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Interval Type-2 Fuzzy Approach for Dynamic Parameter Adaptation in the Bird Swarm Algorithm for the Optimization of Fuzzy Medical Classifier

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Abstract: Optimization is essential for applications since it can improve the results provided in different areas; for this task, it is beneficial to use soft computing techniques, such as bio-inspired algorithms. In addition, it has been shown that if dynamic parameter adaptation is applied to these algorithms, they can provide a better result. For this work, the main contribution is to carry out the dynamic parameter adaptation to the bird swarm algorithm using interval type-2 fuzzy systems to realize a new fuzzy bio-inspired algorithm. The design of the proposed fuzzy system consists of two inputs corresponding to the iterations and diversity. As outputs, it takes the values of C and S, which are parameters to be adjusted by the algorithm. Once the design and the experimentation are realized, they are divided into two study cases. The first consists of a set of complex functions of the Congress of Evolutionary Competition 2017. The second case study consists of optimizing the membership functions in a fuzzy system designed to provide the nocturnal blood pressure profile, which corresponds to a neuro-fuzzy hybrid model to obtain the risk of hypertension. Analyzing the 30 experiments performed in both case studies, we can observe that the results obtained are improved when compared with the original method and other proposed methodologies, achieving good results in the complex functions. In addition, the optimized fuzzy system will reach an average of 97% correct classification. Statistically, it can be concluded that there is significant evidence to affirm that the proposed method provides good results.

Keywords: blood pressure; nocturnal blood pressure profile; hypertension; optimization; fuzzy systems

MSC: 03B52; 03E72; 62P30

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1. Introduction

Optimization is an essential task, which refers to solving a problem as efficiently as possible, using the least number of resources and in the shortest possible time [1]. This task is used to find or approximate the optimal solution in different areas, such as building and environment [2], transit-oriented development [3], agriculture [4], neuroimage [5], and biowaste [6].

Regarding soft computing, nature-inspired algorithms, such as bio-inspired algorithms, are commonly used to solve optimization problems in many areas; an example is the medical areas in which the best possible results are sought [7–9]. There are bio-inspired algorithms that are very good at solving specific problems. Still, in others, the results are not as expected [10–12], which is why sometimes modifications are made to the mentioned metaheuristics. Dynamic parameter adaptation is a technique widely used today to improve the performance of bio-inspired algorithms [13–15], which consists of dynamically changing the values of the parameters that provide better results, and for this, fuzzy inference systems can be used. In addition to the fact that this technique has demonstrated a significant improvement in the results.

The bird swarm algorithm (BSA) has been used in previous works [16], and we have detected several areas of opportunity for improvement. For this reason, in this work, we have proposed to carry out a dynamic parameter adaptation to the BSA to improve the obtained results and its performance, which we call the dynamic bird swarm algorithm (DBSA).

The different parameters used by the BSA are analyzed to realize the presented proposal. The ideal parameters for carrying out the C and S adjustments correspond to the cognitive and social acceleration coefficients. To achieve this, iterations and diversity are used as inputs, and to expand the experimentation, we propose four type-1 fuzzy systems, which present different variations in the rules. In addition, it is experimented with by changing the membership functions (MFs), using trapezoidal and Gaussian in the submitted proposals. Furthermore, the rules and design in the type-1 fuzzy systems are used to test the proposed method using interval type-2 fuzzy systems (IT2FS) for comparing, analyzing, and determining which of the fuzzy proposals achieves better performance.

In the experimentation, we present two case studies. In the first case, we take 10 functions from the Congress of Evolutionary Competition 2017 (CEC2017). For the second case study, we work with optimizing a fuzzy system designed to provide, as a result, the nocturnal blood pressure profiles, which is part of a neuro-fuzzy hybrid model to obtain the risk of developing hypertension in a period [17]. As can be seen in the design of fuzzy systems, the BSA provides the parameters; these are created and adapted to the problem solution for each iteration until they find the vector of data for the best optimization, that is, the improvement of solutions to the problem tackled. Another aspect to consider is that due to the uncertainty that the data handles in the different problems to be solved (in our case, in the medical area), working with them is of great importance because the solutions are considerably improved.

Currently, there is an infinite number of algorithms created for optimization. Still, in particular, the BSA has proven to be effective and efficient in providing solutions to given problems, as mentioned by the author [18,19], where they demonstrate analytically and statistically the improvement in the solutions to the problems raised by both, creating flexible, robust and reliability applications.

The main contribution of this work is to modify the BSA using dynamic parameter adaptation based on type-2 fuzzy logic and present a new model that helps to improve the results. The optimization of the architecture designed in the fuzzy system applies to the medical area, in which it is necessary to provide accurate results about health status, since due to the current pandemic situation in which we live, we require control over our health, specifically in what corresponds to blood pressure, since this is one of the main risk factors that makes us vulnerable to COVID-19.

The rest of the paper is structured as follows: Section 2 describes the basic concepts, Section 3 presents the related works, in Section 4 the material and methods are described, Section 5 explains the results of different experiments and the statistical test, Section 6 describes the discussion, and finally, Section 7 presents the conclusions and future work.

2. Basic Concepts

This section outlines some basic concepts which are needed to explain the proposed approach.

2.1. Bird Swarm Algorithm

The bird swarm algorithm BSA [20] is a recently created algorithm that pretends to mimic the vigilance, foraging, and flight of birds within the swarm, based on social behavior and social interaction, intending to solve optimization problems. The above behaviors are described in five rules:

1. Foraging and vigilance behaviors can change in each bird, modelling a stochastic decision. These behaviors are expressed as follows:

When foraging, each bird is in charge of the food search, which is performed based on its experience and considering the swarm's expertise. Mathematically, foraging can be analyzed as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \left(p_{i,j} - x_{i,j}^{t}\right)C\ rand\ (0,1) + \left(g_j - x_{i,j}^{t}\right)\ S\ rand\ (0,1), \tag{1}$$

where $j \in [1, \ldots, D], rand(0,1)$ independent numbers uniformly distributed in (0,1).

Two important values to consider are C and S, which correspond to the cognitive and social acceleration coefficients. In this case, $p_{i,j}$ corresponds to the best previous position in the i_{th} bird, and g_j is the best previous position shared in the swarm.

Regarding vigilance, each bird tries to move to the center of the swarm to compete with others but to achieve this, each bird that competes does not move directly to the center of the swarm mathematically; it is analyzed as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + A1\left(mean_j - x_{i,j}^{t}\right) \times rand(0,1) + A2\left(p_{k,j} - x_{i,j}^{t}\right) \times rand(-1,1) \tag{2}$$

$$A1 = a1 \times \exp\left(-\frac{pFit_i}{sumFit + \varepsilon} \times N\right) \tag{3}$$

$$A2 = a2 \times exp\left(\left(\frac{pFit_i - pFit_k}{|pFit_k - pFit_i| + \varepsilon}\right)\frac{N \times pFit_k}{sumFit + \varepsilon}\right) \tag{4}$$

k corresponds to a positive integer between 0 and N, $sumFit$ is the sum of the best fitness values of the swarm. ε is used to avoid zero-division error, $pFit_i$ is the best value in the ith position, and $a1$ and $a2$ are positive constants in [0,2]. A1 and A2 correspond to the effect induced by the interference when the birds move to the center of the swarm.

2. At the time of foraging, the birds can record and update the best experiences individually and in the swarm, which corresponds to the food patch, which is used to search for food. When it comes to social information, it is instantly shared among the entire swarm.
3. To maintain vigilance, each bird tries to move to the center of the swarm; with this, the interference induced by competition between the entire swarm can be affected. Birds with the most significant supply have a greater chance of approaching the center of the swarm than those with the smallest supplies.
4. Usually, birds can fly to another site; when this happens, they can switch between producing and scrounging. In this case, the birds with the highest food reserves are producers, and those with low reserves are scrounging. Birds with an intermediate reserve may switch between producer and scrounger. Flight behavior is mathematically expressed as:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + randn(0,1) \times x_{i,j}^{t}, \tag{5}$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \left(x_{k,j}^{t} - x_{i,j}^{t}\right) \times FL \times rand(0,1), \tag{6}$$

In this case, *randn* (0, 1) represents Gaussian distributed random numbers with mean 0 and standard deviation 1. FQ corresponds to a positive integer, meaning the birds can move to another location every FQ interval. FL ($FL \in$ [0, 2]) refers to the scrounger who will follow the producer to search for food.

5. According to their activity, the birds, will perform the following functions: Producers actively search for food, and Scroungers randomly follow a producer to search for food. Figure 1 presents the pseudo-code that corresponds to BSA.

```
Input N: the number of individuals (birds) contained by the population
        M: the maximum number of iterations
        FQ: the frequency of birds' flight behaviors
        P: the probability of foraging for food
        C, S, a1, a2, FL: five constant parameters
t=0;
Initialize the population and define the related parameters
Evaluate the N individuals' fitness value, and find the best solution
While (t < M)
     If (t % FQ ≠ 0)
         For  i = 1 : N
            If rand (0,1) < P
                Birds forage for food (eq. 1)
             Else
                Birds keep vigilance (eq. 2)
            End if
        End for
     Else
        Divide the swarm into two parts: producers and scroungers.
         For i = 1 : N
            if i is a producer
                Producing (eq. 5)
                Else
                Scrounging (eq. 6)
            End if    End For
   End If   Evaluate new solutions
   if the new solutions are better than their previous ones, update then
   Find the best solutions
t=t+1; End while
Output: the individual with the best objective function value in the population
```

Figure 1. Bird swarm algorithm pseudocode.

2.2. Fuzzy Logic

Fuzzy logic began to be studied in the mid-1960s by Professor Lotfi A. Zadeh at the University of California, Berkeley, initially presenting the work of fuzzy sets [21]. Fuzzy systems represent accurate knowledge and data in the same way that human thought does, in addition to defining a non-linear correspondence between one or more input variables and one or more output variables [22,23].

2.3. Interval Type-2 Fuzzy Systems

Interval type-2 fuzzy logic can be viewed as a generalization of type-1 fuzzy logic, which is used to handle a greater amount of uncertainty, and this is achieved through the type-2 membership functions since they use the footprint of uncertainty (FOU), which consists of two type-1 membership functions, in this sense membership to a value in a fuzzy set may be represented by an interval [22,24,25].

2.4. Blood Pressure

To better understand this concept, we begin by defining the heart, a vital organ for the human being and is located between the lungs in the center of the chest [11,12].

The heart has two sides: the right-side pumps blood to the lungs to receive oxygen and remove carbon dioxide, and the left pumps oxygenated blood to the body. It can be observed how the heart acts as a pump that drives blood to our organs, tissues, and cells [26,27].

Blood pressure can be defined as the force exerted by the blood against the walls of the arteries as the heart pumps blood around our body [26].

When measuring blood pressure, we can observe that it provides us with two values, which are defined as systolic and diastolic pressure:

1. Systolic pressure is the highest number and measures the pressure when the heart has to pump the blood towards the arteries.

2. Diastolic pressure is the smallest number, which measures the blood pressure when the heart relaxes between beats. Both measurements are made in millimeters of mercury (mmHg) [28,29].

The normal blood pressure corresponds to measurements below 139 mmHg in systolic pressure and below 89 mmHg in diastolic pressure. These measurements are based on the European guidelines for the management of hypertension [30].

