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Optimisation of Process Parameters using the Hybrid Algorithm of Artificial Bee Colony and Fuzzy Logic Controller

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OF

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CANDIDATES DECLARATION

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

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Dedicated

To

Our Beloved Parents

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Of course, any errors are ours alone. We seek excuses if there is any mistake found in this report.

ABSTRACT

A hybrid Artificial Bee Colony (HABC) algorithm is proposed based on Fuzzy Inference System for solving fuzzy flexible real life optimisation problem. First, the Fuzzy Logic Control provides multiple parameters to an output of single parameter using the fuzzy logic membership function dependent on the input parameter characteristic and the fuzzy logic rules. Second, this single output from the fuzzy logic is optimised by ABC which utilises multiple strategies in a combined way to generate the initial solutions with certain quality. Third, the algorithm is verified in established set of data which demonstrated the effectiveness of the hybrid Algorithm.

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Chapter 1: Introduction

Multi-objective optimization is an area of multiple criteria decision making which is concerned with mathematical optimization problems involving more than one objective function to be optimized simultaneously to provide a useful reliable output. It is also known as multi-objective programming, vector optimization, multicriteria optimization, multiattribute optimization or Pareto optimization. For more than two objectives, the complexities and the number of combinations make traditional calculations impractical. Multi-objective optimisation is a way of finding a solution to problems which satisfies constraints and optimises a function elements, representing the objective functions. These functions form a mathematical description of performance criteria which are generally in conflict with each other. Therefore, the term optimise means to find such solutions which would give the values of all objective functions acceptable to the decision maker.

A multi-objective operation problem is an optimization problem that involves multi objective functions. In mathematical terms, a multi-objective optimization problem can be formulated as

$\min (f_1(x), f_2(x), \ldots\ldots. f_k(x))$

s.t. $x \in X$,

where the integer $k \geq 2$ is the number of objectives and the set X is the fesible set of deccision vectors. The feasible set is typically defined by some constraint functions.

Here the multi-objective optimisation is done using a Hybrid Algorithm which incorporates the Fuzzy Inference System (FIS) and the Artificial Bee Colony Algorithm (ABC),

Hybrid algorithm, which is generally the combines two or more algorithms that solve the same problem, either choosing one or switching between them over the course of the algorithm. It is a combination of two or more algorithms that is designed to yield better performance than the individual algorithm.

Fuzzy logic is a rule-based system which can rely on the practical experience of an operator and particularly useful to capture the knowledge of experienced operator. It is a form of artificial intelligence software; therefore, it would be considered a subset of artificial intelligence. It is included as a member of artificial intelligence toolkit; where together with other components of system can provide useful output. Fuzzy logic are systems are basically used to nonlinear systems which has multiple inputs and multiple outputs. Hence, it has great significance in places where the system cannot be modelled by conventional means. In our purpose we have used the Fuzzy Inference System (FIS) of Matlab.

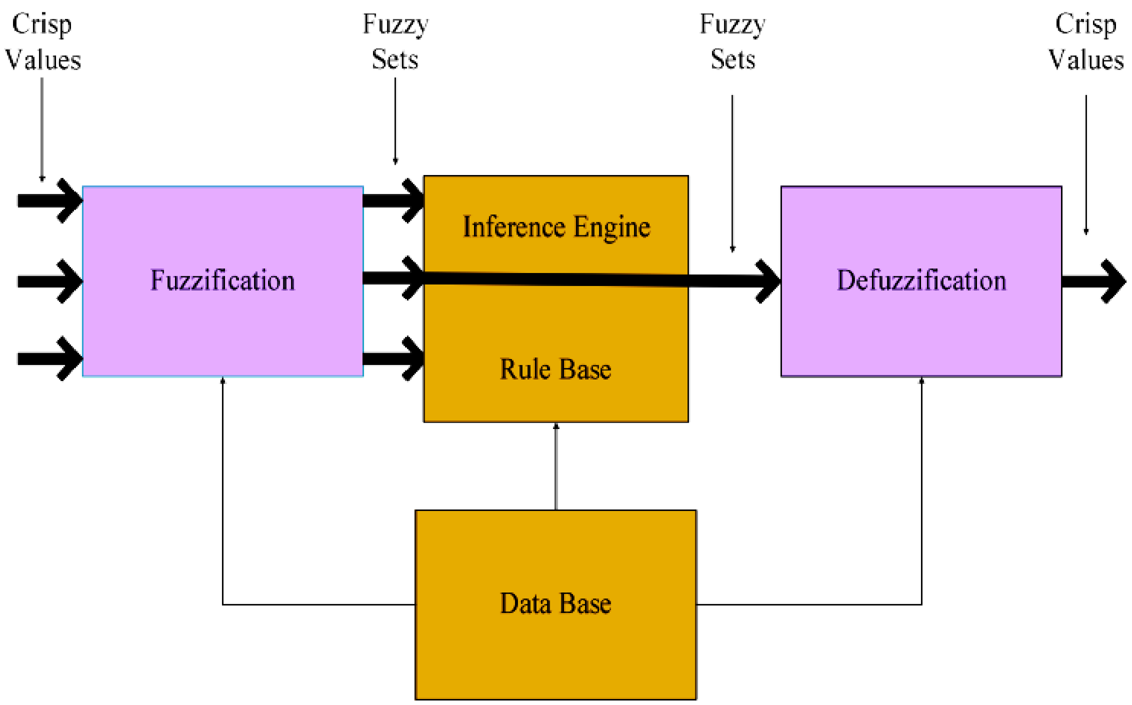

Figure 1: Basic Structure of Fuzzy Inference System (FIS)

In the current work, the output from the fuzzy inference system (FIS) is taken as input for the Artificial Bee Colony (ABC) algorithm which provides the output for the optimum input conditions. We present a generic single-objective approach for the optimization based on another such, relatively new swarm intelligence technique—Artificial Bee Colony (ABC).

(i) Artificial Bee Colony algorithm:

Artificial bee colony (ABC) algorithm is a recently proposed optimization technique which simulates the intelligent foraging behaviour of honey bees. The model consists of three essential components: employed and unemployed foraging bees, and food sources. The first two components, employed and unemployed foraging bees, search for rich food sources, which is the third component, close to their hive. The model also defines two leading modes of behaviour which are necessary for self-organizing and collective intelligence: recruitment of foragers to rich food sources resulting in positive feedback and abandonment of poor sources by foragers causing negative feedback.

In ABC, a colony of artificial forager bees (agents) search for rich artificial food sources (good solutions for a given problem). To apply ABC, the considered optimization problem is first converted to the problem of finding the best parameter vector which minimizes an objective function. Then, the artificial bees randomly discover a population of initial solution vectors and then iteratively improve them by employing the strategies: moving towards better solutions by means of a neighbour search mechanism while abandoning poor solutions. In the current work, we present a generic single-objective approach for the optimization based on another such, relatively new swarm intelligence technique—Artificial Bee Colony (ABC). In social insects, every individual is autonomous. They can only obtain local information, and interact with their geographical neighbours. All these features characterize swarm intelligence. Examples of systems like this can be found in nature, including bee colonies, ant colonies, bird flocking, animal herding, fish schooling etc. Inspired by the bee behaviour, Artificial Bee Colony is one of the generally applicable techniques used for optimizing numerical functions and real-world problems. Compared with GA and other similar evolutionary techniques, ABC has some attractive characteristics and in many cases proved to be more effective. Both GA and ABC have been used extensively for a variety of optimization problems and in most of these cases. ABC has proven to have superior computational efficiency. Further, ABC does not use any gradient-based information. It incorporates a flexible and well-balanced mechanism to adapt to the global and local exploration and exploitation abilities within a short computation time. Hence, this method is efficient in handling large and complex search spaces. ABC with its ability to handle combinatorial explosive problems appears to be very promising for the single-objective optimization problem addressed in this thesis.

(ii) Objectives:

1. To optimise the different process parameter using the Artificial Bee Colony (ABC) algorithm and the Fuzzy Logic Control.
2. To work with Fuzzy Inference System (FIS) and the Artificial Bee Colony (ABC)
3. To produce an effective and reliable Hybrid algorithm for practical use.
4. To verify the experiment using a set of established data set.

