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RESEARCH ARTICLE

Enhancing the Performance of Pressure Regulation via Genetic Algorithm (GA) for Negative Pressure Wound Therapy (NPWT) System

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Abstract Hard-to-heal wounds, such as diabetic foot ulcers, have become a significant healthcare concern with the rising incidence of diabetes. Negative Pressure Wound Therapy (NPWT) has shown advantages over traditional wound management methods, but the classical NPWT controllers have issues with unstable pressure generation and occasional injury. To address this, fuzzy logic has been integrated into NPWT systems to enhance performance. However, fuzzy controllers have limitations due to uncertainty and inconsistency in system design. This study hybridizes a genetic algorithm (GA) with the fuzzy NPWT system to improve negative pressure regulation stability. Comparative performance evaluations showed that GA-fuzzy NPWT reduced the mean steady-state error by 56.60%, increased the rise time by 10.31%, and reduced overshoot by 4.92%. However, the integration of GA also led to an increase in standard deviation, improving accuracy but raising variability in the system.

Keywords: Control system, fuzzy logic, genetic algorithm, negative pressure wound therapy.

Introduction

Negative pressure wound therapy (NPWT) has emerged as an effective approach to accelerating chronic wounds such as diabetic foot ulcers. To ensure the high effectiveness and safety of NPWT, the stability of negative pressure regulation is crucial. Based on [1], the effectiveness of wound healing depends on the wound's optimal moisture level to accelerate the tissue regeneration and healing process. The standard wound healing approach is wound dressing which has the advantage of low cost and simplicity but needs to be changed/monitored regularly and prone to bacterial infection. NPWT is believed as the ideal way to manage wounds due to its ability to trigger multiple biological healing mechanisms, remove exudate and reduce the risk of infection [2].

Even though NPWT has the advantage of various wound applications, those with too small or deep wounds may not be suited to use NPWT. Besides, an optimal range of negative pressure values is crucial to induce wound healing mechanisms. Based on [3], the range of negative pressure that can trigger wound healing mechanisms is from - 75 mmHg to - 250 mmHg. If the negative pressure applied is too high, it can cause a series of side effects such as pain, ischemia, and haemorrhage. On the other hand, if the negative pressure applied is too low, it causes no significant healing effects. Furthermore, [4] showed that - 125 mmHg has the greatest effects on tissue regrowth and granulation formation.

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However, the unstable negative pressure regulation in the NPWT classical controller has caused several side effects such as haemorrhage, bleeding, pain and death [5 - 8]. This means that the pressure regulation in NPWT is extremely crucial to prevent any undesired safety incidents caused to patients. Thus, fuzzy logic has been used to replace classical controllers in NPWT to stabilise pressure and minimise the overshoot due to its ability to handle non-linear tasks and the uncertainty of real-world scenarios [9, 10].

However, the fuzzy controller has limitations of inconsistency in the system modelling due to the rules base and membership functions design are based on human decision or judgement [11, 12]. Also, designing a fuzzy controller requires expertise and the process is time- consuming [13, 14]. Based on various studies, optimization algorithms have been used to optimise the fuzzy controller to enhance the system's stability and performance.

The optimisation algorithms such as Genetic algorithm (GA), Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) have been broadly used and hybridized with fuzzy logic controllers [15 - 19]. The optimisation algorithm can fine-tune the fuzzy parameters such as rule bases and membership functions to make the whole system more adaptive and efficient based on the inputs or environmental changes. While with the current research in NPWT, optimisation is yet to be adopted in the fuzzy controller to ease the designing process as well as pressure regulation’s performance. The optimisation algorithm is required to fine-tune the fuzzy parameters in the fuzzy NPWT system to ensure the consistency of system modelling and at the same time to enhance the performance of pressure regulation which is a critical safety issue for patients.

Thus, in this study, an optimisation algorithm is hybridised with a fuzzy NPWT system by optimising the fuzzy membership functions [20, 21] which can help us to search for the best input membership setting automatically to improve the performance of negative pressure regulation. GA was selected as the choice in this study due to its popularity, ability to adapt to various domains, fast executive time and higher population diversity [22 – 24].

Materials and Methods

Hardware Configuration

NPWT hardware was set up for performance evaluation, the main electrical components are Arduino Mega microcontroller, differential pressure sensor (MPX5100DP) and Boden 12 V diaphragm air pump. The fuzzy NPWT system was then developed by using Python language in PyCharm Community IDE. The code was tested on the NPWT hardware to ensure smooth hardware operation without error. The GA-fuzzy NPWT system was created as an improved version. First, the code was checked to ensure it worked correctly. Then, the system was run to find the best input settings. After that, both systems (the old and new) were tested 10 times each to compare their performance.

Lastly, the system performance metrics were analysed and reported. Three main components were developed in this study: the NPWT hardware, the fuzzy control system and the GA as shown in Figure 1. The fuzzy control system was first developed and integrated with the NPWT hardware as a fuzzy NPWT system. GA was the external component that fine-tuned the input membership functions in the fuzzy control system. After the GA successfully found the best setting or configuration for fuzzy input membership functions, the GA was no longer needed. The best or optimal setting was configured in the fuzzy NPWT system for future operation. The fuzzy and GA-fuzzy NPWT systems were evaluated and compared to verify their performance ability.

