

Fuzzy-Genetic based Approach in Decision Making for Repair of Turbochargers using Additive Manufacturing

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ABSTRACT

Additive manufacturing (AM) is an effective technology for repairing and restoring automotive components. However, the effectiveness of additive manufacturing technology in repair and restoration is highly influenced by several factors related to components and process. The objective of this paper is to improve the decision-making in repair and restoration of a turbocharger with AM. In this article, a Fuzzy-Genetic approach was presented as a decision-making tool for repairing a remanufacturable component. Fuzzy logic (FL) is deployed as the method to model the design parameters of a turbocharger, such as design complexity, failure mode, damage size, disassembleability, preprocessing, temperature, durability, pressure ratio and mass flow rate to model the relationship between the inputs and outputs using Mamdani model with their membership functions. Genetic algorithm optimization method was used to optimize the cost of the repairing process once the decision on whether the turbocharger was repairable was determined by the Fuzzy system. The FL approach applied rules affecting the process, the robustness and accuracy of the model increases with a higher number of rules. The work focuses on the dataset related to design information, which represents as a knowledge base for decision parameters on design optimization to automate repair process during remanufacturing. The results showed the effects of the design parameters on repairing and replacement decisions, and how the fuzzy model related the inputs to the outputs based on the generated rules. In conclusion, FGA method can be used to improve the repair and restoration process of a turbocharger through AM technology.

Keywords: Fuzzy-GA; turbocharger; additive manufacturing; hybrid method.

INTRODUCTION

Additive manufacturing (AM) is the technology used to rebuild manufacturing materials by adding material layer-by-layer to repair the damaged parts. This term includes several other technologies referred to as 3D Printing, Direct Digital Manufacturing (DDM), layered manufacturing, additive fabrication, and Rapid Prototyping (RP) (Gibson et al. 2015). For many years, several concepts have been engaged to decrease and limit the consumption of natural resources, including the circular economy concept. AM

uses far less energy than traditional machining, and personnel and tools that correspond to the circular economy (Gohari et al.2019; Aziz et al. 2021; Seharng et al.2020). The circular economy aims to keep products and components at their highest utility and value in their lifecycle. Consequently, the remanufacturing process, which is one of the most promising product end-of-life (EoL) recovery options, is capable of increasing the longevity of a product that has expired (Kotis. 2021; Jose et al. 2020; Andrew et al. 2013). Therefore, remanufacturing is applied to restore EoL components back to conditions that are closer to their original conditions. Moreover, the

remanufactured components could function just as well as they did when first manufactured. To date, the repair process in remanufacturing is highly dependent on skilled workers who should be able to decide the appropriate restoration techniques, resulting in high time consumption and costs in the long term. With the advent of the additive manufacturing technology, the repair and restoration process can now be automated (Wakiru et al. 2017).

AM is considered as a new technology for repairing and restoring materials, significantly impacting the circular economy strategies. However, there are some constraints in AM repair process due to the geometrical complexity that may lead to several efforts in the redesign of repair process using AM (Sotomayor et al. 2021). Therefore, many researchers have been addressing the need to redesign products in order to overcome and solve design related problems to support AM repair and replacement at the end of their useful life by using a good design and optimization method (Silva et al. 2020). Moreover, the aim of the modeling and optimization method is to facilitate the recovery process of EoL components, leading to product longevity using AM (Rahito et al. 2019).

The optimization process requires setting the inputs or specifications of a component to determine the best solution to a design or problem, and using a mathematical function to maximize or minimize the output (Hadi & Ali. 2020). The input information is the number of parameters (decision variables) and the output information or results are whether the material needs a repair or replace process (Den et al. 2017). Then, the optimization algorithm is applied by researchers and engineers from various fields, such as energy, electrical engineering, control engineering, mechanical engineering and others, in order to optimize the repair process based on the objective function expressed by that material (Afrinaldi et al. 2016).

Artificial intelligence (AI) provides a promising approach in scaling up the repair process using AM technology. The AM technology provides an adaptive slicing algorithm that determines the layer width and thickness of the material based on the minimum value of the deviation between its stepped approximation and the computer added design (CAD) model (Wang et al. 2020). Meanwhile, knowledge-based and expert systems tools can be applied in decision-making in order to develop a sophisticated system to integrate AI in AM design (Leo et al. 2018). Artificial intelligence (AI) techniques that can assist the nature and process of decision-making during repair can be used to incorporate intelligent systems into AM-based repair. The incorporation of intelligent systems in AM repair is anticipated to improve the efficiency of resource use and repair during remanufacturing (Yusoh et al. 2021).

In this paper, the Fuzzy-Genetic Algorithm (FGA) approach was used to model the design parameters of a remanufacturable component, which in this case, was a turbocharger, as inputs and to relate them to the outputs (repair and replacement of the components parts) using the rules and facts applied to the FL inference engine. Subsequently, the repair process was modeled and optimized after the decision was made by the Fuzzy model. The design parameters selected for the modeling process were as follows: design complexity, failure mode, damage severity, preprocessing, mass flow rate, pressure ratio, temperature and durability (Fegade et al. 2015). Each parameter was set to a membership function, which was represented as a range of values (e.g., low, middle and high) to the Fuzzy model. This information was represented as a knowledge base to the inference engine of the Fuzzy logic system to find the best decision of the designed model. Eventually, the genetic algorithm was used to obtain the best cost for the repair process.