2.5. Hypertension

Hypertension or high blood pressure is defined as the sustained elevation of blood pressure above the normal limits determined, taking as reference the European guidelines for the management of hypertension which corresponds to readings above 140/90 mmHg [31–33]. These guidelines classify hypertension in three grades:

- Grade 1 is 140–159 mmHg in systolic pressure or 90–99 mmHg in diastolic pressure.
- Grade 2 is 160–179 mmHg in systolic pressure or 100–109 mmHg in diastolic pressure.
- Grade 3 is 180 or higher mmHg in systolic pressure or 110 or higher mmHg in diastolic pressure.

Additionally, another classification is defined, which is called isolated systolic hypertension, and this may occur when the systolic pressure is higher than or equal to 140 mmHg, but the diastolic pressure is lower than 90 mmHg [30].

When people have this disease, the muscles in the walls of the arteries become stronger and thicker to perform the pumping function. This process of hardening the arteries is known as atherosclerosis, which reduces the space within the arteries and further increases the pressure in them [34–36]. Cycles of increased blood pressure occur slowly over several years without causing symptoms of heart disease [36].

In addition to damaging the heart, this condition damages vital organs such as the brain, kidneys, and eyes, among other causes:

- Cerebral stroke
- Kidney failure
- Myocardial infarction
- Heart failure
- Vascular dementia, among others [29,37].

2.6. Nocturnal Blood Pressure Profile

When ambulatory blood pressure monitoring is carried out over an extended period, it is possible to discover the fluctuations that this has. With this, it has been shown that the circadian profile decreases between 10–20% of the nighttime blood pressure records typically compared to the daytime blood pressure records, known as the Dipper profile. The absence of a decrease in nocturnal blood pressure figures of less than 10% is known as a non-Dipper pattern. When there is a decrease of more than 20% in the blood pressure records, it is known as Extreme Dipper, and when the nocturnal blood pressure values are higher than the daytime values, it is called Riser [28,38,39].

One way to determine this pattern is by obtaining the night/day quotient of the blood pressure readings. Classification of the different nocturnal blood pressure profiles and the corresponding quotient are presented in Table 1.

Table 1. Nocturnal blood pressure profile classification.

Profile	Percentage of Decrease	Quotient
Extreme Dipper	>20%	<0.80
Dipper	10–20%	0.80–0.90
Non-Dipper	<10%	0.91–1.00
Riser	<0%	>1.00

Obtaining this measurement is very important since it has been observed that the non-Dipper pattern is associated with a higher risk of a cardiovascular event [28].

3. Related Works

The process of fuzzy dynamic parameters adaptation has been carried out in different algorithms to solve other problems, and we mention some of these works below.

Sanchez et al. [40] propose performing dynamic parameter adaptation to the particle swarm optimization (PSO) algorithm to design a modular neural network. It is desired to find the best architecture of the modular neural using the proposed method. It is concluded that when compared with other bio-inspired algorithms, similar or better results are obtained, in addition to the fact that it is also observed that the dynamic PSO converges faster than the traditional PSO.

To perform the dynamic parameters adaptation based on interval type-2 fuzzy logic, Olivas et al. [41] propose a method in which they use the current iteration and diversity to control the behavior of the algorithm, and this method was applied to the gravitational search algorithm (GSA). Derived from the experimentation carried out, it is concluded that the presented proposal presents various advantages compared to the original GSA.

Lagunes et al. [42] proposed dynamic parameter adaptation to the stochastic fractal search (SFS) algorithm using type-1 and interval type-2 fuzzy logic. When experimenting with different mathematical functions with the proposed method, better results are obtained compared with the original algorithm and other hybrid proposals.

To improve the performance of the BSA, Melin et al. [43] propose the dynamic parameter adaptation, where the iterations are taken as the input parameter and the C and S parameters as the output. In conclusion, the results are significantly improved when testing mathematical functions and optimizing a fuzzy system applied to the medical area.

At present, soft computing has been used to obtain medical diagnoses of different diseases [44–46], some of which are mentioned below.

Udoh et al. [47] use soft computing to detect prostate cancer. The proposed model is based on the adaptive neuro-fuzzy inference system (ANFIS), which is given as different input symptoms related to the disease. The system was evaluated using prostate cancer information provided by the University of Uyo Teaching, obtaining 95% correct diagnoses.

Ejodamen and Ekong [45] proposed a hybrid model based on fuzzy logic and genetic algorithms to diagnose hormonal imbalance, taking into account 20 symptoms. The tests show that the hybridization of the genetic algorithm and the fuzzy systems provide good results.

Rey et al. [48] proposed a system for computer-aided diagnosis (CAD) which helps to detect pulmonary nodules, which are indicators of the development of lung carcinoma. For this, using the hybridization of techniques for analyzing medical images and soft computing (artificial neural networks, fuzzy systems, and SVM. When carrying out the corresponding experimentation, similar and even better results are obtained than other CAD, demonstrating an 82% sensitivity and 7.3 false positives per study.

For the analysis of diabetic retinopathy, Nallasivan et al. [49] proposed a deep learning method using convolutional neural networks. For this analysis, images of the eye are taken, focusing on the retina's veins, one of the main changes related to this disease. Preprocessing is performed on the image (taking different eye characteristics) and, with the proposed method, good results are obtained when diagnosing diabetic retinopathy.

Thippa et al. [50] proposed a method to predict heart disease using adaptive genetic algorithms with fuzzy logic. The model uses two modules, the first for selecting characteristics and the second for classifying, which is based on fuzzy logic.

4. Materials and Methods

To improve the performance of the BSA algorithm, the dynamic parameter adaptation is carried out the C and S variables, which we name C1 and C2 because of the way they are represented in the algorithm code; this correspond to the cognitive and social acceleration coefficients, which are in the foraging part of the birds as presented in Figure 2. It was decided that we should take these variables due to an exhaustive analysis carried out on all variables of the algorithm and observing that C1 and C2 effected a significant change in the provided results.

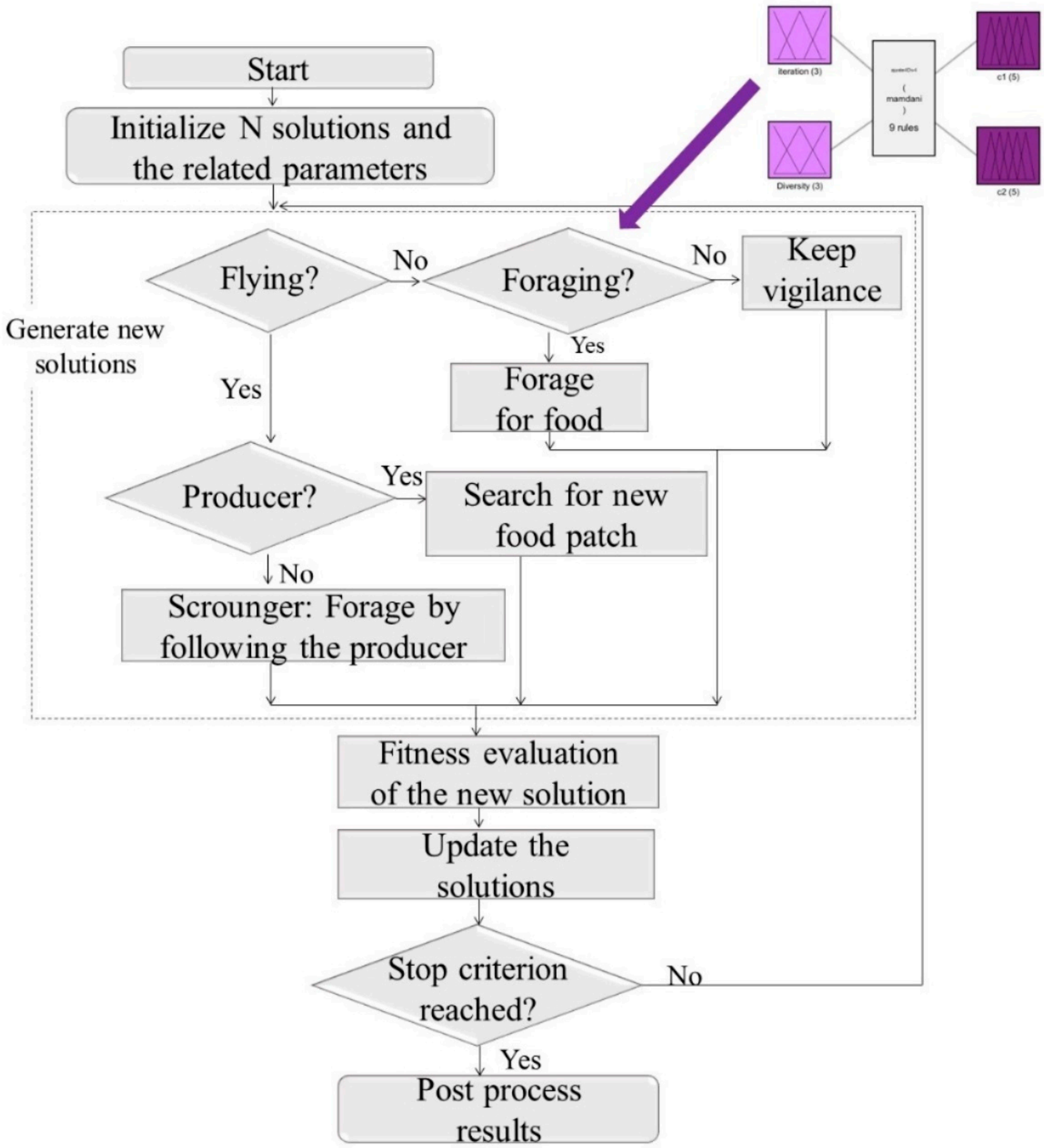

Figure 2. Proposed method of the dynamic bird swarm algorithm.

The proposed fuzzy system to perform the dynamic parameter adaptation corresponds to the Mamdani type. This has two inputs designed with triangular membership functions corresponding to iterations and diversity. Each input has three membership functions and uses as linguistic variables the following terms: "low", "medium", and "high". The outputs correspond to C1 and C2 variables, which have five membership functions, and use "Low", "MediumLow", "Medium", "MediumHigh", and "High" as linguistic values, and this proposal is presented in Figure 3.

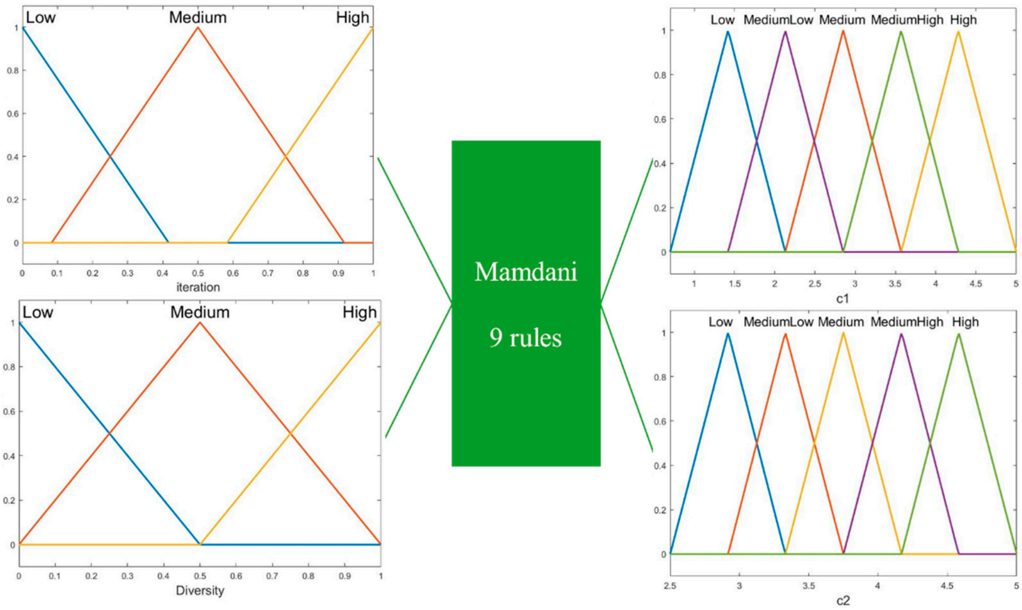

Figure 3. Fuzzy system designed with trapezoidal MFs.

