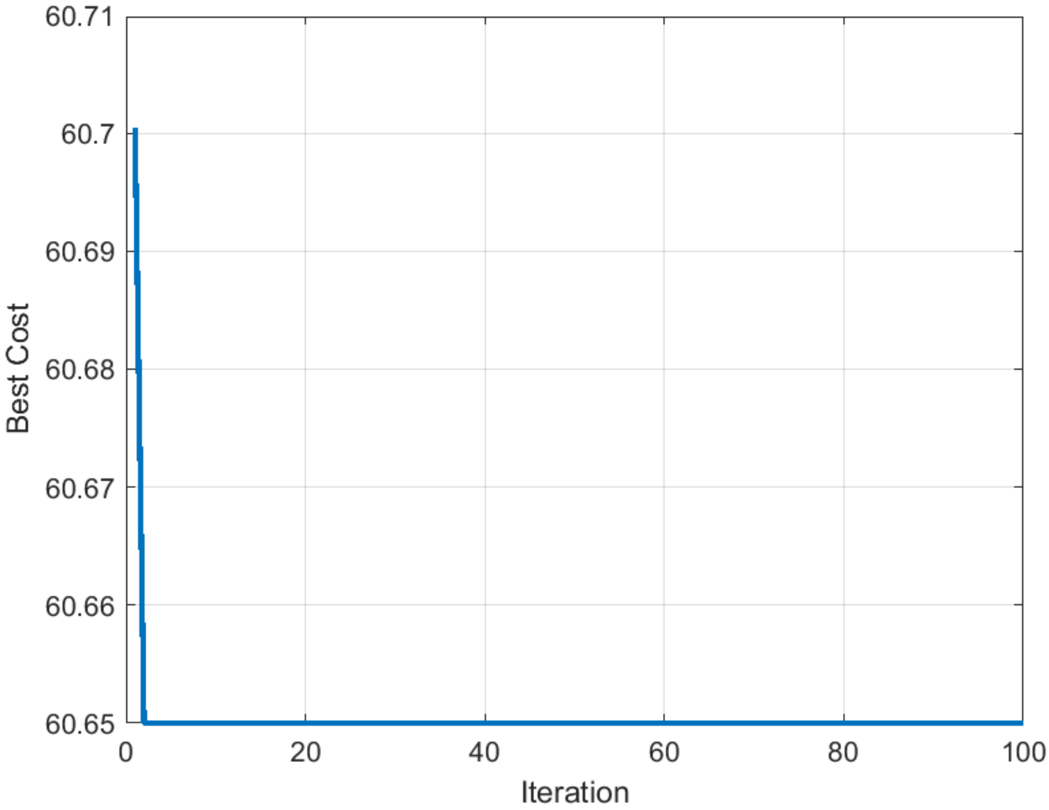

Figure 5. The convergence of PSO

The findings from this optimization study have several practical implications. The optimal duty cycle of 60.65% provides a benchmark for setting operational parameters in real-world HHO generators, ensuring both effective gas production and manageable operating temperatures. Further work could explore hybrid optimization techniques combining PSO with other methods, such as differential evolution or simulated annealing, to enhance the system's efficiency and refine the duty cycle and other operational parameters. Additionally, integrating advanced thermal management solutions could help maintain optimal temperatures and improve efficiency beyond the 13% observed in this study. These solutions include using advanced cooling systems or materials with higher thermal conductivity to dissipate heat more effectively. The result of PSO is presented in **Table 5**.

Table 5. Result of PSO

Duty Cycle (%)	Temperature (°C)	Production Time of HHO gas in 500ml (min)	Efficiency (%)
60.65	76.103	3.319	13.682

4. CONCLUSION

In this study, the PSO was proposed. The framework combined PSO with regression analysis to produce the objective function for process evaluation. The application of PSO to optimize the duty cycle of an HHO generator has demonstrated significant improvements in operational performance. The optimized duty cycle of 60.65% resulted in a stable temperature of 76 °C and an efficiency of 13%. These findings validate the efficacy of PSO in

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optimizing complex systems and provide a solid foundation for further enhancements in HHO generator technology. Future research should focus on integrating more sophisticated optimization algorithms and advanced thermal management techniques to push the boundaries of efficiency and performance. Additionally, further development is needed to simplify the adjustment of the duty cycle in experimental settings, potentially by translating the optimized results into more practical integer values.

6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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