(iii) Organization of the thesis:

This thesis comprises of seven chapters. ***Chapter 1*** gives a brief overview of the background and concept of this study. Finally, significance of the research and the objectives of this study are summarized. This chapter also outlines the organization of this dissertation.

A comprehensive literature review is given in the ***Chapter 2***, which categorized into three sections. First section describes the existing researches on Multi-objective optimisation. In the second section, Works done on multi-objective optimisation using ABC algorithm are discussed. Finally, extensive literature review on process is discussed such as process parameter and their effect, process modelling and process control.

Chapter 3 describes the methodology of the experiment. The steps including the experiment is described in a flow chart.

Chapter 4 *describes* the modelling the Fuzzy Control Logic structure, which is developed with the help of a computer based software named MATLAB **2010.** Moreover, we analysis the error by comparing our experimental data with the equational data. The equation was formed by the software.

Chapter 5 **presents** the brief discussion about Artificial Bee Colony (ABC) Algorithm. It also presents how it works.

In ***Chapter 6*** our programmed result is compared with set of data. The conclusions and summary of the contributions are presented in ***Chapter 7***.

Chapter 2: Historical review

(i) Existing research on algorithm:

In pursuit of finding solution to the optimization problems many researchers have been drawing inspiration from the nature [1]. A lot of such biologically inspired algorithms have been developed namely genetic algorithm (GA) [2], particle swarm optimization (PSO) [3], artificial immune system (AIS) [4] and artificial bee colony (ABC) [5]. These algorithms with their stochastic means are well equipped to handle such problems. Over the past two decade, a lot of successful multi-objective algorithms based on such biologically inspired algorithms to optimize multi-objective problems were proposed in literature, such as Pareto-archived evolution strategy (PAES) [6], Pareto envelope-based selection algorithm (PESA)-II [7], nondominated sorting genetic algorithm II (NSGAII) [8], strength Pareto evolutionary algorithm (SPEA2) [9], indicator-based evolutionary algorithm (IBEA) [10], multi-objective particle swarm optimization (MOPSO) [11], multi-objective evolutionary algorithm based on Decomposition (MOEA/D) [18], two lbests multi-objective particle swarm optimization (2 LB-MOPSO) [12], multi-objective differential evolution (MODE) based on summation of normalized objective values and diversified selection (SNOV-DS) [13] and so on. The primary reason for this is their ability to find multiple Pareto-optimal solutions in one single simulation run.

(ii) Work done on Artificial Bee Colony (ABC) algorithm:

Artificial bee colony (ABC) algorithm is one of the most recently introduced swarm-based algorithms. ABC has been found to be successful in a wide variety of optimization tasks [14]. Recently it had been extended to deal with multiple objectives, such as vector evaluated artificial bee colony (VEABC) [15], multi-objective artificial bee colony (MOABC) [16] and so on. ABC seems particularly suitable for multi-objective optimization mainly because ABC has proven to have superior computational efficiency [17] and does not use any gradient-based information. In this paper, we present a novel multi-objective approach called ‘‘hybrid multi-objective artificial bee colony’’ (HMOABC) to solve the burdening optimization model of silencer based on ABC algorithm. Pareto-optimal solutions solved by HMOABC have better global convergence local diversity and shorter running time. This algorithm has distinct advantage in burdening optimization of silencer which needs multiple representative optimum solutions, but the goal cannot be achieved via single objective optimization algorithm. And then the priority of feasible solutions is achieved by the method of sorting Pareto solutions based on fuzzy set theory [18]. The term swarm is used for an aggregation of animals like fishes, birds and insects such as ants, termites and bees performing collective behaviour. The individual agents of these swarms behave without supervision and each of these agents has a stochastic behaviour due to her perception in the neighbourhood. SI is defined as the collective behaviour of decentralized and self-organized swarms. Well known examples of which are bird flocks and the colony of social insects such as ants and bees. The intelligence of the swarm lies in the networks of interactions among these simple agents, and between agents and the environment. SI is becoming increasingly important research area for computer scientists, engineers, economists, bioinformaticians, operational researchers, and many other disciplines. This is because the problems that the natural intelligent swarms can solve (finding food, dividing labour among nestmates, building nests etc.) have important counterparts in several engineering areas of real world. Two important approaches which are based on ant colony, called ant colony optimization (ACO), described by Dorigo et al. (1991) and based on bird flocking, called particle swarm optimization (PSO) introduced by Kennedy and Eberhart (1995) have proposed, in 1990s. Both approaches have been studied by many researchers and their several new versions have been described and applied to solve real-world problems in different areas. So many papers related with their applications have been presented to the literature and several survey papers regarding these studies have been prepared (Eberhart et al. 2001; Reyes-Sierra and Coello 2006; Blum 2005; Dorigo and Blum 2005). The term swarm is used for an aggregation of animals like fishes, birds and insects such as ants, termites and bees performing collective behaviour. The individual agents of these swarms behave without supervision and each of these agents has a stochastic behaviour due to her perception in the neighbourhood. SI is defined as the collective behaviour of decentralized and self-organized swarms. Well known examples of which are bird flocks and the colony of social insects such as ants and bees. The intelligence of the swarm lies in the networks of interactions among these simple agents, and between agents and the environment. 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So many papers related with their applications have been presented to the literature and several survey papers regarding these studies have been prepared (Eberhart et al. 2001; Reyes-Sierra and Coello 2006; Blum 2005; Dorigo and Blum 2005). The self-organization and division of labour features (Bonabeau et al. 1999) and the satisfaction principles (Millonas 1994) required by SI are strongly and clearly can be seen in honey bee colonies, the researchers have recently started to be interested in the behaviour of these swarm systems to propose new intelligent approaches, especially from the beginning of 2000s. The first comprehensive survey on the algorithms related to the bee SI and their applications was prepared by Karaboga and Akay (2009c) .The survey shows that many algorithms have been developed by researchers depending on different intelligent behaviours of honey bee swarms in the last decade. The studies are mainly based on the dance and communication, task allocation, collective decision, nest site selection, mating, marriage, reproduction,foraging, floral and pheromone laying and navigation behaviours of the swarm. Some known algorithms based on bee SI are virtual bee, the bees, BeeAdHoc, the marriage in honeybees, the BeeHive, bee system, bee colony optimization and ABC.

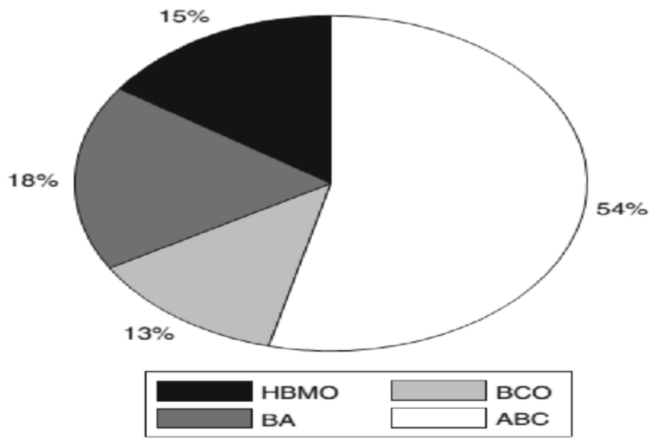

Figure 2: Percentages of publications regarding to some algorithms based on bee swarms Some known algorithms based on bee SI are virtual bee, the bees, BeeAdHoc, the marriage in honeybees, the BeeHive, bee system, bee colony optimization and ABC. Virtual bee algorithm was developed by Yang (2005) to solve the numerical function optimizations. In the model, a swarm of virtual bees are generated and they are allowed to move randomly in the phase space and these bees interact when they find some target nectar. Nectar sources correspond to the encoded values of the function. The solution for the optimization problem can be obtained from the intensity of bee interactions. The bees algorithm was described by Pham et al.(2005) and mimics the foraging behaviour of honey bees. In its basic version, the algorithm performs a kind of neighbourhood search combined with random search and can be used for both combinatorial

optimization and functional optimization. BeeAdHoc algorithm, defined by Wedde and Farooq (2005), is a routing algorithm for energy efficient routing in mobile adhoc networks. The algorithm is inspired by the foraging principles of honey bees.