To obtain the iterations, the percentage of the current iteration concerning the total iterations is calculated. This is interpreted in the following way: when the algorithm is just executing, the iteration takes a low value; as the execution progresses, it will gradually increase until it ends; at this point, the iterations will be high or very close to 100% [51]. This behavior can be represented mathematically as follows:

$$iteration = \frac{Current\ iteration}{Total\ nummber\ iterations} \tag{7}$$

Diversity refers to the degree of dispersion of individuals and is expressed mathematically as follows:

$$Diversity\ (S(t)) = \frac{1}{n_s} \sum_{i=1}^{n_s} \sqrt{\sum_{j=1}^{n_x} \left(X_{ij}(t) - \overline{X}_j(t)\right)^2} \tag{8}$$

where S refers to the population, n_s corresponds to the number of individuals in the population, n_x is the number of dimensions of the individuals, X_{ij} refers to the position of individual i, and $\overline{X}$ corresponds to the best individual position [41].

For this work, we experimented with four fuzzy systems in which the variation made was in the part of the rules. In Figure 4, the set of rules is presented where C1 decreases and C2 increases.

1. If (iteration is Low) and (Diversity is Low) then (c1 is High)(c2 is Low)
2. If (iteration is Medium) and (Diversity is Low) then (c1 is MediumHigh)(c2 is MediumLow)
3. If (iteration is Low) and (Diversity is Medium) then (c1 is MediumHigh)(c2 is Medium)
4. If (iteration is Low) and (Diversity is High) then (c1 is MediumHigh)(c2 is MediumLow)
5. If (iteration is Medium) and (Diversity is Medium) then (c1 is Medium)(c2 is Medium)
6. If (iteration is Medium) and (Diversity is High) then (c1 is MediumLow)(c2 is MediumHigh)
7. If (iteration is High) and (Diversity is Low) then (c1 is Medium)(c2 is High)
8. If (iteration is High) and (Diversity is Medium) then (c1 is MediumLow)(c2 is MediumHigh)
9. If (iteration is High) and (Diversity is High) then (c1 is Low)(c2 is High)

Figure 4. Fuzzy rules proposed for the first fuzzy system.

Figure 5 shows the fuzzy rules in which C1 is increasing, and C2 is decreasing.

1. If (iteration is Low) and (Diversity is Low) then (c1 is Low)(c2 is High)
2. If (iteration is Medium) and (Diversity is Low) then (c1 is MediumLow)(c2 is MediumHigh)
3. If (iteration is Low) and (Diversity is Medium) then (c1 is Medium)(c2 is MediumHigh)
4. If (iteration is Low) and (Diversity is High) then (c1 is MediumLow)(c2 is MediumHigh)
5. If (iteration is Medium) and (Diversity is Medium) then (c1 is Medium)(c2 is Medium)
6. If (iteration is Medium) and (Diversity is High) then (c1 is MediumHigh)(c2 is MediumLow)
7. If (iteration is High) and (Diversity is Low) then (c1 is Medium)(c2 is High)
8. If (iteration is High) and (Diversity is Medium) then (c1 is MediumHigh)(c2 is MediumLow)
9. If (iteration is High) and (Diversity is High) then (c1 is High)(c2 is Low)

Figure 5. Fuzzy rules proposed for the second fuzzy system.

Figure 6 presents the fuzzy rules set corresponding to C1, which maintains medium–low iterations, and C2 maintains medium–high iterations.

1. If (iteration is Low) and (Diversity is Low) then (c1 is Low)(c2 is High)
2. If (iteration is Medium) and (Diversity is Low) then (c1 is MediumLow)(c2 is MediumLow)
3. If (iteration is Low) and (Diversity is Medium) then (c1 is Low)(c2 is Medium)
4. If (iteration is Low) and (Diversity is High) then (c1 is Medium)(c2 is MediumLow)
5. If (iteration is Medium) and (Diversity is Medium) then (c1 is Medium)(c2 is Medium)
6. If (iteration is Medium) and (Diversity is High) then (c1 is Medium)(c2 is MediumHigh)
7. If (iteration is High) and (Diversity is Low) then (c1 is Medium)(c2 is High)
8. If (iteration is High) and (Diversity is Medium) then (c1 is MediumHigh)(c2 is MediumHigh)
9. If (iteration is High) and (Diversity is High) then (c1 is High)(c2 is High)

Figure 6. Fuzzy rules proposed for the third fuzzy system.

Figure 7 illustrates the fuzzy rule set in which C1 and C2 are kept at high and medium–high values.

1. If (Iteration is Low) and (Diversity is Low) then (c1 is High)(c2 is High)
2. If (Iteration is Medium) and (Diversity is Low) then (c1 is High)(c2 is MediumHigh)
3. If (Iteration is Low) and (Diversity is Medium) then (c1 is High)(c2 is Medium)
4. If (Iteration is Low) and (Diversity is High) then (c1 is Medium)(c2 is MediumHigh)
5. If (Iteration is Medium) and (Diversity is Medium) then (c1 is Medium)(c2 is Medium)
6. If (Iteration is Medium) and (Diversity is High) then (c1 is Medium)(c2 is MediumLow)
7. If (Iteration is High) and (Diversity is Low) then (c1 is MediumLow)(c2 is Medium)
8. If (Iteration is High) and (Diversity is Medium) then (c1 is Medium)(c2 is MediumLow)
9. If (Iteration is High) and (Diversity is High) then (c1 is Low)(c2 is Low)

Figure 7. Fuzzy rules proposed for the fourth fuzzy system.

Using the same structure and rules of the fuzzy system described above, in addition to making a comparison to determine which of these the best results are obtained, a fuzzy system using Gaussian membership functions is designed, presented in Figure 8.

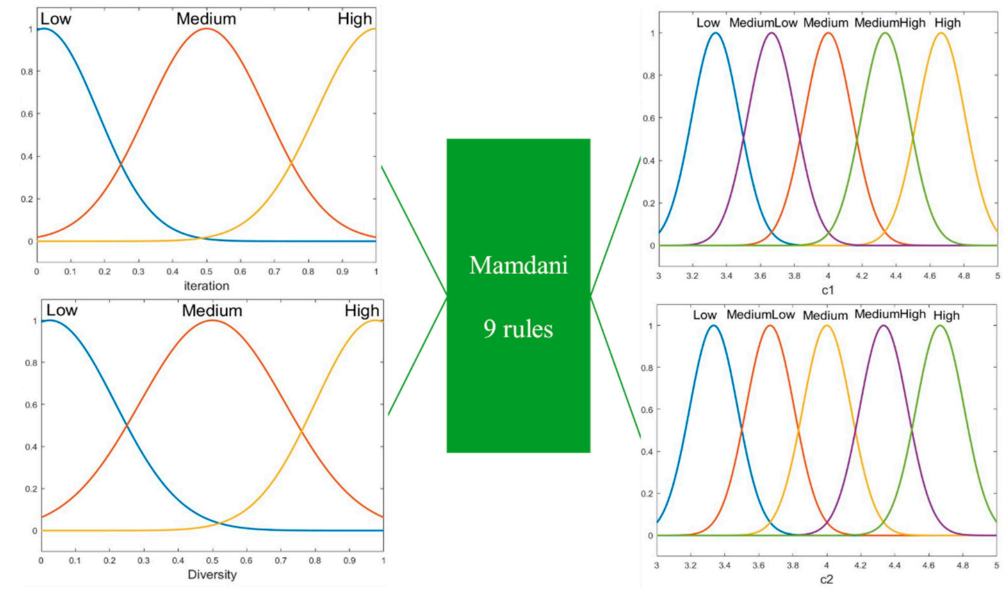

Figure 8. Fuzzy system proposed for the dynamic parameter adaptation designed with Gaussian MFs.

4.1. Design of the Interval Type-2 Fuzzy Systems

To compare results and analyze which obtains a better performance of the BSA, it is decided to take the structure and rules and implement them in the interval type-2 fuzzy systems (IT2FS). In Figure 9, the design used for the IT2FS is presented; it is worth mentioning that it manually adjusts the footprint of uncertainty. The comparison carried out has the objective of analyzing the performance and comparing the results with the type-1 fuzzy system since, as is known, the membership functions of IT2FS are characterized by upper and lower membership functions, where the interval between these two can have a better performance than the type-1 fuzzy system since, due to the nature of IT2FS, it can handle a higher degree of uncertainty.

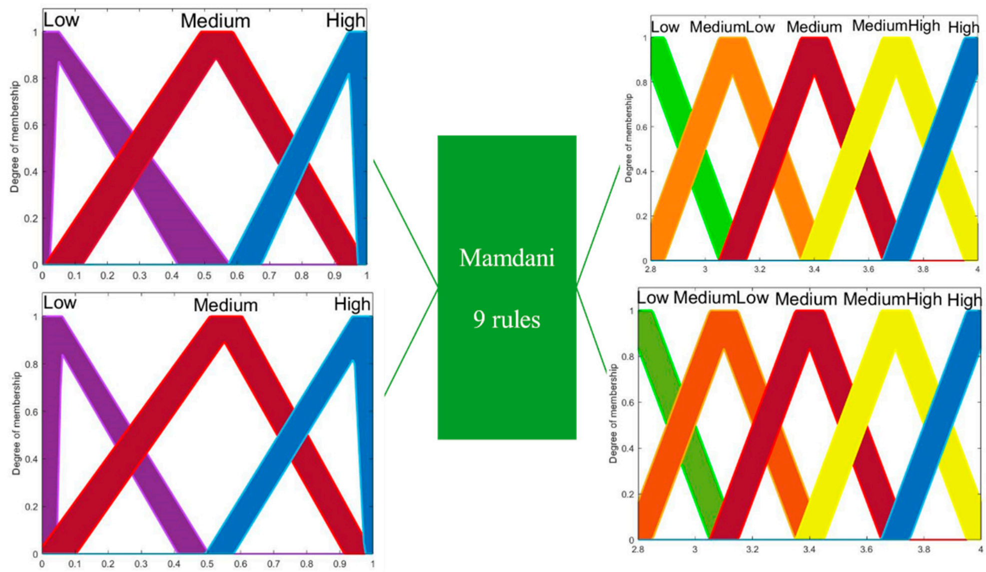

Figure 9. IT2FS proposed for the parameter dynamic adaptation using trapezoidal MFs.

Similarly, an IT2FS is designed using Gaussian membership functions, as shown in Figure 10.