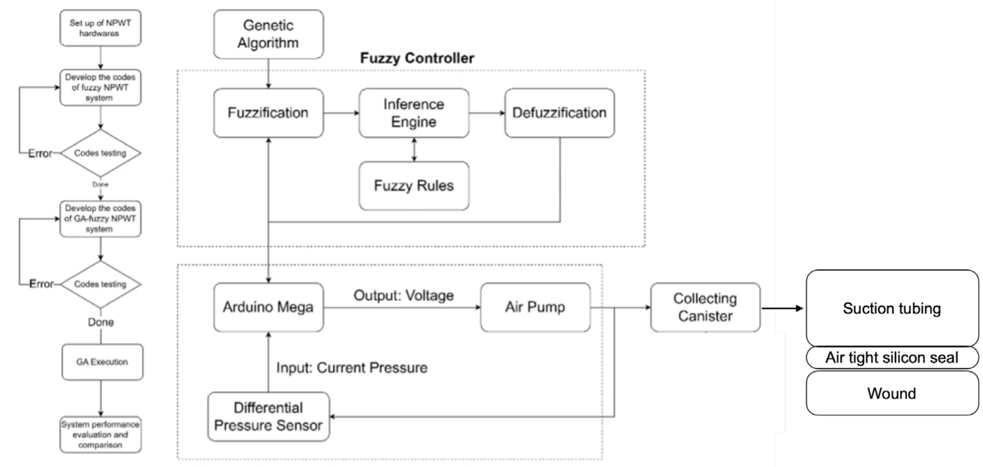


Figure 1. The research flowchart and the graphical abstract

Fuzzy Logic Design and Implementation in NPWT System

The system was on, and the air pump was run to create a negative pressure environment approaching the desired target of 125 mmHg [4]. The differential pressure sensor detected the negative pressure and sent the analogue input signal to the Arduino Mega microcontroller board. The input pressure reading was sent to and processed by the fuzzy logic controller to determine the output voltage of the air pump speed which is predefined in fuzzy logic rules (refer to Table 1). If the pressure value is high, then the air pump decreases speed and returns the negative pressure to the desired value. While, if the pressure value is low, then the air pump increases the speed to maintain the negative pressure at the desired value. This was a closed- loop feedback control system with a preset time. The time was counted once the system started to operate, the system will check on the counting time each time after controlling the air pump speed. If the counting time is less than or equal to the setting time, the system continues to operate. If the counting time is more than the setting time, the system exits the loop and stops the operation. The input variable is the current pressure detected by the differential pressure sensor and divided into five fuzzy sets. The membership functions are trapezoidal for fuzzy sets of "very high" and "very low", while the rest of the three middle fuzzy sets are in triangular membership functions as shown in Figure 2. The pressure range for five input fuzzy sets is listed below:

Table 1. The range of current pressure for each of the 5 fuzzy sets

Input	Fuzzy Sets	Range (Max = ∞)
Current Pressure (mmHg)	Very High	135 – ∞
	High	125 – 145
	Normal	115 – 135
	Low	105 – 125
	Very Low	0 – 115

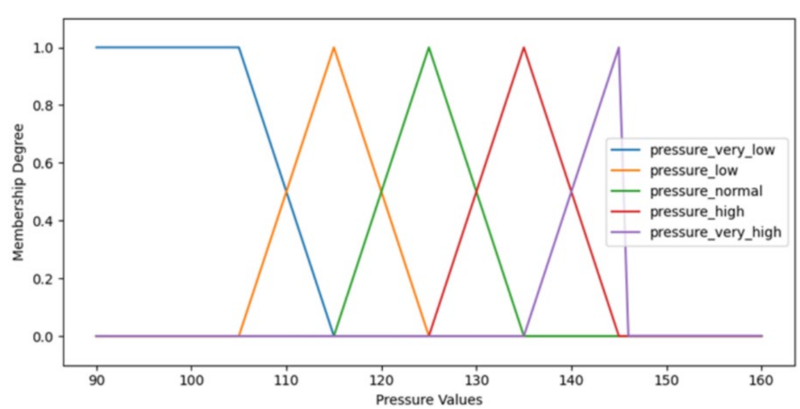


Figure 2. The membership function of the input variable

On the other hand, the output variable is the motor voltage contributing to the air pump speed which is determined by the input value after processing by a fuzzy logic system. The air pump speed is also divided into five fuzzy sets. Each of the fuzzy sets was in a triangular membership function as shown in Figure 2. The pressure range for five output fuzzy sets is listed below:

Table 2. The range of air pump speed for each of the five fuzzy sets

Input	Fuzzy Sets	Range (Max = 1)
Air Pump Speed	Very High	0.75 – 0.85
	High	0.70 – 0.80
	Normal	0.65 – 0.75
	Low	0.60 – 0.70
	Very Low	0.55 – 0.65