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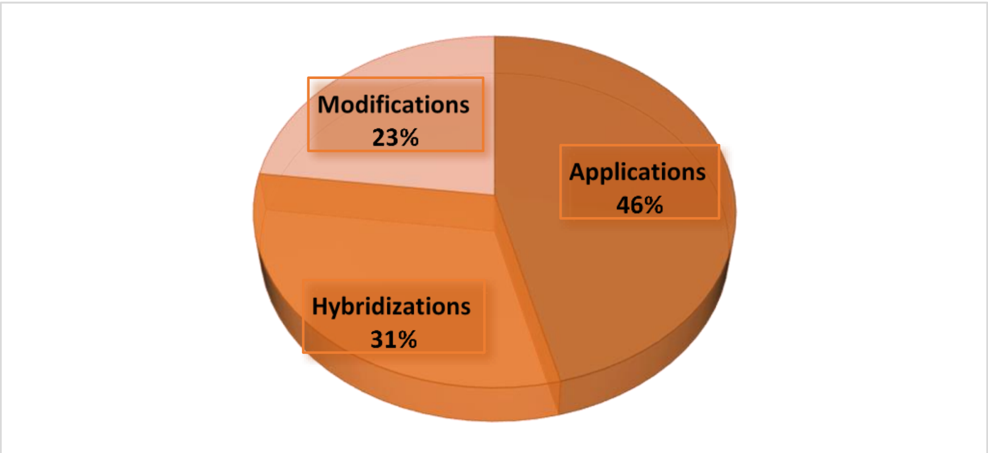

Figure 3: The Distribution Of Published Research Articles On ABC

(iii) Concluding Remarks:

From extensive literature review, we have seen that hybrid algorithm using the fuzzy logic and Artificial Bee Colony algorithm is used in other purposes. Hence, this type of analysis done with Artificial Bee Colony algorithm and fuzzy is new type of Hybrid algorithm which is proposed in this work.

Chapter 3: Methodology

In multi-objective optimisation, the parameters are set in the algorithm which their characteristic nature. These includes all the input and output parameters. In these work the Hybrid Algorithm mainly consists of Fuzzy Logic Control, for which we have used Matlab 2010 version Fuzzy Inference System (FIS) and the Artificial Bee Colony (ABC) algorithm.

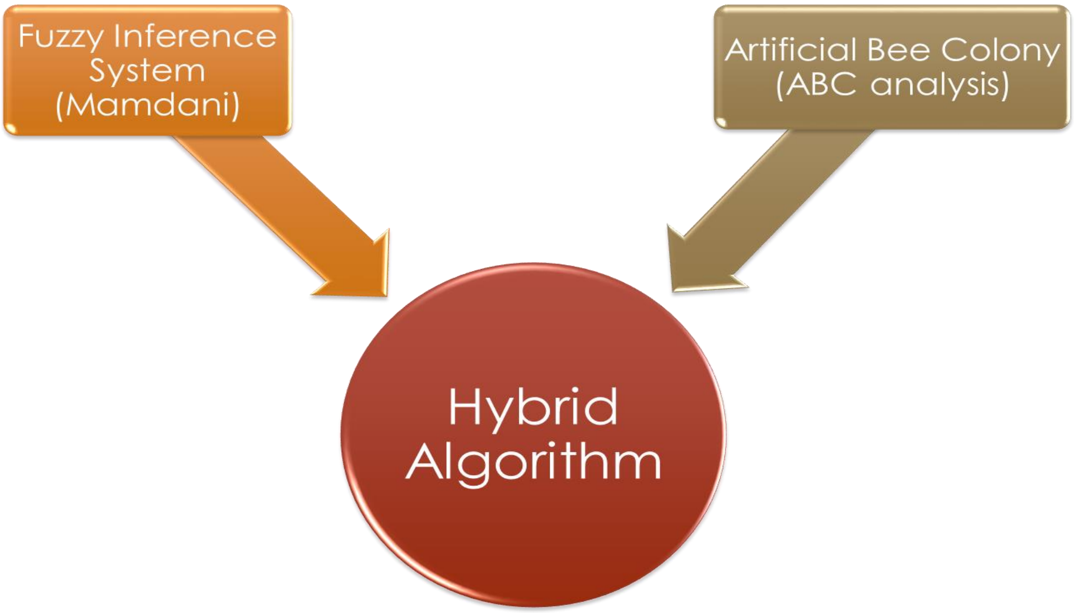

Figure 4: Components of Hybrid Algorithm.

The input and output of the Fuzzy Control Logic is set on the Fuzzy Inference System (FIS) and the corresponding rules were set in the Fuzzy Inference System (FIS). These in turns generates a single parameter from multiple inputs which is then optimised using the Artificial Bee Colony (ABC) algorithm. The Hybrid algorithm was then analysed on a set of data for proper functionality and effectiveness.

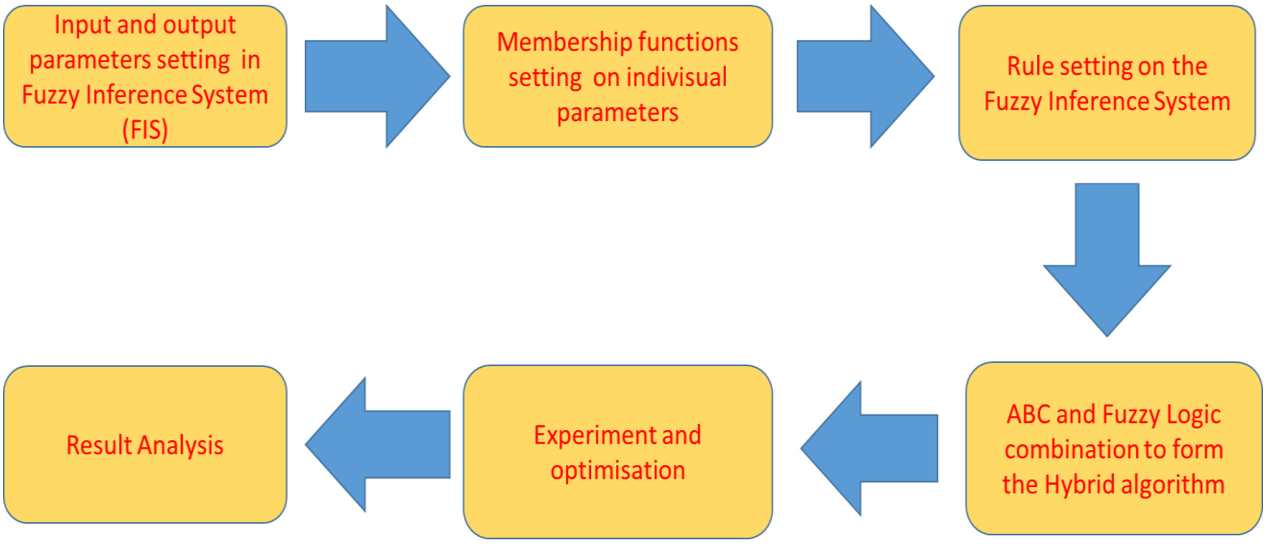

Figure 5: Different steps included in this work.

Chapter 4: Design of Algorithm

In this work, our aim was to create a Hybrid algorithm for real life applications. For this purpose, Fuzzy Inference System of Matlab 2010 version was used. It is obvious that the characteristic of input parameters affect the output parameters. These input and output parameters characteristic are set by the Fuzzy membership function and its nature of normalised data. But we have limitations of making number of sections or range for fuzzy inference system. To get rid of these problem simple overlapping sections are used for different categories for each of the fuzzy parameters. In our purpose we have used five categories for each parameters namely high, high-medium, medium, low-medium and low.

As mentioned early these optimisation algorithm uses four input parameters. These four parameters are converted to single parameter using the Fuzzy Inference System. Finally, these single parameter is optimised using the Artificial Bee Colony Algorithm. Obtained optimised results are then compared with similar analysis done with different methods.

The Fuzzy Inference System (FIS) consists of four input parameters namely back pressure, plate 1, plate 2 and plate 3. These are analogous to the real life problem that has been used to support the success of the algorithm. The parameters are of real life silencer where the pressure of different plate has been used for Fuzzy Inference System input parameters. The motive or objective is to propose a design for the silencer analysis based on the minimising the backpressure of these plates that would eventually help to increase the durability of the silencer design. Hence, after taking the maximum Fuzzy output from the set of data, the Artificial Bee

Colony (ABC) algorithm would provide the optimum design conditions for the silencer. Eventually, the output will provide the pertition size, no of pertition and the size of pertition.