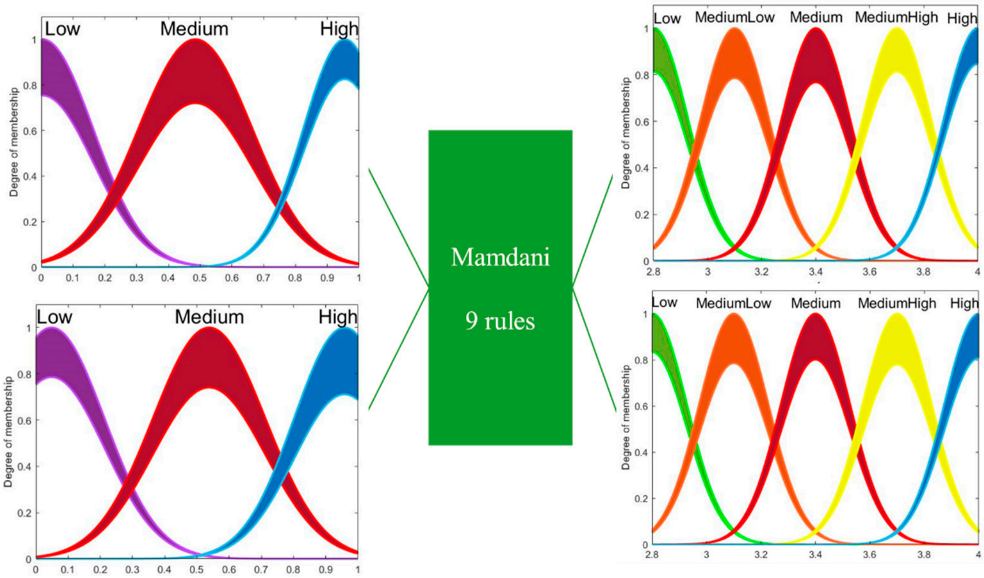

Figure 10. IT2FS proposed for the parameter dynamic adaptation using Gaussian MFs.

4.2. Study Cases

4.2.1. Design of Experiments Using CEC 2017 Functions

In the first phase of the experimentation, the parameters presented in Table 2 are used as a basis, and these are taken from [52] to compare results. As mentioned above, it was decided to adjust C1 and C2 due to the different manual tests that were performed, changing the different parameters used in the algorithm, and observing which of these was a more significant change in the results.

Table 2. Parameters used to solve the complex function of CEC2017.

	M	**pop**	**dim**	**FQ**	**a1**	**a2**	**c1**	**c2**
BSA	1500	30	30	3	1	1	1.5	1.5
DBSA	1500	30	30	3	1	1	Dynamic	Dynamic

In this case study, experimentation is performed with 10 functions of the CEC2017, from which six unimodal functions, one hybrid function, and three multimodal functions are taken; the objective of this experiment is that the algorithm reaches the minimum value of each function.

In Table 3, the functions used are listed. Column 1 presents the function type, column 2 corresponds to the function number, column 3 lists the name, and column 4 displays the minimum value.

Table 3. Mathematical complex function of CEC2017.

		Name Function	**Fi**
Unimodal Benchmark functions	5	Shifted and Rotated Rastrigin's Function	500
	6	Shifted and Rotated Expanded Scaffer's F6 Function	600
	7	Shifted and Rotated Lunacek Bi Rastrigin's Function	700

Table 3. *Cont.*

		Name Function	Fi
	8	Shifted and Rotated Non-Continuous Rastrigin's Function	800
	9	Shifted and Rotated Levy Function	900
	10	Shifted and Rotated Schwefel's Function	1000
Hybrid benchmark functions	11	Hybrid Function 1 (N = 3)	1100
Multimodal benchmark functions	21	Composition Function 1 (N = 3)	2100
	22	Composition Function 2 (N = 3)	2200
	23	Composition Function 3 (N = 4)	2300
		[−100, 100]	

4.2.2. Optimization of Medical Fuzzy System

To apply the proposed method in the solution of a different problem and analyze its performance, this is used in the optimization of the parameters of a fuzzy system, and this is part of a neuro-fuzzy hybrid model for the diagnosis of hypertension [17,53–55].

The fuzzy system to be optimized provides the nocturnal blood pressure profile being consulted. This result is of utmost importance since this diagnosis can prevent a future cardiovascular event [38,39]. Optimization is performed as follows:

We have a database with records of the blood pressure, which are separated into daytime and nighttime readings of systolic and diastolic pressure, respectively. The DBSA is used to optimize the parameters of the membership functions of the fuzzy system until the one that generates the best results is found. As a fitness function, the mean square error (MSE) is used, which compares the results and obtains the fuzzy function that generates lower errors. The MSE is expressed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2 \tag{9}$$

Figure 11 illustrates how the DBSA works in solving this optimization problem.

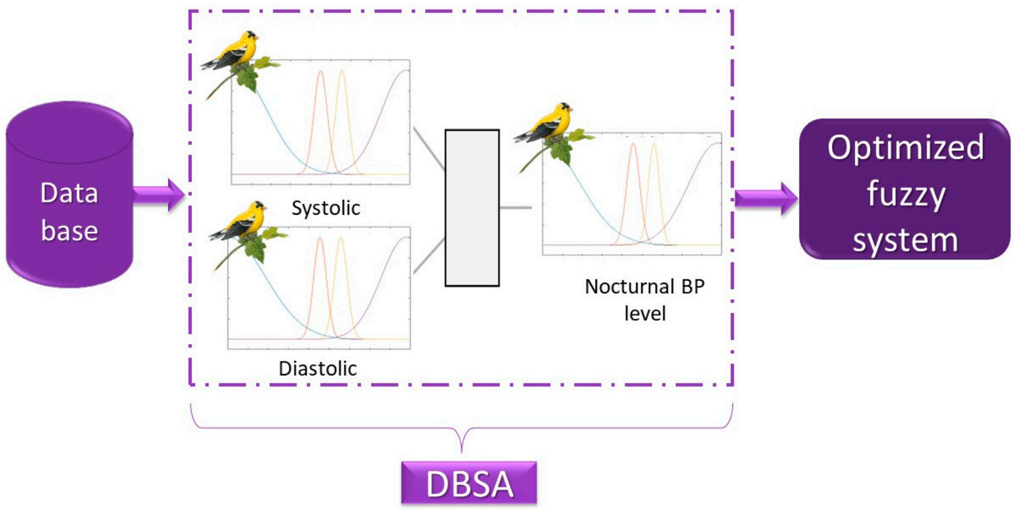

Figure 11. DBSA applied in the optimization of fuzzy system.

The fuzzy classifier of the nocturnal blood pressure profile is designed with two inputs; these refer to the quotient of the systolic and diastolic pressure and are granulated with four trapezoidal membership functions, using as linguistic values: "GreaterFall", "Fall", "Increase", and "GreaterIncrease". In this case, the nocturnal profile level corresponds to the output, and this uses four membership functions which are assigned "ExtremeDipper", "Dipper", "NonDipper", and "Riser" as linguistic values. Figures 12 and 13 present the inputs, while in Figure 14, the output is illustrated.

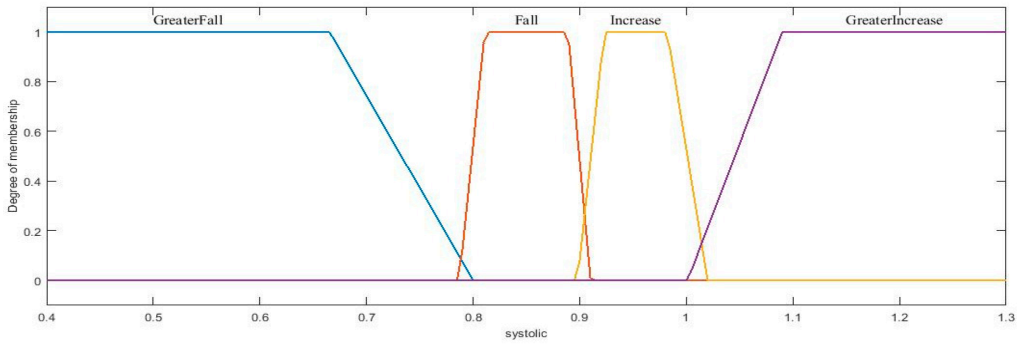

Figure 12. Systolic quotient input.

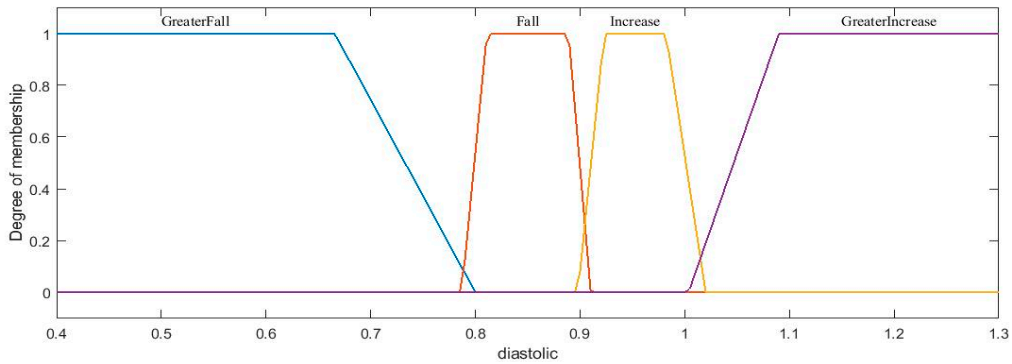

Figure 13. Diastolic quotient input.

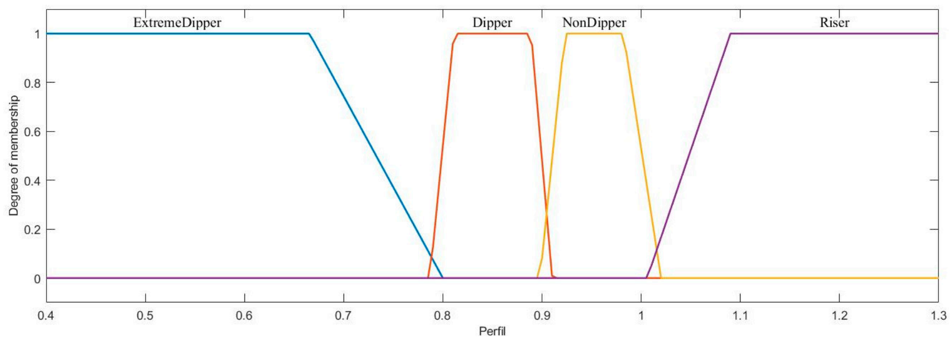

Figure 14. Nocturnal blood pressure level output.

To compare results, we also designed a fuzzy system with Gaussian membership functions using two inputs that refer to the systolic and diastolic pressure quotient and determine the following terms as linguistic values: "GreaterFall", "Fall", "Increase", and "GreaterIncrease". The output corresponds to the nocturnal blood pressure level, which is designed with four membership functions using the linguistic variables "ExtremeDipper", "Dipper", "NonDipper", and "Riser". In Figures 15 and 16, the inputs are presented, while in Figure 17, the output is presented.

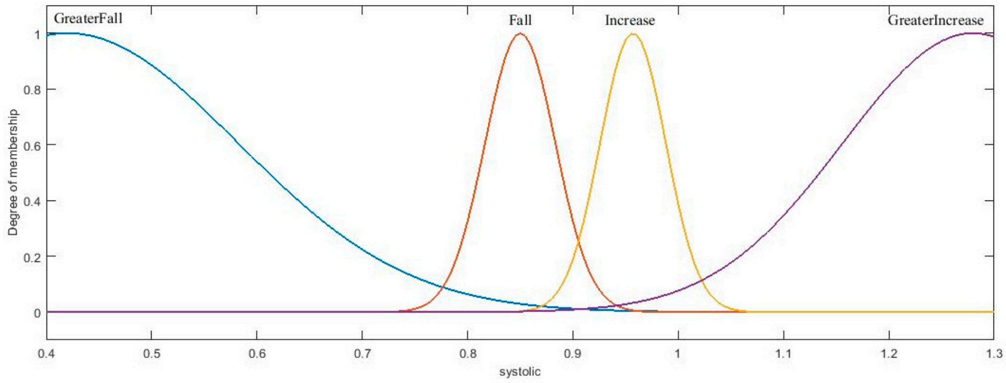

Figure 15. Systolic quotient input.