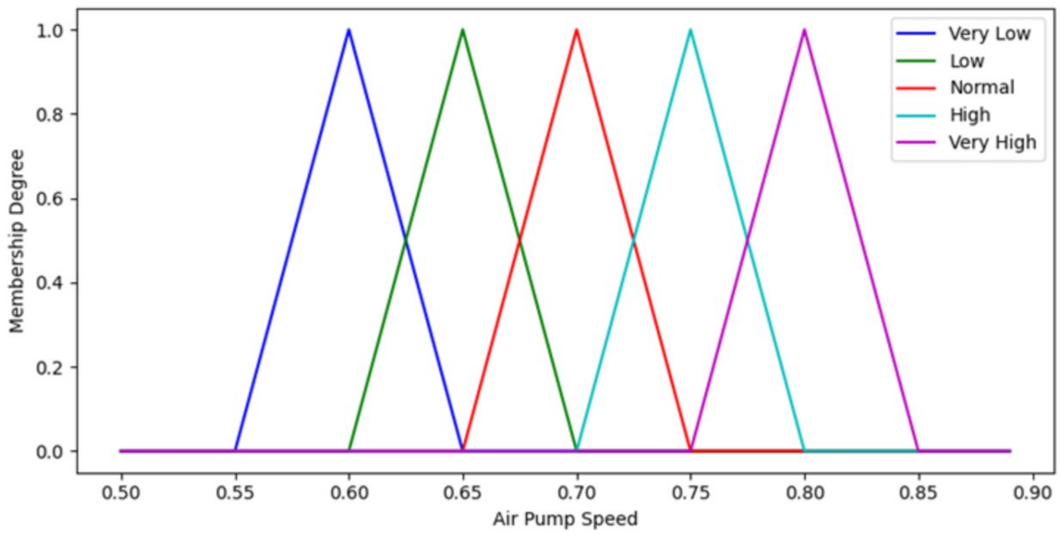


Figure 3. The membership function of the output variable

Fuzzy Control System Implementation

Fuzzification is a process that converts the crisp or precise value into fuzzy sets by predefined input membership functions. This process allows the system to respond to real-world scenarios more accurately because it can manage the information imprecisely or uncertainly [25, 26]. First, the input pressure value was mapped into the input membership functions to obtain the membership degree (0-1) accordingly. The input membership degrees were subsequently mapped to the output membership functions. The system inference engine applied the fuzzy rules to generate the output fuzzy sets.

This process is known as rule evaluation using the fuzzy AND operator. While the fuzzy OR operator was used to aggregate the resulting output fuzzy sets before defuzzification. Defuzzification is a process that converts the aggregated fuzzy set into a crisp output so that the actuator (air pump) can interpret this precise value [27]. In this study, we used the Centroid method for defuzzification, it determined the centre of mass of the aggregated fuzzy set and provided a single crisp output value that represents the average weightage of the fuzzy set [28]. The stability and performance of a fuzzy system rely on the fuzzy rules set which is the core component of the fuzzy inference system. The six rules used in this system are shown in Figure 4. Generally, the pressure value is indirectly proportional to the air pump speed. The sixth rule is to act as a safety measure to prevent the pressure from going too high which can cause safety concerns for patients.

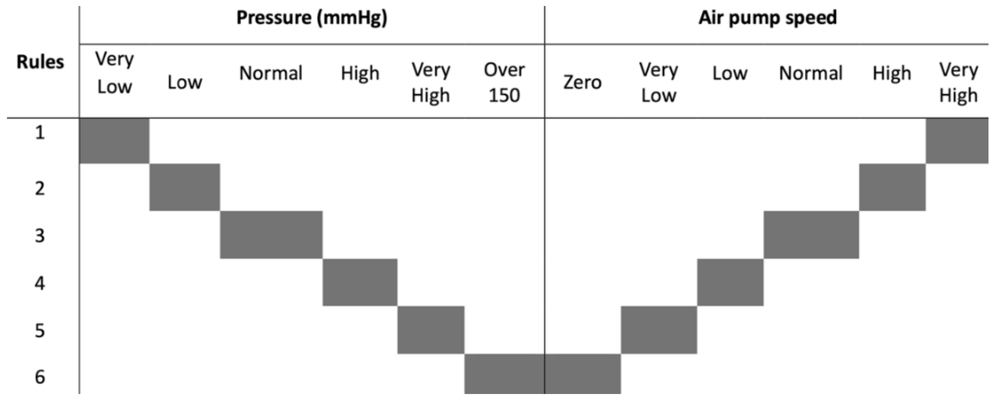


Figure 4. The fuzzy rules base of the fuzzy NPWT system

First, when the system was on, the GA started to initialise the chromosomes in the initial population. Four chromosomes with five genes each were randomly generated in the initial population, the "number" in the gene representing the half-width setting of the input fuzzy sets. These chromosome settings were configured in the input membership function of the fuzzy NPWT system, and the system ran one by one to evaluate their fitness according to the fitness function.