(i) Fuzzy Inference System (FIS)

The input and output parameters are set in the Fuzzy Inference System of Matlab 2010 version. For each of input parameters the normalised range has been equally divided into five sections. These are high, high-medium, medium, low-medium and low.

4.1.1 Setting membership functions

For each of the input and the output parameters, the trapezoidal membership function and triangular membership function has been used. It is primarily used for uniform value for certain range and then uniform change over certain range.

In these membership functions, range from 0 to 0.25 is categorised as LOW, 0.15 to 0.45 is categorised as LOW MEDIUM, 0.35 to 0.65 is categorised as MEDIUM, 0.55 to 0.85 is categorised as HIGH MEDIUM and 0.75 to 1 is categorised as HIGH.

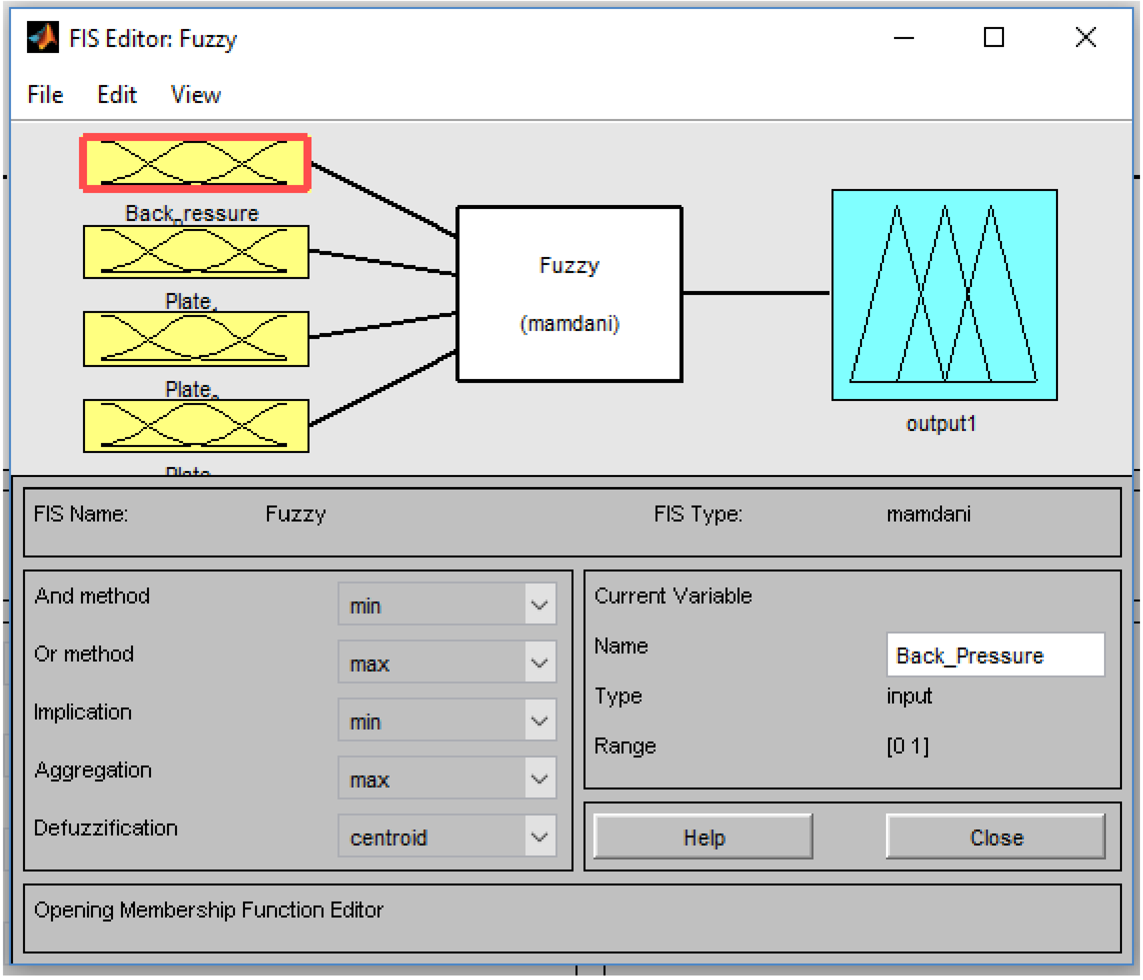

Figure 6: Setting of different parameters in Fuzzy Inference System.

Similarly, all the input and output parameters are set with triangular and trapezoidal membership function. The ranges of corresponding membership function are also set in the similar way. The ranges for input and output parameters require normalised data. Here, in this work the input data which are to be analysed are normalised.

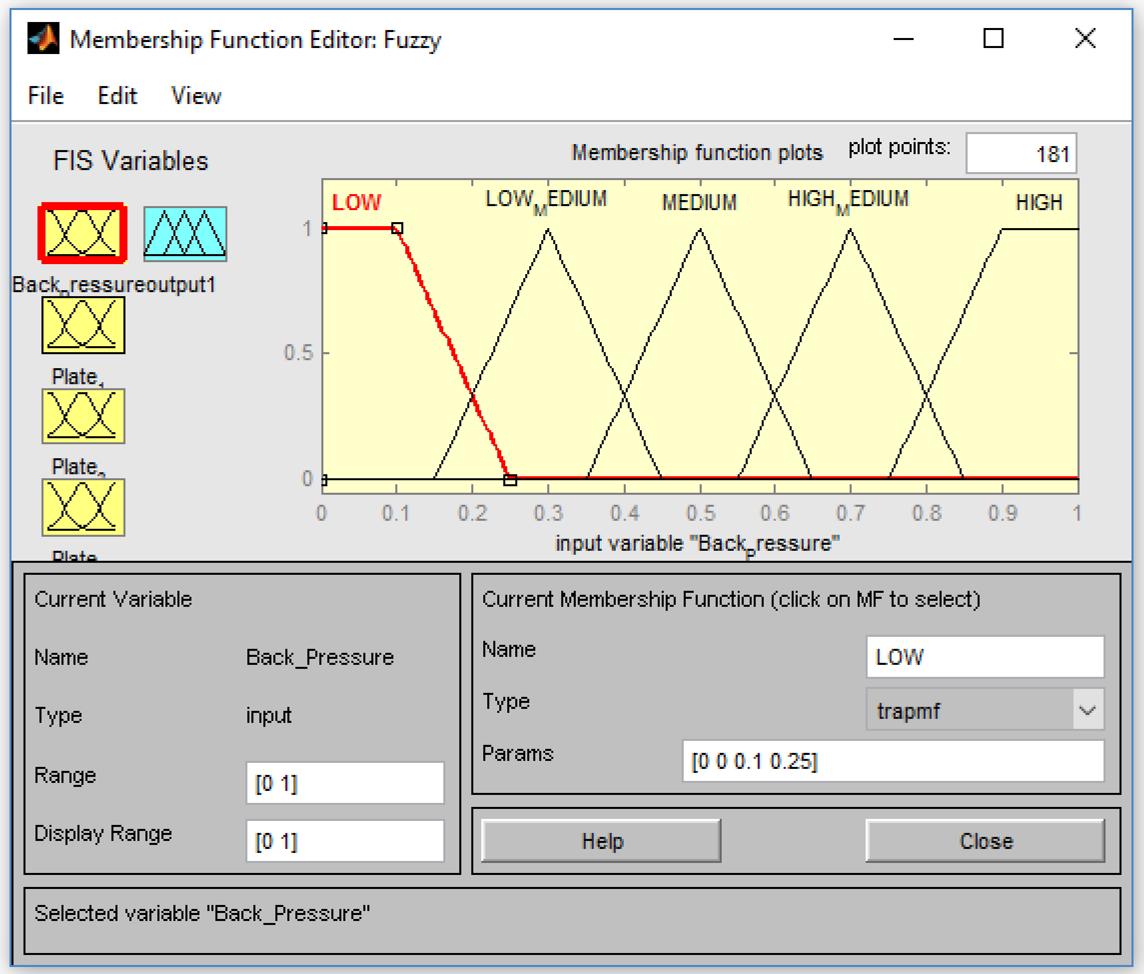

Figure 7: Setting membership function for each input parameters.