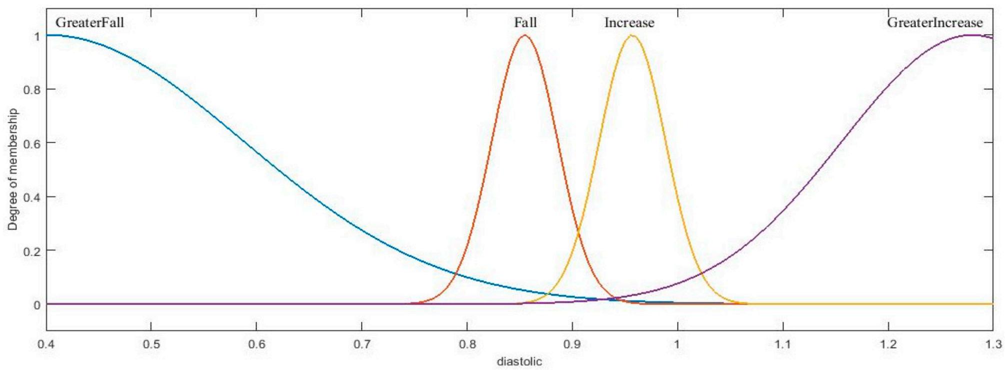

Figure 16. Diastolic quotient input.

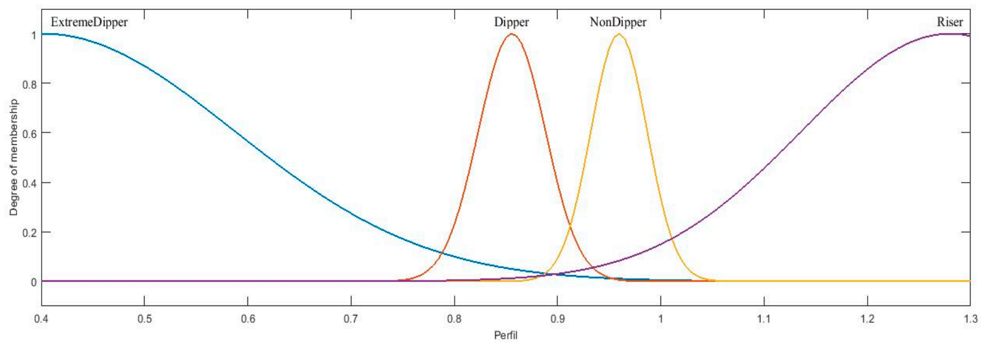

Figure 17. Nocturnal blood pressure level output.

In both fuzzy systems, four fuzzy rules are used, as follows:

1. If SystolicQuotient is "*GreaterFall*" and DiastolicQuotient is "*GreaterFall*" then Level is "*ExtremeDipper*".
2. If SystolicQuotient is "*Fall*" and DiastolicQuotient is "*Fall*" then Level is *Dipper*.
3. If SystolicQuotient is "*Increase*" and DiastolicQuotient is "*Increase*" then level is "*NonDipper*".
4. If SystolicQuotient is "*GreaterIncrease*" and DiastolicQuotient is "*GreaterIncrease*" then Level is "*GreaterRiser*".

5. Results

The results obtained when using the DBSA for solving problems of the CEC2017 are presented in Table 4. This experimentation corresponds to the dynamic parameter adaptation applying the different proposed type-1 fuzzy systems. We can analyze the results obtained that the proposed method provides better results than the original algorithm.

The fuzzy system number four uses triangular membership functions and has rules with high and medium–high values, and the fuzzy system obtained the best result in 5 of the 10 functions studied. The better results obtained are highlighted in bold type.

Regarding the dynamic parameters adaptation using the IT2FS, it is observed that the best results are obtained using fuzzy system four, which is implemented with Gaussian membership functions and uses rules with high and medium–high values, obtaining the best results in 4 of the 10 functions examined. Table 5 presents the results obtained, and as with the type-1 fuzzy system, the result is improved compared to the original algorithm.

Compared with the method proposed by [52], the results of dynamic parameter adaptation present a hybridization of the FA and the PSO, which was named HFPSO. Table 6 shows the comparison made, and it can be observed that the DBSA provides better results in 8 of the 10 experiments.

For the second case study, 30 experiments were carried out using type-1 fuzzy system number four, which was designed for the dynamic parameter adaptation, this being the one with which the best results were obtained. In this case, the DBSA is used to optimize the fuzzy system for obtaining the nocturnal blood pressure profile. Table 7 presents the percentage of correct classification in the different experiments performed; column 2 corresponds to the fuzzy system with trapezoidal membership functions, while column 3 corresponds to the fuzzy system with Gaussian membership functions, where we can observe that in several of the fuzzy systems, a 100% correct classification is achieved.

Regarding the optimization of the nocturnal blood pressure profile fuzzy system with trapezoidal membership functions, a classification comparison is performed using the non-optimized fuzzy system and the fuzzy improvement obtained from an optimization previously carried out with the chicken swarm optimization (CSO) algorithm [56], which are presented in Table 8. In columns 2 and 3, the real information is presented, in columns 4 and column 5, the results obtained with the non-optimized fuzzy system are presented, in columns 6 and 7, the results obtained with the optimization carried out using the CSO algorithm are listed, and finally, in columns 9 and 10, the optimization carried out with the DBSA is presented. We can observe that the non-optimized fuzzy system performs incorrectly in seven classifications, and the fuzzy system optimized with the CSO algorithm performs incorrectly in seven classifications; these can be identified with italics. We can determine that our proposal performs 100% of classification correctly, thus providing a guideline to determine that DBSA is a good method for optimizing fuzzy systems.

For the optimization performed to the fuzzy system of nocturnal blood pressure profile with Gaussian membership functions, a classification comparison is carried out, which is presented in Table 9. Columns 2 and 3 describe the real information, in columns 4 and column 5, the results obtained with the non-optimized fuzzy system are presented, columns 6 and 7 show the result obtained in the optimization carried out with the CSO, and finally, in columns 9 and 10, the optimization carried out with the DBSA is presented. The results may indicate that the non-optimized fuzzy system performs seven classifications incorrectly, whereas the optimized fuzzy system with the CSO algorithm performs two classifications incorrectly; these can be identified with italics. Regarding the proposed method, it can be observed that it performed 100% of classifications correctly, the proposed model being applicable for this type of optimization problem.

Table 4. Result of DBSA using type-1 fuzzy systems in CEC2017 functions.

No	Fi	Original	1st FIS		2nd FIS #2		3rd FIS		4th FIS	
			Triang	Gauss	Triang	Gauss	Triang	Gauss	Triang	Gauss
5	500	8.396×10^2	7.529×10^2	7.428×10^2	7.404×10^2	7.436×10^2	7.569×10^2	7.563×10^2	$\mathbf{7.359 \times 10^2}$	7.382×10^2
6	600	6.732×10^2	6.458×10^2	6.456×10^2	$\mathbf{6.510 \times 10^2}$	6.518×10^2	6.559×10^2	6.563×10^2	6.494×10^2	6.491×10^2
7	700	1.355×10^3	1.082×10^3	1.082×10^3	1.093×10^3	1.084×10^3	1.125×10^3	1.122×10^3	$\mathbf{1.070 \times 10^3}$	1.093×10^3
8	800	1.075×10^3	1.002×10^3	1.002×10^3	9.989×10^2	1.005×10^3	1.011×10^3	1.013×10^3	9.971×10^2	$\mathbf{9.925 \times 10^2}$
9	900	7.602×10^3	4.100×10^3	4.110×10^3	4.310×10^3	4.072×10^3	4.825×10^3	4.654×10^3	$\mathbf{3.775 \times 10^3}$	4.389×10^3
10	1000	7.243×10^3	7.399×10^3	7.408×10^3	7.261×10^3	7.358×10^3	7.278×10^3	7.285×10^3	7.451×10^3	$\mathbf{7.063 \times 10^3}$
11	1100	5.349×10^3	6.303×10^3	1.791×10^3	1.678×10^3	1.784×10^3	1.783×10^3	1.780×10^3	1.763×10^3	$\mathbf{1.580 \times 10^3}$
21	2100	2.645×10^3	2.508×10^3	2.512×10^3	2.516×10^3	2.513×10^3	2.531×10^3	2.534×10^3	$\mathbf{2.497 \times 10^3}$	2.513×10^3
22	2200	8.184×10^3	4.513×10^3	4.233×10^3	4.230×10^3	4.200×10^3	4.376×10^3	$\mathbf{4.179 \times 10^3}$	4.328×10^3	4.278×10^3
23	2300	3.352×10^3	3.043×10^3	3.008×10^3	3.033×10^3	3.012×10^3	3.063×10^3	3.054×10^3	$\mathbf{2.979 \times 10^3}$	2.891×10^3

Table 5. Result of DBSA using IT2FS in CEC2017 functions.

No	Fi	Original	1st FIS		2nd FIS		3rd FIS		4th FIS	
			Triang	Gauss	Triang	Gauss	Triang	Gauss	Triang	Gauss
5	500	8.4010^2	7.434×10^2	7.453×10^2	$\mathbf{7.320 \times 10^2}$	7.320×10^2	7.488×10^2	7.523×10^2	7.383×10^2	7.364×10^2
6	600	6.732×10^2	6.518×10^2	6.522×10^2	$\mathbf{6.461 \times 10^2}$	6.454×10^2	6.516×10^2	6.515×10^2	6.505×10^2	6.505×10^2
7	700	1.355×10^3	1.122×10^3	1.120×10^3	1.084×10^3	1.080×10^3	1.113×10^3	1.111×10^3	1.114×10^3	$\mathbf{1.074 \times 10^3}$
8	800	1.075×10^3	9.976×10^2	$\mathbf{9.963 \times 10^2}$	1.006×10^3	1.003×10^3	1.006×10^3	1.014×10^3	1.011×10^3	9.983×10^2
9	900	7.602×10^3	4.69×10^3	4.748×10^3	4.090×10^3	4.049×10^3	4.647×10^3	4.522×10^3	4.586×10^3	$\mathbf{3.874 \times 10^3}$
10	1000	7.243×10^3	$\mathbf{6.916 \times 10^3}$	6.944×10^3	7.372×10^3	7.431×10^3	7.245×10^3	7.290×10^3	7.263×10^3	7.407×10^3
11	1100	5.349×10^3	$\mathbf{1.581 \times 10^3}$	1.590×10^3	1.784×10^3	1.814×10^3	1.718×10^3	1.808×10^3	1.775×10^3	1.785×10^3
21	2100	2.645×10^3	2.528×10^3	2.526×10^3	2.512×10^3	2.504×10^3	2.526×10^3	2.528×10^3	2.527×10^3	$\mathbf{2.500 \times 10^3}$
22	2200	8.184×10^{03}	4.480×10^3	4.596×10^3	$\mathbf{4.053 \times 10^3}$	4.236×10^3	4.455×10^3	4.250×10^3	4.190×10^3	4.315×10^3
23	2300	3.352×10^{03}	3.067×10^3	3.064×10^3	3.016×10^3	3.000×10^3	3.049×10^3	3.042×10^3	3.046×10^3	$\mathbf{2.987 \times 10^3}$

Table 6. Comparison with the HFPSO method.