After getting the fitness value, the system came to the termination step to decide whether to stop the system or not. There are two termination criteria in this GA execution: the fitness value was equal to zero or the generation executed exceeded 200. If the termination criteria are not met, then the system moves on to parent selection. The initial four chromosomes with respective fitness values were arranged in ascending order and the two chromosomes with the lowest fitness values were selected as parents for crossover and mutation. Two children were generated from the two parents to make the next total population of four. Then, these new chromosomes were configured and evaluated again by running the fuzzy NPWT system to obtain their respective fitness value. These steps were continuously repeated until the termination criteria were met

Chromosome Encoding & Initialisation

In this study, the gene in the chromosome was represented by the half-width from each input triangular membership function as shown in Figure 5, thus there were 5 genes in each chromosome. Generally, the widths of 5 fuzzy sets were adjusted to achieve the best input membership functions based on the fitness function. Since there are five genes in a chromosome and each of the genes can have five possibilities of value, thus the total solutions are $5^5 = 3125$. In addition, there are a few preconditions in this study. First, the triangular memberships were assumed to be symmetrical. Secondly, each fuzzy set's peak "b" was fixed and only the widths of triangular membership were modifiable, represented by "a" and "c".

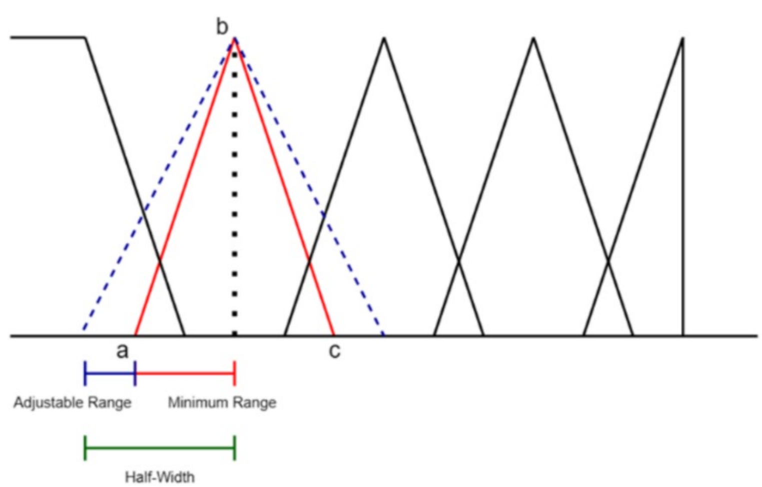


Figure 5. The visual representation of GA adjusting parameters (input membership functions)

The maximum area of width which can be adjusted by the GA is represented by the blue dotted line. While the minimum area of width of the fuzzy set is represented by the red solid line. The adjustable area by the GA is equal to the maximum area minus the minimum area of the triangular fuzzy set. The number of the population set in this study is four for the initial population as well as for the subsequent population. First, the four chromosomes in the initial population were randomly generated and evaluated according to fitness function to determine the fitness value. The best four chromosomes were selected from the previous generation as parents and another 2 children were generated via crossover and mutation to maintain a population of four across all the generations as shown in Figure 6.

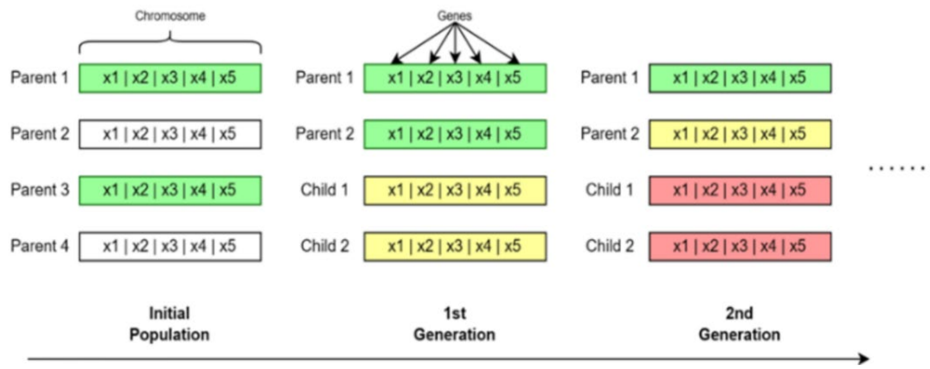


Figure 6. Illustration of the selection of parent chromosomes in GA

Genetic Algorithm Optimization: Fitness Evaluation, Selection, and Performance Validation

Fitness Evaluation

In this study, we focused on the stability of negative pressure regulation, thus the focused parameters are mean steady-state error and the standard deviation error. The mean of steady-state error measures the average difference between the desired pressure value and the current pressure value. On the other hand, the standard deviation in this context measures how dispersed or variation of a set of pressure values is collected. Both parameters were calculated ten seconds after the system started to operate, this is because the pressure is considered as settled after ten seconds. The equations are as follows:

$$Steady\ State\ Error = Desired\ pressure - Current\ Pressure \quad (1)$$

$$Standard\ Deviation = \sqrt{\frac{Squared\ Difference\ of\ mean}{Total\ Number\ of\ Data\ point\ in\ population}} \quad (2)$$