4.1.2 Setting rules in Fuzzy Inference System

Fuzzy rules were set which were based on the averrage of the input parmeters. A total of 625 rules were set in the rules for the Fuzzy Inference System (FIS). This is simply the different conditions for each of the input and output parameters (i.e 5*5*5*5 = 625).

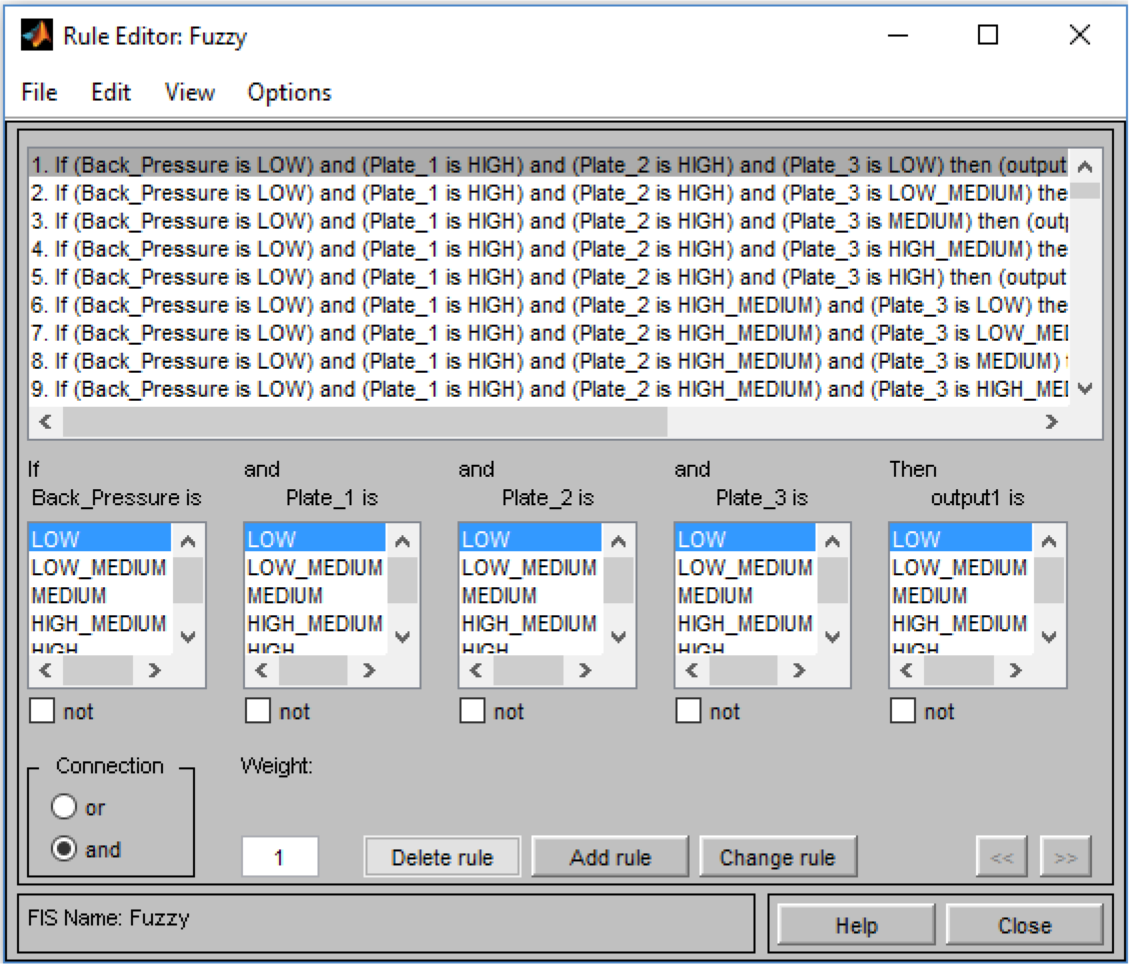

Figure 8: Setting rules in the Fuzzy Inference System (FIS).

The rules are the average of the input parameters which are calcuted using standard spreedsheet pakage. Here, in this work Ms Excel is used for determining diffferent number of rules possible in this system.

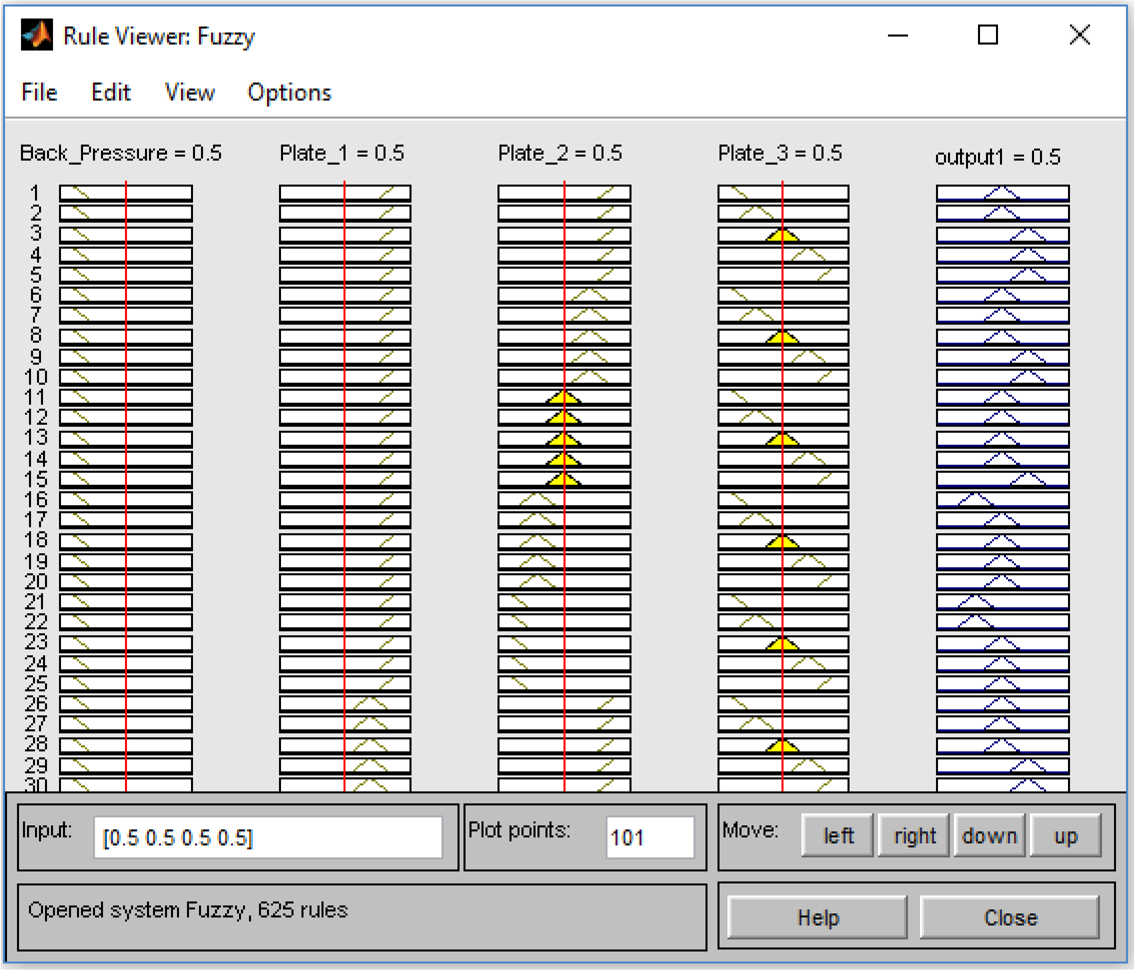

Figure 9: All the rules of the Fuzzy Inference System is input in the system.

(ii) Conduction of different analysis

A set of twenty expeiments has been used for the optimsation of the input parameters. These optimsation is then compared with the optimisation of this hybrid algorithm.