Function	Min	HFPSO	Original	DBSA Triangular	DBSAT2 Gauss
5	500	7.43×10^2	8.40×10^2	$\mathbf{7.359 \times 10^2}$	7.364×10^2
6	600	6.54×10^2	6.732×10^2	$\mathbf{6.494 \times 10^2}$	6.505×10^2
7	700	$\mathbf{1.063 \times 10^3}$	1.355×10^3	1.070×10^3	1.074×10^3
8	800	1.017×10^3	1.075×10^3	$\mathbf{9.971 \times 10^2}$	9.983×10^2
9	900	9.04×10^3	7.602×10^3	$\mathbf{3.775 \times 10^3}$	3.874×10^3
10	1000	7.49×10^3	7.243×10^3	7.451×10^3	$\mathbf{7.407 \times 10^3}$
11	1100	2.28×10^3	5.349×10^3	$\mathbf{1.763 \times 10^3}$	1.785×10^3
21	2100	2.51×10^3	2.645×10^3	$\mathbf{2.497 \times 10^3}$	2.500×10^3
22	2200	5.80×10^3	8.184×10^3	4.328×10^3	$\mathbf{4.315 \times 10^3}$
23	2300	$\mathbf{2.96 \times 10^3}$	3.352×10^3	2.979×10^3	2.987×10^3

Table 7. Percentage of success in each experiment.

No	FISTra	FISGauss
1	100%	93%
2	93%	93%
3	100%	100%
4	100%	97%
5	93%	93%
6	97%	93%
7	97%	100%
8	93%	100%
9	93%	100%
10	97%	100%
11	100%	93%
12	100%	93%
13	100%	100%
14	100%	100%
15	93%	100%
16	87%	87%
17	100%	93%
18	100%	100%
19	90%	100%
20	100%	100%
21	100%	100%
22	87%	100%
23	100%	93%
24	100%	100%
25	93%	97%
26	93%	100%
27	100%	90%
28	100%	90%
29	100%	100%
30	100%	100%

Table 8. Comparative of the results provided for the nocturnal blood pressure profile optimized using trapezoidal membership functions.

No	Real Values		Non-Optimized FS		CSO		DBSA	
	Level	Quotient	Linguistic Output	Fuzzy Result	Linguistic Output	Fuzzy Result	Linguistic Output	Fuzzy Result
1	ExtremeDipper	0.76	ExtremeDipper	0.60	ExtremeDipper	0.61	ExtremeDipper	0.61
2	Dipper	0.89	Dipper	0.85	Dipper	0.86	Dipper	0.89
3	Dipper	0.81	Dipper	0.85	Dipper	0.86	Dipper	0.83
4	Dipper	0.82	Dipper	0.85	Dipper	0.86	Dipper	0.85
5	No Dipper	0.91	***Dipper***	***0.85***	***Dipper***	***0.85***	NonDipper	0.94
6	Dipper	0.87	Dipper	0.85	Dipper	0.86	Dipper	0.85
7	ExtremeDipper	0.77	***Dipper***	***0.85***	***Dipper***	***0.85***	ExtremeDipper	0.61
8	NonDipper	0.90	***Dipper***	***0.85***	***Dipper***	***0.85***	NonDipper	0.94
9	NonDipper	0.94	NonDipper	0.96	NonDipper	0.96	NonDipper	0.94
10	Dipper	0.83	Dipper	0.85	Dipper	0.85	Dipper	0.85
11	NonDipper	0.92	***Dipper***	***0.85***	***Dipper***	***0.85***	NonDipper	0.94
12	ReverseDipper	1.03	ReverseDipper	1.16	ReverseDipper	1.1	ReverseDipper	1.15
13	Dipper	0.84	Dipper	0.85	Dipper	0.86	Dipper	0.85
14	ReverseDipper	1.07	ReverseDipper	1.17	ReverseDipper	1.16	ReverseDipper	1.16
15	NonDipper	0.91	***Dipper***	***0.85***	***Dipper***	***0.85***	NonDipper	0.94
16	Dipper	0.82	Dipper	0.85	Dipper	0.86	Dipper	0.85
17	Dipper	0.86	Dipper	0.85	Dipper	0.85	Dipper	0.85
18	NonDipper	0.90	***Dipper***	***0.85***	***Dipper***	***0.85***	NonDipper	0.94
19	Dipper	0.84	Dipper	0.85	Dipper	0.85	Dipper	0.85
20	NonDipper	0.93	***Dipper***	***0.85***	***Dipper***	***0.85***	NonDipper	0.94
21	NonDipper	0.93	NonDipper	0.96	NonDipper	0.96	NonDipper	0.94
22	Dipper	0.83	Dipper	0.85	Dipper	0.86	Dipper	0.85
23	NonDipper	0.92	NonDipper	0.96	NonDipper	0.97	NonDipper	0.94
24	ExtremeDipper	0.72	ExtremeDipper	0.59	ExtremeDipper	0.61	ExtremeDipper	0.60
25	Dipper	0.85	Dipper	0.85	Dipper	0.86	Dipper	0.85
26	Dipper	0.89	Dipper	0.85	Dipper	0.85	Dipper	0.85
27	Dipper	0.89	Dipper	0.85	Dipper	0.85	Dipper	0.85
28	NonDipper	0.93	NonDipper	0.96	NonDipper	0.96	NonDipper	0.94
29	NonDipper	0.94	NonDipper	0.96	NonDipper	0.96	NonDipper	0.94
30	Dipper	0.83	Dipper	0.85	Dipper	0.86	Dipper	0.85

Table 9. Comparative of the results provided for the nocturnal blood pressure profile optimized using Gaussian membership functions.

No	Real		Non-Optimized FS		CSO		DBSA	
	Level	Quotient	Linguistic Output	Fuzzy Result	Linguistic Output	Fuzzy Result	Linguistic Output	Fuzzy Result
1	ExtremeDipper	0.76	ExtremeDipper	0.64	ExtremeDipper	0.71	ExtremeDipper	0.61
2	Dipper	0.89	Dipper	0.85	Dipper	0.89	Dipper	0.89
3	Dipper	0.81	*ExtremeDipper*	*0.77*	Dipper	0.84	Dipper	0.83
4	Dipper	0.82	*ExtremeDipper*	*0.79*	Dipper	0.84	Dipper	0.85
5	NonDipper	0.91	*Dipper*	*0.89*	NonDipper	0.91	NonDipper	0.94
6	Dipper	0.87	Dipper	0.83	Dipper	0.87	Dipper	0.85
7	ExtremeDipper	0.77	ExtremeDipper	0.66	ExtremeDipper	0.78	ExtremeDipper	0.61
8	NonDipper	0.90	*Dipper*	*0.86*	NonDipper	0.91	NonDipper	0.94
9	NonDipper	0.94	NonDipper	0.96	*Dipper*	*0.87*	NonDipper	0.94
10	Dipper	0.83	*ExtremeDipper*	*0.79*	Dipper	0.84	Dipper	0.85
11	NonDipper	0.92	NonDipper	0.94	NonDipper	0.93	NonDipper	0.94
12	ReverseDipper	1.03	ReverseDipper	1.10	ReverseDipper	1.03	ReverseDipper	1.15
13	Dipper	0.84	Dipper	0.82	Dipper	0.85	Dipper	0.85

Table 9. *Cont.*

No	Real		Non-Optimized FS		CSO		DBSA	
	Level	**Quotient**	**Linguistic Output**	**Fuzzy Result**	**Linguistic Output**	**Fuzzy Result**	**Linguistic Output**	**Fuzzy Result**
14	ReverseDipper	1.07	ReverseDipper	1.13	ReverseDipper	1.15	ReverseDipper	1.16
15	NonDipper	0.91	NonDipper	0.90	*Dipper*	*0.86*	NonDipper	0.94
16	Dipper	0.82	*ExtremeDipper*	*0.79*	Dipper	0.84	Dipper	0.85
17	Dipper	0.86	Dipper	0.82	Dipper	0.85	Dipper	0.85
18	NonDipper	0.90	*Dipper*	*0.88*	NonDipper	0.91	NonDipper	0.94
19	Dipper	0.84	Dipper	0.80	Dipper	0.85	Dipper	0.85
20	NonDipper	0.93	NonDipper	0.95	NonDipper	0.94	NonDipper	0.94
21	NonDipper	0.93	NonDipper	0.96	NonDipper	0.94	NonDipper	0.94
22	Dipper	0.83	Dipper	0.80	Dipper	0.84	Dipper	0.85
23	NonDipper	0.92	NonDipper	0.92	NonDipper	0.92	NonDipper	0.94
24	ExtremeDipper	0.72	ExtremeDipper	0.63	ExtremeDipper	0.61	ExtremeDipper	0.60
25	Dipper	0.85	Dipper	0.83	Dipper	0.85	Dipper	0.85
26	Dipper	0.89	Dipper	0.82	Dipper	0.89	Dipper	0.85
27	Dipper	0.89	Dipper	0.83	Dipper	0.89	Dipper	0.85
28	NonDipper	0.93	NonDipper	0.95	NonDipper	0.93	NonDipper	0.94
29	NonDipper	0.94	NonDipper	0.96	NonDipper	0.94	NonDipper	0.94
30	Dipper	0.83	Dipper	0.81	Dipper	0.85	Dipper	0.85

Table 10 compares the classification percentage obtained by the 30 experiments in the optimizations [56]. We can see that the classification percentage is higher with a fuzzy system optimized with the proposed method, 97% for both membership functions.

Table 10. Comparative of the different optimization results.

CSO		DBSA	
Trapezoida_lMF	**Gaussian_MF**	**Trapezoidal_MF**	**Gaussian_MF**
91.46%	87.59%	97%	97%

Figures 18 and 19 illustrate the trapezoidal membership functions optimized with the DBSA corresponding to the input. In contrast, Figure 20 shows the membership functions optimized by DBSA which correspond to the output.

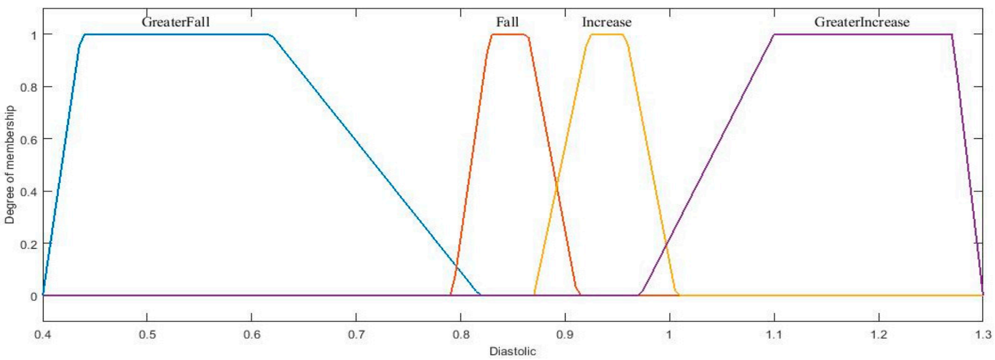

Figure 18. Optimized systolic quotient input.