Both parameters mentioned above were included as part of the fitness function. The lower the fitness value, the better the solution. Thus, zero was the target value for termination criteria, however, an ideal fitness value of zero can never be achievable. Therefore, a maximum of 200 generations was set as the additional termination criteria. Besides, the standard deviation in the fitness equation below was minus by an offset of 20 due to NPWT system modelling. Two hundred times hardware trials were conducted to determine the standard deviation value, the standard deviation range was from 18.72 to 34.64. Since the value cannot approach zero, an offset must be established to fit the fitness function. Based on the data distribution graph plotted in Appendix A, a value of 20 was determined as offset to ensure the occurrence and lead to a lower value of fitness during the GA execution. Furthermore, each of the parameters was assigned 50 % of weightage as below:

$$Fitness\ value = [0.5\ \times\ Steady\ state\ error\ +\ 0.5\ \times\ (Standard\ deviation\ -\ 20)] \quad (3)$$

Parent Selection, Crossover & Mutation

The selection in this study was based on rank-based selection. This selection method can decrease the likelihood of the solution converging prematurely and stuck at the local minimum [29, 30]. After fitness evaluations in each generation, the chromosomes were arranged in ascending order based on their fitness values. The top 2 with the lowest fitness values representing the best solution were selected for the next generation, while the rest of the 2 chromosomes were eliminated. This process is crucial to ensure that only the fittest chromosomes are passed from generation to generation mimicking biological natural selection. Crossover and mutation are the core operators in GA. Crossover exchanges genetic information between two parents to produce a new offspring or child. Mutation is another process which randomly alters the value of genes to ensure the GA is not stuck in the local optimal solution. In this study, a single crossover occurred at a probability of 100 %, while two-point mutations occurred at a probability of 80 % to increase the genetic diversity in a population since the population size in this study is small [30]. The crossover is useful for exploitation that larger the searching space; the mutation provides an effective exploration within the solution space. In short, both operators need to be balanced to search for optimal or near-optimal solutions for complex problems.

Performance Validation and Comparison

Several parameters were determined for performance evaluation and comparison between the general fuzzy NPWT system and the GA-fuzzy NPWT system. The parameters are mean steady- state error, standard deviation, rise time and overshoot percentage. For the general fuzzy NPWT system, the input membership function of “10” half-width for each fuzzy set was executed 10 times and the average values for each parameter mentioned above were calculated. On the other hand, GA was iterated 3 times to search for the best input membership setting. The best membership setting with the lowest fitness value was then selected. The best input membership setting was configured in the GA-fuzzy NPWT system and executed 10 times to obtain the performance parameters in an average manner. The comparison table and bar graph were constructed for better visualisation and comparison purposes. Also, the percentage change of parameters was calculated for the GA-fuzzy NPWT system based on the fuzzy NPWT system using the formula below:

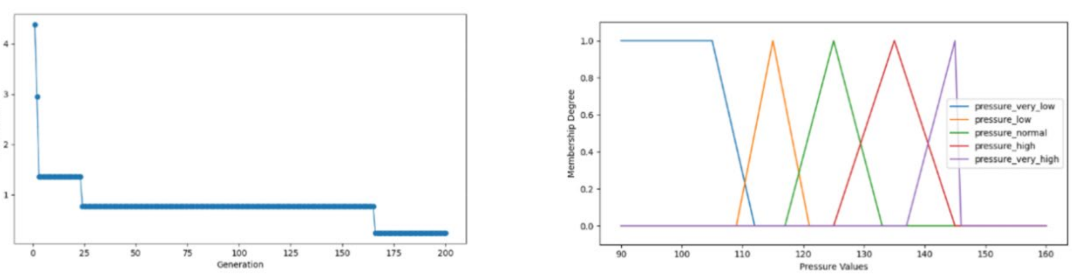
$$Percentage\ Decrease = \frac{Initial\ value - New\ Value}{Initial\ Value}\ x\ 100 \quad (4)$$

$$Percentage\ Increase = \frac{New\ value - initial\ Value}{Initial\ Value}\ x\ 100 \quad (5)$$

Results

Genetic Algorithm Execution

To summarise all the 3 GA executions, Table 3.0 was constructed for comparison. The third GA execution was the best and lowest fitness value of 0.24 among others with a converging generation of 166 as shown in Figure 7. Therefore, its input membership setting of [7, 6, 8, 10, 8] was chosen and used for further validation experiments (see Table 3).



(a) (b)

Figure 7. The convergence curve (a) and the plotted input membership function (b) of the best GA execution

Table 3. Summary of GA execution

Number of Execution	Generation to Coverage	Best Fitness Value	Best Input Membership Function
First	17	0.71	[8, 6, 9, 10, 9]
Second	25	0.73	[7, 9, 8, 9, 7]
Third	166	0.24	[7, 6, 8, 10, 8]

Performance Validation & Comparison

After optimisation of the fuzzy input membership function, validations were done for both systems to determine their performance competency. Each input membership setting was validated 10 times and their representing pressure graphs are shown in Figure 8.