4.2.1 Data used for analysis

Back Pressure	Plate 1	Plate 2	Plate 3
0.2254	0.3234	0.3828	0.3007
0	0	0	0
0.5704	0.6347	0.6484	0.6732
0.3451	0.3234	0.2656	0.3791
0.662	0.6886	0.7422	0.6275
0.4366	0.3772	0.3594	0.3333
1	1	1	1
0.7746	0.6886	0.625	0.7059
0.6056	0.6766	0.7266	0.6536
0.2887	0.2335	0.1875	0.2288
0.2183	0.2395	0.2891	0.1895
0.6761	0.6647	0.6328	0.6928
0.1408	0.1916	0.2031	0.2092
0.7465	0.7126	0.7109	0.6732
0.4437	0.4551	0.4609	0.4444

0.4437	0.4551	0.4609	0.4444
0.4437	0.4551	0.4609	0.4444
0.4437	0.4551	0.4609	0.4444

Table 1: Data used for analysis.

4.2.2 Optimum results to be compared:

The optimum results are compared with the previoiusly obtained optimsation results obtained through differrent method. The results are to be compared with the followings results.

	Petition Size	No of Perforation	Size of Perforation
Optimized	75.00	8	8.50

Table 2: Optimised results that are to compared with.

Chapter 5: Artificial Bee Colony (ABC) Algorithm

(i) Introduction

Artificial Intelligence (AI) is one of the oldest and best known research fields. There are different definitions in the literature for AI of that the most widely used one belongs to John McCarthy, who defined it as "the science and engineering of making intelligent machines" (McCharty 2007). Computational intelligence (CI) is a fairly new research area and commonly referred to as AI, too. It is defined as the study of the design of intelligent agents where an intelligent agent is a system that perceives its environment and then takes actions to maximize its chances of success. While CI techniques are counted as AI techniques, there is a clear difference between them. For example, CI uses subsymbolic knowledge processing whereas classical AI uses symbolic approaches. CI includes a set of nature-inspired computational methodologies and approaches to address complex problems of the real world applications. Subjects in CI include neural networks which are trainable systems with very strong pattern recognition capabilities, fuzzy systems which are techniques for reasoning under uncertainty and evolutionary computation (EC) which is a form of stochastic optimization search. Forms of EC include swarm intelligence (SI) based algorithms and evolutionary algorithms. The evolutionary algorithms usually begin with a population of organisms (initial solutions) and then allow them to mutate and recombine, selecting only the fittest to survive each generation (refining solutions).The well-known evolutionary algorithms are genetic algorithms (GA), genetic programming, evolution strategies (ES), evolution programming and differential evolution (DE)

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5.2.1 General features of intelligent swarms

There are so many kind of swarms in the world. It is not possible to call all of them intelligent or their intelligence level could be vary from swarm to swarm. Self-organization is a key feature of a swarm system which results collective behaviour by means of local interactions among simple agents (Bonabeau et al. 1999).Bonabeau et al.(1999) interpreted the self-organization in swarms through four characteristics:

(i) **Positive feedback:** promoting the creation of convenient structures. Recruitment and reinforcement such as trail laying and following in some ant species can be shown as example of positive feedback.

(ii) **Negative feedback:** counterbalancing positive feedback and helping to stabilize the collective pattern. In order to avoid the saturation which might occur in terms of available foragers a negative feedback mechanism is needed.

(iii) **Fluctuations:** random walks, errors, random task switching among swarm individuals which are vital for creativity. Randomness is often significant for emergent structures since it enables the discovery of new solutions.

(iv) **Multiple interactions:** agents in the swarm use the information coming from the other agents so that the information spreads throughout the network.

Additional to these characteristics, performing tasks simultaneously by specialized agents, called division of labour, is also an important feature of a swarm as well as self-organization for the occurrence of the intelligence (Bonabeau et al. 1997). According to Millonas, in order to call a swarm intelligent, the swarm must satisfy the following principles (Millonas 1994): (i) The swarm should be able to do simple space and time computations (the proximity principle).

(ii) The swarm should be able to respond to quality factors in the environment (the quality principle).

(iii) The swarm should not commit its activities along excessively narrow channels (the principle of diverse response).

(iv) The swarm should not change its mode of behaviour upon every fluctuation of the environment (the stability principle).

(v) The swarm must be able to change behaviour mode when needed (the adaptability principle).

5.2.2 Foraging behaviour of honey bees

The minimal model of forage selection that leads to the emergence of collective intelligence of honey bee swarms consists of three essential components: food sources, employed foragers and unemployed foragers, and the model defines two leading modes of the behaviour: the recruitment to a rich nectar source and the abandonment of a poor source.

(i) Food Sources: The value of a food source depends on many factors such as its proximity to the nest, its richness or concentration of its energy, and the ease of extracting this energy. For the sake of simplicity, the "profitability" of a food source can be represented with a single quantity (Seeley 1995).

(ii) Employed foragers: They are associated with a particular food source which they are currently exploiting or are "employed" at. They carry with them information about this particular source to the hive and the information can be the distance and direction from the nest, the profitability of the source and share this information with a certain probability.

(iii) Unemployed foragers: They are continually at look out for a food source to exploit. There are two types of unemployed foragers: scouts, searching the environment surrounding the nest for new food sources and onlookers waiting in the nest and establishing a food source through the information shared by employed foragers. The mean number of scouts averaged over conditions is about 5–10% of other bees (Seeley 1995).

The exchange of information among bees is the most important occurrence in the formation of the collective knowledge. While examining the entire hive it is possible to distinguish between some parts that commonly exist in all hives. The most important part of the hive with respect to exchanging information is the dancing area. Communication among bees related to the quality of food sources takes place in the dancing area. This dance is called a waggle dance. Since information about all the current rich sources is available to an onlooker on the dance floor, probably she watches numerous dances and decides to employ herself at the most profitable source. There is a greater probability of onlookers choosing more profitable sources since more information is circulated about the more profitable sources. Hence, the recruitment is proportional to the profitability of the food source (Tereshko and Loengarov 2005).

In the case of honey bees foraging behaviour, the four characteristics defined in the Sect.5.2.1 on which self-organization relies can be expressed as follows:

(i) **Positive feedback:** As the nectar amount of a food source increases, the number of onlookers visiting it increases proportionally.

(ii) **Negative feedback:** The exploitation process of poor food sources is stopped by bees.

(iii) **Fluctuations:** The scouts carry out a random search process for discovering new food sources.

(iv) **Multiple interactions:** Employed bees share their information about food sources with their nest mates (onlookers) waiting on the dance area. When the foraging behaviour of honey bees explained above is re-examined, it is seen that the principles defined by Millonas (1994) are fully satisfied.

5.2.3 Algorithmic structure of ABC

As in the minimal model of forage selection of real honey bees, the colony of artificial bees in ABC contains three groups of bees: employed bees associated with specific food sources, onlooker bees watching the dance of employed bees within the hive to choose a food source, and scout bees searching for food sources randomly. Both onlookers and scouts are also called unemployed bees. Initially, all food source positions are discovered by scout bees.

There after, the nectar of food sources are exploited by employed bees and onlooker bees, and this continual exploitation will ultimately cause them to become exhausted. Then, the employed bee which was exploiting the exhausted food source becomes a scout bee in search of further food sources once again. In other words, the employed bee whose food source has been exhausted becomes a scout bee. In ABC, the position of a food source represents a possible solution to the problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. In the basic form, the number of employed bees is equal to the number of food sources (solutions) since each employed bee is associated with one and only one food source.

The general algorithmic structure of the ABC optimization approach is given as follows:
Initialization Phase

REPEAT

Employed Bees Phase

Onlooker Bees Phase

Scout Bees Phase

Memorize the best solution achieved so far

UNTIL(Cycle=Maximum Cycle Number or a Maximum CPU time)

In the initialization phase, the population of food sources (solutions) is initialized by artificial scout bees and control parameters are set.

In the employed bees phase, artificial employed bees search for new food sources having more nectar within the neighbourhood of the food source in their memory. They find a neighbour food source and then evaluate its fitness. After producing the new food source, its fitness is calculated and a greedy selection is applied between it and its parent. After that, employed bees share their food source information with onlooker bees waiting in the hive by dancing on the dancing area.