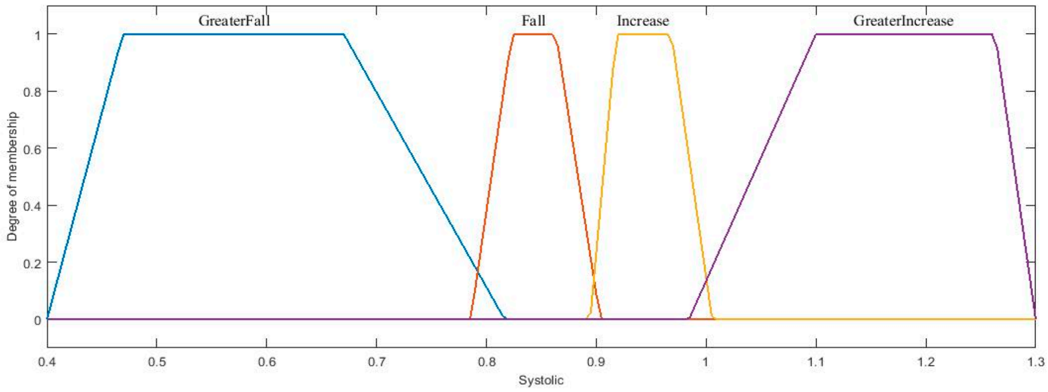

Figure 19. Optimized diastolic quotient input.

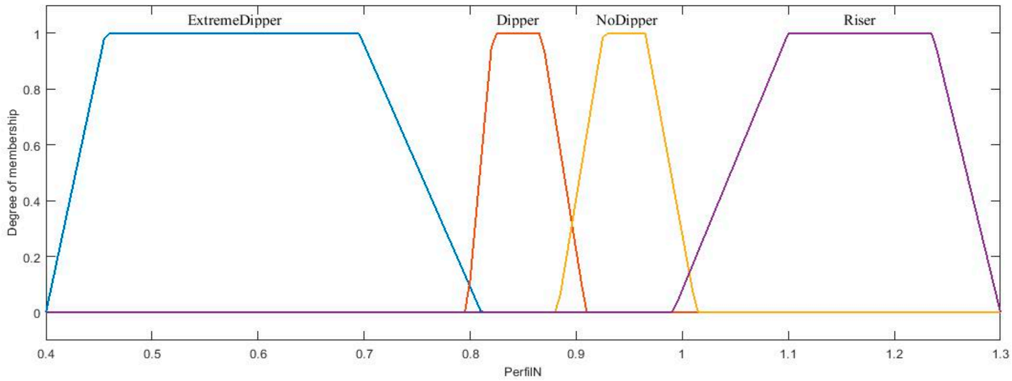

Figure 20. Optimized nocturnal blood pressure output.

Figures 21 and 22 present the Gaussian membership functions optimized with the DBSA corresponding to the inputs, while Figure 23 illustrates the membership functions corresponding to the output.

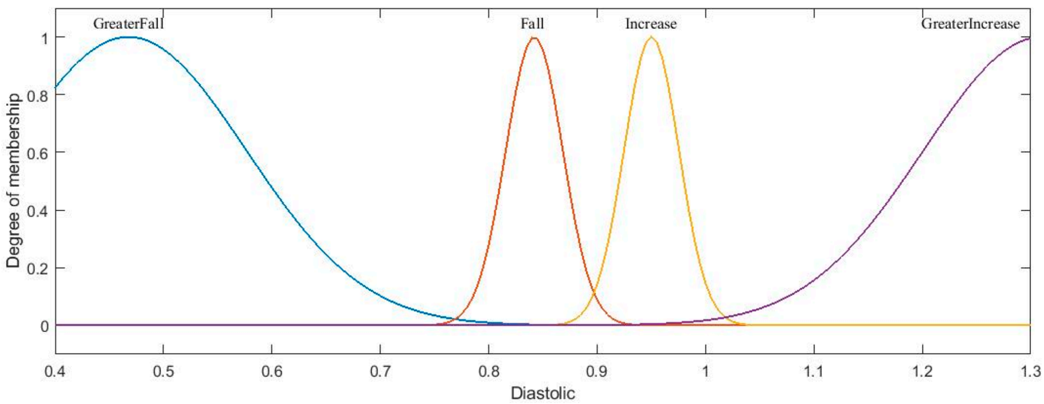

Figure 21. Optimized systolic quotient input.

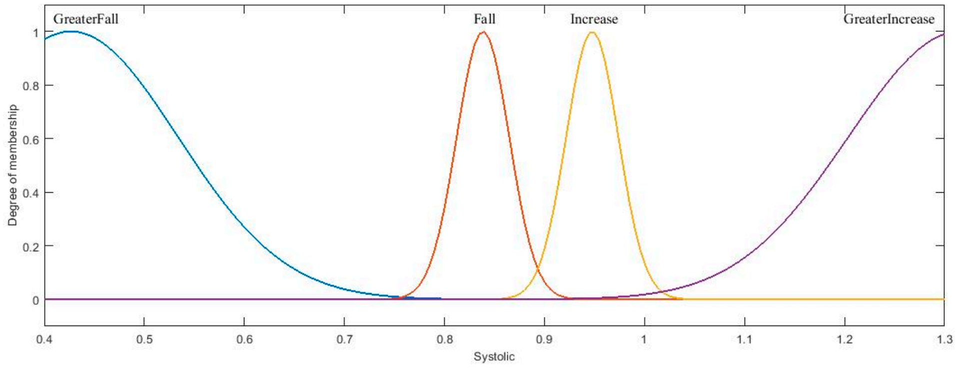

Figure 22. Optimized diastolic quotient input.

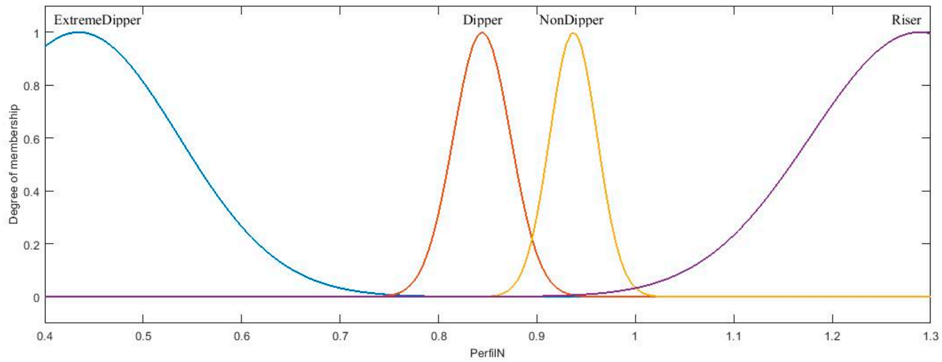

Figure 23. Optimized nocturnal blood pressure level output.

Table 11 presents the parameters used by the optimized and non-optimized fuzzy classifier, being a, b, c, and d for each parameter used in the trapezoidal membership functions.

Table 11. Parameters used for the nocturnal blood pressure classifier design with trapezoidal membership function.

Inputs and Output	MFs	Non-Optimized Parameters				Optimized Parameters			
		a	b	c	d	a	b	c	d
SystolicQuotient	*GreaterFall*	0.4	0.4	0.6655	0.8	0.4	0.469	0.67	0.8166
	Fall	0.787	0.811	0.889	0.9102	0.7858	0.8232	0.8636	0.9035
	Increase	0.898	0.923	0.9821	1.02	0.8945	0.918	0.9684	1.005
	GreaterIncrease	1.001	1.09	1.3	1.3	1.001	1.09	1.236	1.3
DiastolicQuotient	*GreaterFall*	0.4	0.4	0.6655	0.8	0.4	0.4366	0.6182	0.8182
	Fall	0.787	0.811	0.889	0.9102	0.7921	0.8277	0.8644	0.9117
	Increase	0.898	0.923	0.9821	1.02	0.87	0.9224	0.9581	1.006
	GreaterIncrease	1.004	1.09	1.3	1.3	0.972	1.1	1.27	1.3
Nocturnal blood pressure profile level	*ExtremeDipper*	0.4	0.4	0.6655	0.8	0.4	0.456	0.6951	0.8105
	Dipper	0.787	0.811	0.889	0.9102	0.7972	0.8212	0.8673	0.9093
	NonDipper	0.898	0.923	0.9821	1.02	0.8822	0.9257	0.965	1.013
	Riser	1.006	1.09	1.3	1.3	0.9912	1.1	1.236	1.3

Table 12 presents the parameters used by the optimized and non-optimized fuzzy classifier. In this case, a represents the mean and b the standard deviation used in each Gaussian membership function.

Table 12. Parameters used for the nocturnal blood pressure classifier design with Gaussian membership function.

Inputs and Output	MFs	Non-Optimized Parameters		Optimized Parameters	
		a	**b**	**a**	**b**
SystolicQuotient	*GreaterFall*	0.42	0.162	0.4266	0.1071
	Fall	0.82	0.03337	0.8385	0.02628
	Increase	0.957	0.03122	0.9478	0.02611
	GreaterIncrease	1.28	0.1236	1.316	0.1119
DiastolicQuotient	*GreaterFall*	0.402	0.1854	0.4674	0.1088
	Fall	0.8548	0.0313	0.842	0.02634
	Increase	0.957	0.0315	0.9502	0.0254
	GreaterIncrease	1.28	0.1236	1.31	0.1091
Nocturnal blood pressure profile level	*ExtremeDipper*	0.402	0.1854	0.4343	0.1017
	Dipper	0.8558	0.0325	0.8442	0.02911
	NonDipper	0.9595	0.0273	0.9371	0.02413
	Riser	1.28	0.1438	1.288	0.1104

The adjustment made by the DBSA for fuzzy systems that use Gaussian and trapezoidal membership functions, although it seems minimal, helped to improve the classification.

As seen in the experimentation carried out, the BSA generates the data sets given for the optimization of the membership functions; this method updates its fitness in each function until it finds the best one, generating the best vector of data for an optimal solution.

5.1. Statistical Test

5.1.1. Statistical Test for CEC 2017 Functions

The parametric Z-test is used to perform the statistical analysis, the objective being to compare the results obtained throughout the experimentation. Mathematically, the statistical test is expressed as:

$$Z = \frac{(\overline{X}_1 - \overline{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \tag{10}$$

where $\overline{x}_1 - \overline{x}_2$ is the difference between the sample mean, $\mu_1 - \mu_2$ is the difference between the population mean, $\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$ are the population standard deviation and $(n_1,\ n_2)$ are the sample size.

It should be clarified that the statistical analysis for the functions of the CEC2017 is carried out concerning the work presented by Berkan (Aydilek, 2018), which took the parameters used in its methodology to apply it in the DBSA and make a fair comparison.

In the experiments carried out with the complex mathematical functions (CEC2017), where type-1 fuzzy systems are used to perform the dynamic parameter adaptation, the following is established as a null hypothesis: the results provided by the DBSA are greater than or equal to the results of the HFPSO method. The alternative hypothesis proves that the results provided by DBSA are lower than those obtained by the HFPOS method. Table 13 lists the statistical parameters used for this problem.

Table 13. Parameters used in Z-Test for DBSA vs. HFPSO.

Parameter of Z-Test for DBSA vs. HFPSO	
Critical Value (Z_c)	1.64
Confidence interval	95%
H_0	$\mu1 \geq \mu2$
H_a (Claim)	$\mu1 < \mu2$
Alpha	0.05

The results of the Z-test applied to the 10 CEC2017 functions are presented in Table 14. Columns 2 and 3 show the results of the HFPSO and its standard deviation; columns 4 and 5 present the results of the DBSA with the type-1 fuzzy system that uses trapezoidal membership functions and its standard deviation. In column 6, the results of the Z-Test are described, and column 7 indicates if significant evidence to reject the null hypothesis exists (S) or not (NS). It can be observed that in 5 of the 10 functions used, and there is evidence supporting the claim that our proposal provides less error than the HFPSO.