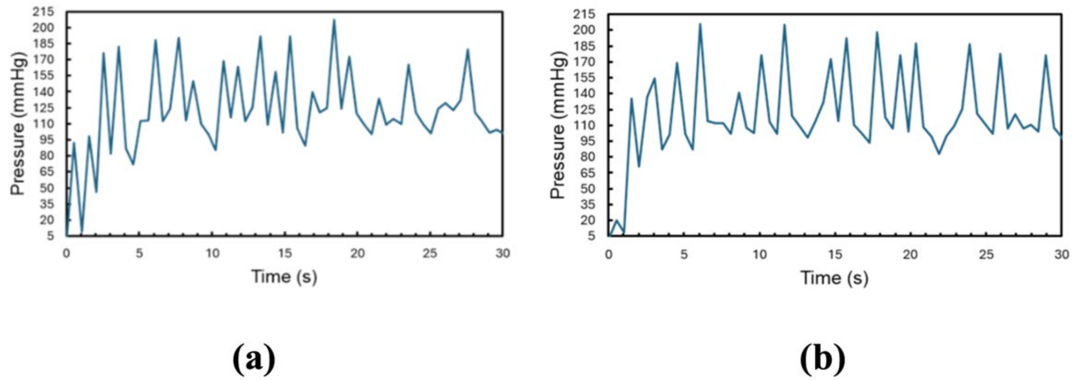


Figure 8. The graph of pressure versus time for the general input membership function (a) and GA-optimised input membership function (b)

The performance metrics comparison between 2 different input membership function settings. Figure 9 shows the bar graph of mean values versus performance metrics for general and GA-optimised memberships. A percentage change of each performance metric has been demonstrated in Table 4.

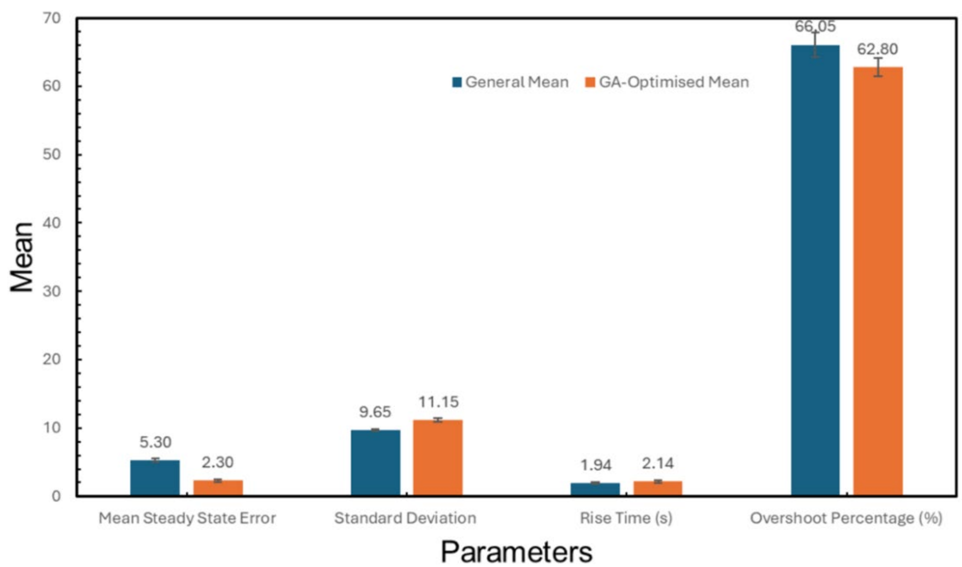


Figure 9. The bar graph of mean values versus performance metrics for general and GA- optimized memberships.

Table 4. The percentage change for each performance parameter

Parameter	General Input Membership Function	GA-Optimised Input Membership Function	Percentage Change (%)
Mean Steady- State Error	5.30	2.30	- 56.60
Standard Deviation	9.65	11.15	+ 15.54
Rise Time (s)	1.94	2.14	+ 10.31
Overshoot percentage (%)	66.05	62.80	- 4.92

Discussion

A stable pressure generation is critical in the NPWT context to ensure patient safety and comfort. Also, a consistent fuzzy NPWT system with minimal developing time is needed to enhance the performance of the fuzzy NPWT system and ease the modelling process. The hybridization of GA into the fuzzy NPWT system has been proposed and brought a promising result. First, the GA was executed 3 times to avoid bias and the best input membership function based on the lowest fitness value was selected. Each GA was set to iterate for 200 maximum generations with around five percent of searching space to total solutions. There is no one-size-fits-all number of iterations for all GA to search for the best solution. In this study, maximum generation was set as the additional termination criteria which is also the most common method used by other researchers [32, 33]. Through experimental trials for this study context, 200 maximum generations were pretty enough to produce the best solution without being stuck in local optimal.