In the onlooker bees phase, artificial onlooker bees probabilistically choose their food sources depending on the information provided by the employed bees. For this purpose, a fitness based selection technique can be used, such as the roulette wheel selection method. After a food source for an onlooker bee is probabilistically chosen, a neighbourhood source is determined, and its fitness value is computed. As in the employed bees phase, a greedy selection is applied between two sources.

In the scout bees phase, employed bees whose solutions cannot be improved through apredetermined number of trials, called “limit”, become scouts and their solutions are abandoned. Then, the scouts start to search for new solutions, randomly. Hence, those sources which are initially poor or have been made poor by exploitation are abandoned and negative feedback behaviour arises to balance the positive feedback.

These three steps are repeated until a termination criteria is satisfied, for example a maximum cycle number or a maximum CPU time.

5.2.4 The ABC Algorithm Used for Unconstrained Optimization Problems:

In ABC algorithm the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. First half of the colony consists of the employed artificial bees and the second half includes the onlookers. For every food source, there is only one employed bee. In other words, the number of employed bees is equal to the numberof food sources around the hive. The employed bee whose the food source has been abandoned by the bees becomes a scout.

In ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees or the onlooker bees is equal to the number of solutions in the population.

At the first step, the ABC generates a randomly distributed initial population P(G=0)of SN solutions (food source positions), where SN denotes the size of population.

Each solution x_i (i=1,2, ..., SN)is a D-dimensional vector. Here, D is the number of optimization parameters. After initialization, the population of the positions (solutions) is subjected to repeated cycles, C=1,2, ..., MCN, of the search processes of the employed bees, the onlooker bees and scout bees. An employed bee produces a modification onthe position (solution) in her memory depending on the local information (visual information) and tests the nectar amount (fitness value) of the new source (new solution). Provided that the nectar amount of the new one is higher than that of the previous one, the bee memorizes the new position and forgets the old one. Otherwise she keeps the position of the previous one in her memory. After all employed bees complete the search process, they share the nectar information of the food sources and their position information with the onlooker bees on the dance area. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability related to its nectar amount. As in the case of the employed bee, she produces a modification on the position in her memory and checks the nectar amount of the candidate source. Providing that its nectar is higher than that of the previous one, the bee memorizes the new position and forgets the oldone.

An artificial onlooker bee chooses a food source depending on the probability value associated with that food source, P_i , calculated by the following expression (1):

$$P_i = \frac{F(\theta i)}{\sum_{k=1}^{S} F(\theta k)} \quad (1)$$

Where,

P_i: The probability of selecting the i^{th} employed bee

S : The number of employed bees

θ_i: The position of the i^{th} employed bee

$F(\theta_i)$: The fitness value

In order to produce a candidate food position from the old one in memory,

the ABC uses the following expression (2):

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \qquad (2)$$

where $k \in \{1,2,..., SN\}$ and $j \in \{1,2,..., D\}$ are randomly chosen indexes. Althoughkis determined randomly, it has to be different from i. $\varphi_{i,j}$ is a random number between [-1, 1]. It controls the production of neighbour food sources around $x_{i,j}$ and represents the comparison of two food positions visually by a bee. As can be seen from (2), as the difference between the parameters of the $x_{i,j}$ and $x_{k,j}$ decreases, the perturbation on the position $x_{i,j}$ gets decrease, too.

Thus, as the search approaches to the optimum solution in the search space, the step length is adaptively reduced.

If a parameter value produced by this operation exceeds its predetermined limit, the parameter can be set to an acceptable value. In this work, the value of the parameter exceeding its limit is set to its limit value. The food source of which the nectar is abandoned by the bees is replaced with a new food source by the scouts. In ABC, this is simulated by producing a position randomly and replacing it with the abandoned one. In ABC, providing that a position can not be improved further through a predetermined number of cycles, then that food source is assumed to be abandoned. The value of predetermined number of cycles is an important control parameter of the ABC algorithm, which is called "limit" for abandonment. Assume that the abandoned source is x_i and $j \in \{1,2,..., D\}$, then the scout discovers a new food source to be replaced with x_i. This operation can be defined as in (3) $x_i^j = x_{min}^j + rand(0,1)(x_{max}^j - x_{min}^j)$ (3)

After each candidate source positionvi,j is produced and then evaluated by the artificial bee, its performance is compared with that of its old one. If the new food has an equal or better nectar than the old source, it is replaced with the old one in the memory. Otherwise, the old one is retained in the memory. In other words, a greedy selection mechanismis employed as the selection operation between the old and the candidate one. It is clear from the above explanation that there are four control parameters used in the ABC: The number of food sources which is equal to the number of employed or onlooker bees (SN), the value oflimit, the maximum cycle number (MCN).

Detailed pseudo-code of the ABC algorithm is given below:

1: Initialize the population of solutions $x_{i,j}$, i=1...SN,j=1...D

2: Evaluate the population

3: cycle=1

4: repeat

5: Produce new solutions $\upsilon_{i,j}$ for the employed bees by using (2) and evaluate them

6: Apply the greedy selection process

7: Calculate the probability values $P_{i,j}$ for the solutions $x_{i,j}$ by (1)

8: Produce the new solutions $\upsilon_{i,j}$ for the onlookers from the solutions $x_{i,j}$ selected depending on $P_{i,j}$ and evaluate them

9: Apply the greedy selection process

10: Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution $x_{i,j}$ by (3)

11: Memorize the best solution achieved so far

12: Cycle=cycle+1

13: Until cycle=MCN

5.2.5 ABC Flowchart

The Flow chart of the Artificial Bee Colony Optimization is given below:

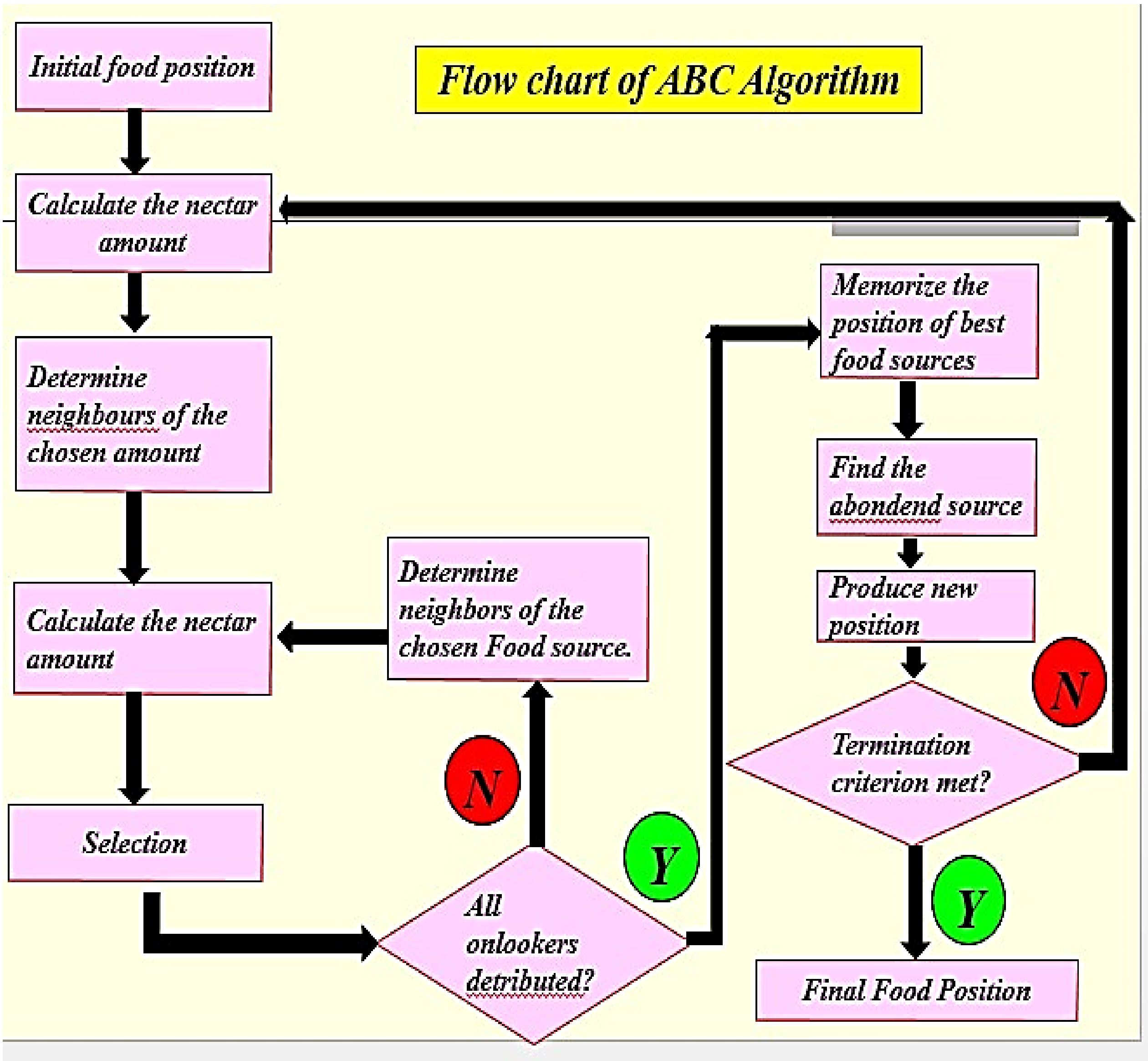

Figure 10: Flow Chart Of ABC

Chapter 6: Result Analysis

Optimized Process parameters	
Parameters	Results of ABC and Desirability Analysis
Maximum Fuzzy code	0.0909815
Pertition size	75 mm
No of Perforation	8
Size of Perforation	8.5 mm
Verification of Results	
% Error	
0%	

Table 3: Results analysis

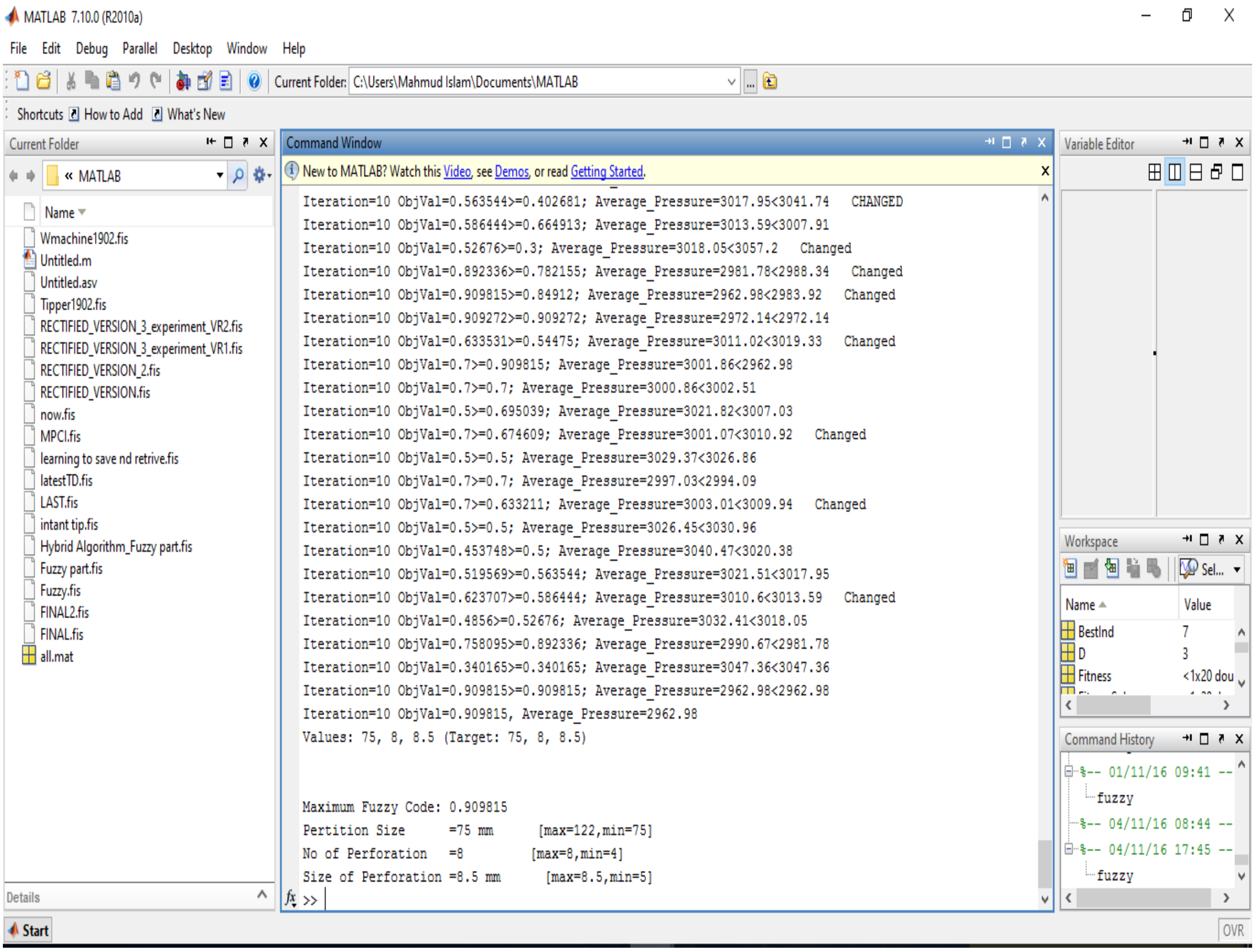

Figure 11: Final optimised output.

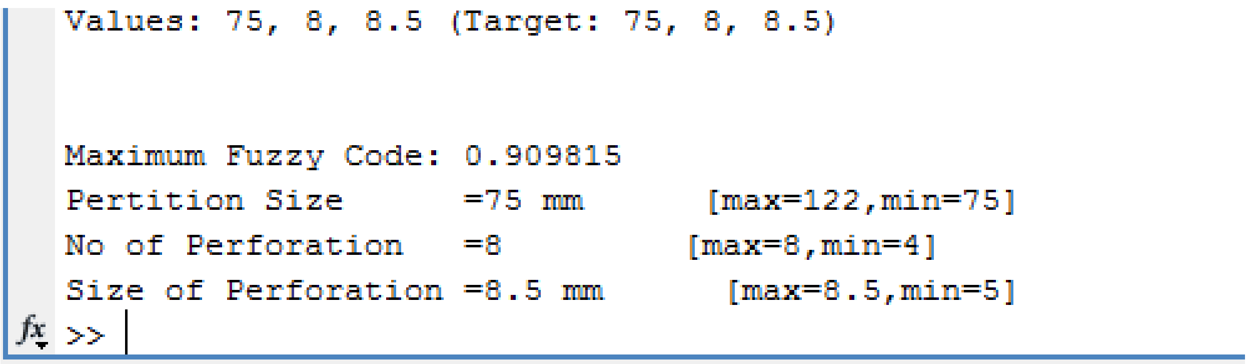

Figure 12: Final optimised output

The output show similar results which are shown in the results of the Hybrid algorithm. The optimisation done using other method of analysis shows the exact same results. The performance of the algorithm was studied for different number of iteration. It is observed that results are quite accurate if the number of iteration is increased. However, with increasing the number of iteration the algorithm computation time increases. So inorder to to reach a optimum result solution, a minimum accurate number of iteration has to be used. In this project, we have seen that the results doesnot show accurate results if iteration number is less than ten. In this work, we have seen that the minimum iteration number is ten which provides acurate and precise results. Hence, the time required to reach optimisation results is minimum for ten number of iteration. In addition, the algorithm showed good stability for the number of times it was run.

Chapter 7: Conclusion

In this part of the thesis, Hybrid Algoruthm was used to determine the optimum results for the real life system . Using the data, the algorithm was verified.

ABC Algorithm model had been developed by using MATLAB in a nice way. Then we optimized the datas by using ABC algorithm. The initial optimisation value differs from the data set to be compared with the set of data. Some other inspections are:

- It’s because program results are not accurate for few number of iteration.
- Sometimes the assumptions and contants in the algorithm produce small deviations.
- Overall percentage of error is minimal.

It has been analyzed that the experimental data and equational data are quite similar except some data. From this, we can conclude that the objectives of our project has been achieved.

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