Table 14. Statistical test results for CEC2017 functions using type-1 fuzzy systems.

Function	HFPSO	DE	DBSA FisT1	D.E	Z Test	Evidence
5	7.43×10^2	2.83×10^1	7.3594×10^2	4.1862×10^1	−1.384	NS
6	6.54×10^2	1.49×10^1	6.4937×10^2	9.9485×10^0	−2.791	S
7	1.06×10^3	3.82×10^1	1.0695×10^3	5.2146×10^1	1.548	NS
8	1.02×10^3	3.49×10^1	9.9711×10^2	3.0107×10^1	−4.991	S
9	9.04×10^3	2.42×10^3	3.7745×10^3	1.2676×10^3	−19.283	S
10	7.49×10^3	9.11×10^2	7.4514×10^3	8.4525×10^2	−0.322	NS
11	2.28×10^3	6.81×10^2	1.7630×10^3	2.2155×10^2	−7.25	S
21	2.51×10^3	2.92×10^5	2.4966×10^3	3.3743×10^1	0	NS
22	5.80×10^3	3.26×10^1	4.3283×10^3	2.5558×10^3	−5.742	S
23	2.96×10^3	7.41×10^1	2.9792×10^3	1.0784×10^2	1.527	NS

Regarding the experiments performed in solving the complex mathematical functions using IT2FS, it is established as a null hypothesis that the results obtained by the DBSA are greater than or equal to the results obtained by the HFPSO method. The alternative hypothesis demonstrates that the results provided by DBSA are lower than those obtained by the HFPSO method. Table 13 also lists the statistical parameters used for this problem.

The results obtained in the Z-test applied to the 10 functions of the CEC2017 are presented in Table 15. Columns 2 and 3 show the results of the HFPSO and its standard deviation; column 4 and column 5 list the results of our proposal using IT2FS using trapezoidal membership functions and their standard deviation. In the sixth column, we have described the results of the Z-Test, and in column 7, it is indicated if significant evidence to reject the null hypothesis exists (S) or not (NS). As can be observed, in 5 of the 10 functions used, there is evidence to support the claim that our proposal provides less error than the HFPSO

Table 15. Statistical test results for CEC2017 functions using IT2FS.

Function	HFPSO	DE	DBSA FisT2	D.E	Z Test	Evidence
5	7.43×10^2	2.83×10^1	7.364×10^2	3.930×10^1	−1.445	NS
6	6.54×10^2	1.49×10^1	6.505×10^2	1.040×10^1	−1.651	S
7	1.06×10^3	3.82×10^1	1.074×10^3	5.390×10^1	1.514	NS
8	1.02×10^3	3.49×10^1	9.983×10^2	2.850×10^1	−4.883	S
9	9.04×10^3	2.42×10^3	3.874×10^3	1.310×10^3	−18.788	S
10	7.49×10^3	9.11×10^2	7.407×10^3	8.413×10^2	−0.645	NS
11	2.28×10^3	6.81×10^2	1.785×10^3	3.203×10^2	−6.512	S
21	2.51×10^3	2.92×10^5	2.500×10^3	3.570×10^1	0	NS
22	5.80×10^3	3.26×10^1	4.315×10^3	2.580×10^3	−5.775	S
23	2.96×10^3	7.41×10^1	2.987×10^3	1.010×10^2	2.395	NS

5.1.2. Statistical Test for Optimization of the Nocturnal Blood Pressure Profile Fuzzy Classifier

Similarly, for this second case study, a statistical analysis was performed applying the Z-test to observe the results obtained from the different optimizations performed in the fuzzy system that provides the nocturnal blood pressure profile. In this case, 30 experiments are carried out with the CSO and DBSA algorithms, respectively, optimizing the fuzzy system that uses trapezoidal membership functions and comparing the results obtained, which correspond to the classification percentage.

As a null hypothesis, it may establish that the means of the results obtained by the fuzzy classifier optimized with the DBSA algorithm are lower than or equal to the average of the results of the fuzzy classifier obtained with the CSO. The alternative hypothesis suggests that the means of the classification obtained by the fuzzy system optimized with the DBSA algorithm are more significant than those obtained by the fuzzy system optimized with the CSO. Table 16 presents the parameters of the Z-test.

Table 16. Parameters used in Z-Test for DBSA vs. CSO.

Parameters of Z-Test for DBSA vs. CSO	
Critical Value (Z_c)	1.645
Confidential interval	95%
H_0	$\mu 1 \leq \mu 2$
H_a (Claim)	$\mu 1 > \mu 2$
Alpha	0.05

Table 17 present the descriptive statistics used in this test, where *Var* is the variable to compare, *Obs* is the number of experiments, and *SD* corresponds to the standard deviation.

Table 17. Z-test descriptive statistics.

Var	Obs	Mean	S. D
DBSA	30	97	0.1213
CSO	30	91.458	1.944

The results obtained using equation 10 are presented in Table 18, where Z represents the observed value, Z_c corresponds to the critical value, and α is its alpha value.

Table 18. Z-test results.

Z	15.607
p-value	0
α	0.05
Z_c	1.645

Derived from the result of the p-value, which is less than the level of significance, alpha = 0.05, the null hypothesis is rejected, so the following is concluded: there is enough evidence, at the 5% level of significance, to support the claim that the averages of the classification in DBSA are more significant than the classification with CSO.

The second statistical study carried out in this case study corresponds to the optimization of the fuzzy system that provides the nocturnal blood pressure profile with Gaussian membership functions, for which 30 different experiments are performed using CSO and DBSA algorithms, respectively, for comparing results.

As a null hypothesis, it may be established that the means of the classification obtained by the fuzzy classifier optimized with the DBSA algorithm are lower than or equal to the mean of the results of the fuzzy classifier obtained with the CSO. The alternative hypothesis suggests that the means of the results obtained by the fuzzy classifier optimized with the DBSA algorithm are more significant than the means of the results obtained with the fuzzy classifier provided by CSO. In this case, the parameters shown in Table 16 are also used.

Table 19 presents the descriptive statistics used in this test.

Table 19. Z-test descriptive statistics.

Var	Obs	Mean	S. D
DBSA	30	97	0.1161
CSO	30	87.50	2.390

The results obtained using equation 10 are presented in Table 20, where Z corresponds to the observed value, Zc is the critical value, and α is its alpha value.

Table 20. Z-test results.

Z	21.746
p-value	0
α	0.05
Z_c	1.645

Derived from the result of the p-value, which is less than the level of significance, alpha = 0.05, the null hypothesis is rejected, so the following is concluded: there is enough evidence at the 5% level of significance to support the claim that the averages of the classification in DBSA are more significant than the classification with CSO.

5.1.3. ANOVA Test for Optimization of the Nocturnal Blood Pressure Profile Fuzzy Classifier

Another metric with which we can analyze the results obtained in the classification of patients in obtaining the nocturnal blood pressure profile is the ANOVA statistic, with which we can determine if the average obtained with each of the membership functions used is the same. The comparison of the information is made with the previous work [56], from which we take the average of patients classified correctly.

Table 21 compares the results obtained with the trapezoidal membership functions.

Table 21. ANOVA comparing results of trapezoidal MFs.

Source of Variance	SS	df	MS	F	p-Value	F Critic
Between groups	422.68	1	422.68	37.43	8.71×10^{-8}	4.01
Within Groups	655.00	58	11.29			
Total	1077.68	59				

Once the corresponding calculations have been made and the results obtained in the variable F compared against the critical value, it is concluded with a 5% confidence level that the average of the data has a statistical difference.

Table 22 presents the information to compare experiments with the Gaussian membership functions. Analyzing the critical F with the F obtained, it can be concluded that the data groups present different averages. We can conclude that the 5% confidence level also shows a statistical difference in the data.

Table 22. ANOVA comparing results of Gaussian MFs.

Source of Variance	SS	df	MS	F	p-Value	F Critic
Between groups	1306.67	1	1306.67	117.72	1.39×10^{-15}	4.01
Within Groups	643.79	58	11.10			
Total	1950.46	59				

Once all the experiments have been carried out, and with the results obtained, we can observe that the changes in the data are not abrupt. Still, they improve in the part of the mathematical functions and the correct classification of patients. In this sense, we can say that the proposed method is precise; it helps to improve the optimization of the studied problems.

6. Discussion

The dynamic parameter adaptation performed in this work, called DBSA, aims to improve the efficiency of the BSA. It is used to optimize mathematical functions and applied in optimizing the real problem, which corresponds to obtaining the nocturnal blood pressure profile. It is worth mentioning that we also tested the dynamic parameter adaptation with IT2FS. Analyzing the obtained results, we can interpret that our proposal provides satisfactory results when compared with the original method and even compared to other methodologies. In this presented proposal, where the diversity is used as input in addition to iterations, it is helpful for solving mathematical problems as applicable in optimizing the parameters of fuzzy systems. It is demonstrated through statistical analysis that there is a significant improvement in 5 of the 10 mathematical complex functions of the CEC2017. Similarly, we present an improvement in the classification in the optimized fuzzy system, and it can be concluded that we found sufficient evidence to determine that our proposal provides better results. We can also determine that the proposed method can be implemented to solve problems in different areas. It would be engaging in future work to test the proposal in problems within the industry; it could be the case of optimization in a particular robotic arm movement. Some other problems that could be resolved are in the medical area, for example, the classification of blood pressure and heart rate, or in the area of computer vision to enhance medical images. The next challenge is to test the DBSA in other types of problems, for example, the optimization of an artificial neural network's architecture or even control problems.

7. Conclusions

This work implements dynamic parameter adaptation in the BSA using fuzzy logic to improve its performance. Four different type-1 fuzzy systems are proposed, where the variation is made in the part of the rules. In addition, the difference between this research and previous works is that a second input is added to the fuzzy systems, which corresponds to the diversity in the bird population. To analyze its performance, an IT2FS was also tested. The performance of our proposal is studied by applying it to the solution of two case studies. In the first one, the proposal is analyzed by experimenting with 10 complex functions of the CEC 2017, where, with the results collected, it can be observed that the DBSA provides good results in 5 of the 10 functions, compared to the HFPSO method, in addition to also providing better results when compared to the original method.

Regarding the proposed fuzzy systems, the system obtaining the best results is number 4, which has rules with high and medium–high values. The experimentation with the IT2FS achieved the best results with the fuzzy system number 4, which uses Gaussian membership functions. In the second case study, corresponding to the optimization applied in the fuzzy inference system designed to obtain the nocturnal blood pressure profile, we experimented with a type-1 fuzzy system using both trapezoidal and Gaussian membership functions to determine which one obtained a better classification. The results were similar, reaching a 97% correct classification in an average of the 30 experiments performed for each obtained fuzzy system. It compares these results with previous experimentation with the CSO algorithm, where the proposed method yields better classification results. The results obtained show us the best performance of the method, using two different types of membership functions, even so, the limitations that could exist are that the algorithm can be stuck in a local optimum and, in this way, already could not improve vector data that optimizes membership functions. It is concluded statistically and with different metrics that the DBSA improves performance compared to the original method and presents better performance compared to other bio-inspired algorithms, such as the CSO. As future work, it is intended to apply the proposed method to other optimization problems, where noise can be considered, in this way fully exploiting the IT2FS, and thinking about optimizing the fuzzy systems that perform the dynamic parameter adaptation.

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