Based on Table 3, the third GA execution was the best and lowest fitness value of 0.24 among others with a converging generation of 166. The fitness value of zero is always impossible in real-world scenarios, the fitness value of 0.24 indicates the input membership function of [7, 6, 8, 10, 8] has achieved the lowest steady-state error and standard deviation compared to other best input membership functions from each GA execution. Therefore, the best input membership setting of [7, 6, 8, 10, 8] from the third execution was chosen and used for further validation experiments (Table 3). Through the comparison of pressure graphs in Figure 10 above in terms of naked-eye visualisation, the amplitudes for both groups of the graphs are likely the same along with time. This indicates that the membership function optimised by GA was not likely to reduce the oscillating amplitude throughout the whole operating period. The oscillating amplitude for both pressure graphs is about ± 15 mmHg from the desired pressure value. Due to the fuzzy system design, the repetitive and short damping effect is observed over time in two groups. The 6th fuzzy rule was purposely designed for the patient safety issue, the air pump speed becomes zero or stopped once the negative pressure exceeds 150 mmHg. Once the air pump stops pumping, the air influxes into the wound dressing causing a drop in negative pressure. The drop in the negative pressure causes the air pump to pump more again to maintain the desired pressure. Also, another reason was the medical grade of PU film dressing used was breathable [34] which is not 100 % sealed to ensure the wound has a better oxygen supply and maintains an optimal moisture condition [1]. Therefore, the pressure graph in this study would not have the damping effect and settle down like other underdamped systems due to the specific system design for NPWT.

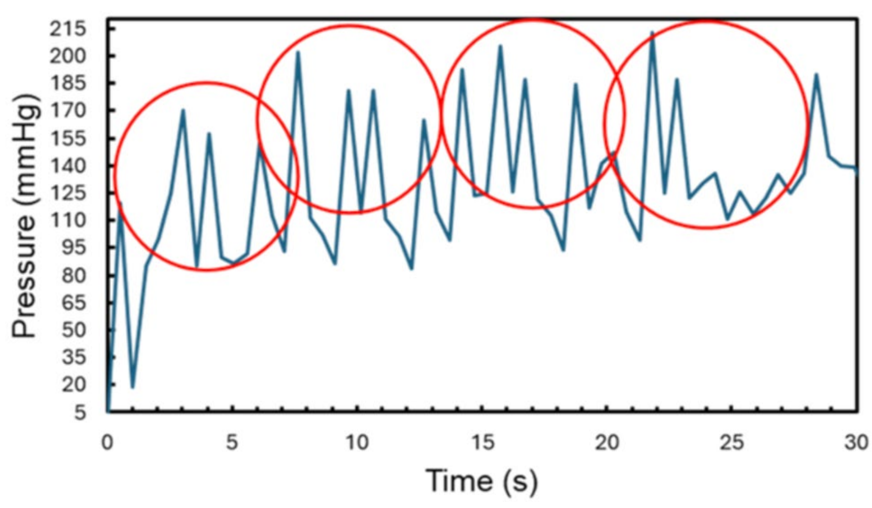


Figure 10. A repetitive and short damping effect in the system

Relating to the theory of damping characteristics, a leak decremented the force balance in the system and caused the pressure to oscillate more with worsened damping [35, 36]. At the same time, this led to some overshot in a system instead of having an ideal theoretical damping effect that reduces oscillating amplitude over time [37]. Based on Figure 3.2, two different fuzzy input membership system settings were compared: general versus GA-optimized. The validation was run 10 times for each setting as mentioned in the methodology. The performance parameters compared were mean steady-state error, standard deviation, rise time, and overshoot percentage. The general membership setting has obtained an averaged mean steady-state error of 5.30 while the GA-optimized membership setting has achieved an averaged mean steady-state error of 2.30. This indicates that the GA improved the accuracy of the fuzzy NPWT system by reducing the mean steady-state error which made the system have a higher capability of maintaining the pressure closer to the target negative pressure value (125 mmHg) along with time.

The great reduction of mean steady-state error by GA was 56.60 %. Besides, in terms of averaged standard deviation, the general membership setting obtained a value of 9.65 while the GA-optimized membership setting obtained a value of 11.15. There was an increase of 1.50 with a percentage of 15.54 %. Indicating that GA in this study did not help to reduce the standard deviation of the fuzzy NPWT system. The rise in standard deviation means the system variability was increased after the GA optimization. The increased standard deviation (15.54% higher in the GA-optimized system) is a trade-off resulting from the GA's optimization process, which prioritized minimizing the steady-state error (reduced by 56.60%) and overshoot (reduced by 4.92%). The higher variability arises from reduced overlapping in fuzzy Sets; GA optimized the input membership functions by narrowing their widths, decreasing overlap between adjacent sets. While this improved precision, it made the system more sensitive to minor pressure fluctuations, leading to less smooth transitions and higher output variability. Future work will integrate Gaussian membership functions and a finer actuator to mitigate variability without compromising accuracy. Notably, the observed remains within safe clinical limits for NPWT (-125 ± 25 mmHg) [4], ensuring patient safety despite higher variability. Moreover, while this study focused on optimizing pressure regulation at -125 mmHg, the clinically established target for optimal granulation tissue formation, the need to validate system performance across NPWT's full therapeutic range (-75 to -250 mmHg) is required for future studies. Hardware limitations in the current experimental setup, particularly the fixed calibration range of the 12V diaphragm pump, precluded testing of multiple pressure targets. Future iterations will incorporate a programmable pump and adaptive GA tuning to dynamically optimize membership functions across pressures, ensuring broader clinical applicability while maintaining the stability advantages demonstrated in this work. This can be explained by the overlapping of fuzzy sets in the GA-optimised input membership setting has been reduced after the optimisation, unlike the general input membership setting which has maximal overlapping. Studies showed that the higher the overlapping with the adjacent fuzzy sets, the smoother the transitions between fuzzy sets [38, 39]. An unsmooth transition can cause the system to become more sensitive to small changes in input pressure reading. Indicating that small fluctuations in input can cause abrupt variations in the output, thus directing the control action to be less smooth and inconsistent.

To solve this issue, the Gaussian membership function can be used instead of the triangular membership function to ensure a smoother transition [40] even with the decrease in the overlapping area via GA optimisation. Next, the rise time was used to compare the two membership settings. Generally, the lower the rise time, the better the system performance because the quicker the system achieves the target pressure level. However, in the NPWT context, we expect an acceptable long rise time, this is because a rapid or sudden rise in the negative pressure may cause shocking pain or bleeding to the patient. A longer rise time can let the patient slowly adapt to the suction force without any discomfort. While variability falls within safe limits, future iterations will incorporate patient-reported comfort scores into the GA fitness function to explicitly optimize for both stability and tolerability. Preliminary simulations suggest a 20% weight adjustment toward standard deviation reduction could lower fluctuations by ~15% without compromising steady-state accuracy. The average rise time for general and GA-optimised membership settings were 1.94 seconds and 2.14 respectively. There was an insignificant rise of 0.2 seconds with 10.31 %. The 0.2 seconds longer may not have a substantial effect on the patient's comfort, thus further validation can be made to confirm this argumentative outcome. In addition, the general membership setting has an average overshoot percentage of 66.05 % and the GA-optimised membership setting has an average overshoot percentage of 62.80 %. The overshoot reduction percentage is 4.92 %. This indicates that the GA can help the fuzzy NPWT system by reducing the pressure from going beyond the desired pressure value which is a positive result. To add on, the overshoot percentage for both groups was around 60 % and above which is not that ideal, but this may be due to the partial-leaking feature in the fuzzy NPWT system as discussed above. Another suspecting reason was the overpowering of the 12 V air pump, the bigger motor has limitations in adjusting a fine pressure change and low responsiveness due to its high power and inertia. The percentage change of each parameter has been presented in Table 4. The 12V pump's fixed power output, while suitable for demonstrating core algorithm performance, restricted fine pressure adjustments. Future implementations will employ variable-power pumps with dynamic voltage/PWM control to better exploit the GA-fuzzy system's optimization capabilities.

Conclusion

In conclusion, stable pressure generation is crucial during the NPWT to guarantee patient safety and a consistent fuzzy NPWT system with low developing time is needed to enhance the system performance. The fuzzy membership function is the core component of a fuzzy logic system. The configuration of membership functions significantly affects the performance of the whole system. Traditionally, people set up the membership functions by experience or continuous testing to determine the best one. In this study, GA was used to ease the process and help search for optimal input membership functions that can be adopted in the fuzzy NPWT system to create a better negative pressure regulation system. This proposed method is time- and labour-saving. The hybridisation of GA into the fuzzy NPWT system has shown promising results. The averaged mean steady-state error was greatly reduced from 5.30 to 1.94, a reduction of 56.60 %, and the overshoot percentage was reduced from 66.05 % to 62.80 % with a percentage decrease of 4.92 %. On the other hand, the GA optimisation comes with a trade-off which increases the standard deviation by 15.54 % from 9.65 to 11.15. While the GA-optimized system achieved significant improvements in steady-state error and overshoot, the increased standard deviation (15.54%) reflects a sensitivity trade-off from reduced fuzzy set overlap. Future work will integrate Gaussian membership functions and a finer actuator to mitigate variability without compromising accuracy. Notably, the observed standard deviation (11.15 mmHg) remains within safe clinical limits for NPWT (-125 ± 25 mmHg), ensuring patient safety despite higher variability. The GA did not substantially affect other performance parameters like rise time with an increase of 10.31 % from 1.94 seconds to 2.14 seconds. Overall, the GA greatly enhanced the accuracy of the fuzzy NPWT system, but it also raised the variability of the fuzzy NPWT system in this study. Nevertheless, the promising results show we have taken a great step forward by adopting an optimisation algorithm in the NPWT context. There are several limitations in this study. In terms of hardware, the power of the air pump used in this study may be too high, which is 12 V. A little pumping effort from the air pump can cause a big pressure change. Thus, it caused the system to have a higher overshoot percentage and a high standard deviation. The recommendation for this issue is to use a finer air pump which can adjust the pressure minorly. In terms of system modelling, gaussian membership functions can be the alternative to triangular membership functions to solve the unsmoothed transition between fuzzy sets to ensure a low system variability. Secondly, only the input membership function was included in the GA optimisation in this study due to time constraints. The output membership functions can be included in the future to make the study more comprehensive. However, this may lead to a high demand for computational sources, programming knowledge as well as time. Thus, a balance should be made between the experimental outcomes and the ready resources.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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