During the repair process, there are decisions parameters that must be considered to improve the design of the product in order to return to its original state with the same or higher quality. These parameters influence the decision on whether the component needs repair or replacement. Consequently, the process of decision making prior to repair and replacement can be modeled using fuzzy-based systems that have the ability to realize an input–output relation as a synthesis of multiple simple inputs–output. The multiple-objectives, simultaneous optimization is essential to be the survival of the cost function (fittest) by using the genetic algorithm (GA) that has two computational elements that work together as the Fuzzy logic (FL), and is applicable to many hard optimization problems, like optimization of linear and nonlinear functions. The fusion of FL system and GA allows the modeling of real-world problems. Fuzzy-Genetic Algorithm (FGA) is defined as an ordering sequence of instructions in which some of the instructions or algorithm components are designed with the use of Fuzzy logic-based tools (Saini et al. 2004).

This paper is organized as follows: Section 2 (Methodology) provides a brief introduction of the case example, namely the turbocharger design and parameters addressed in the proposed FGA model. The simulation results of the Fuzzy-based model and GA as a hybrid method are presented in Section 3 (Results). In Section 4 (Discussion), details on the implementation of the FGA hybrid method and the impact of the input parameters on decision making and optimization are presented. The paper provides a conclusion of the research findings and suggestions for future work in Section 5.

METHODOLOGY

In this section, the methodology of the paper is presented and discussed. The development of the FGA model is explained step-by-step to show the principal operation, followed by the decision on whether the turbocharger component needs repair or replacement, and to optimize the repair process using GA.

TURBOCHARGER

For the purpose of this study, a turbocharger was selected as a case example. Turbochargers are commonly repaired during remanufacturing as they are of high value. A turbocharger is a compressor used to raise the mass flow rate of air in order to increase the power of the engine. In addition, it differs from a typical compressor as it is usually driven by a turbine, using the input air to increase its pressure and yet feeding more air into the cylinders to increase the power of the engine (Chen et al. 2012). A turbocharger normally consists of three parts: the turbine housing, turbine wheel and compressor side. The turbine housing is made to withstand highly exhausted temperature using cast iron. The turbine wheel is made from cast nickel to support high temperature and pressure. Meanwhile, the compressor side is divided into two parts, the cover and the compressor wheel, which are made from different aluminum alloys or aluminum only (Herzwan et al. 2019).

During its useful life cycle, a turbocharger is continuously subjected to pressure, temperature and air flow rate (Fegade et al. 2015). There are also other parameters related to the turbocharger design: design

complexity, durability and disassembleability. On the other hand, there are parameters that do not necessarily affect materials longevity, such as preprocessing, failure mode and damage size. Table 1 shows the turbocharger's design parameters, which are the inputs to the FL model. The input variables are defined as follows:

1. Design complexity is the structure complexity of the component to be repaired.
2. Failure mode is any change in shape, size, or material properties.
3. Disassembly is the ability to break down a component into separate parts.
4. Damage size is the percentage of damage on the component to be repaired.
5. Preprocessing is the ability to prepare the component by brushing and cleaning it.
6. Durability is the ability of a material to be structurally serviceable and to withstand against pressure and damage.
7. Pressure ratio is the ratio of the pressure that a material can withstand.
8. Mass flow rate is the flow percentage that the material can handle without causing damage.
9. Temperature is the degree of temperature that a material can withstand (Fegade et al. 2015).

TABLE 1. Design parameters of the turbocharger

Input variables	Range
Design complexity	Simple: 0%-50%, medium: 25%-75%, complex: 50%-100%
Failure mode	True: 0%-75%, False: 25%-100%
Disassembling	True: 0%-75%, False: 25%-100%
Damage size	Min_d: 0%-50%, partially: 25%-75%, max_d: 50%-100%
Preprocessing	True: 0%-75%, False: 25%-100%
Durability	Weak: 0%-50%, medium: 25%-75%, strength: 50%-100%
Pressure ratio	Low:3-3.5, middle:3.25-3.75, high: 3.5-4
Mass flow rate	Low: 60-70, middle:65-75, high: 70-80
Temperature	Low :900-975, middle:950-1000, high:975-1000

Each input-output parameter was set at either three ranges: low, middle and high or true and false. The purpose was to determine which of these ranges were real data in

order to decide if the component could be repaired or replaced. All of these turbocharger design parameters were considered in order to test the effectiveness of the FGA model.

FUZZY LOGIC SYSTEM

FL is a method of solving uncertain problems by translating its knowledge to the computer with values between zero and one (Kamble & Rewaskar 2018). The FL system consists of four main parts: fuzzifier, rules, inference engine, and defuzzifier (Figure 1). FL is very flexible and versatile. It has an intelligent strategy, an application-appropriate interface, an aggregate of several control algorithms, and a straightforward computing and learning system (Maher et al.2023).

First of all, the design parameters (inputs) were defined as linguistic variables and terms. Next, the membership function for each parameter was constructed depending on actual knowledge. Then, the Fuzzy inference engine was used to assign the possible rules for the input parameters to cover approximately all possibilities (knowledge base) of the input effects. Finally, the Fuzzy system converted the crisp values into Fuzzy values using the input membership functions (Fuzzification) as shown in Figure 2.

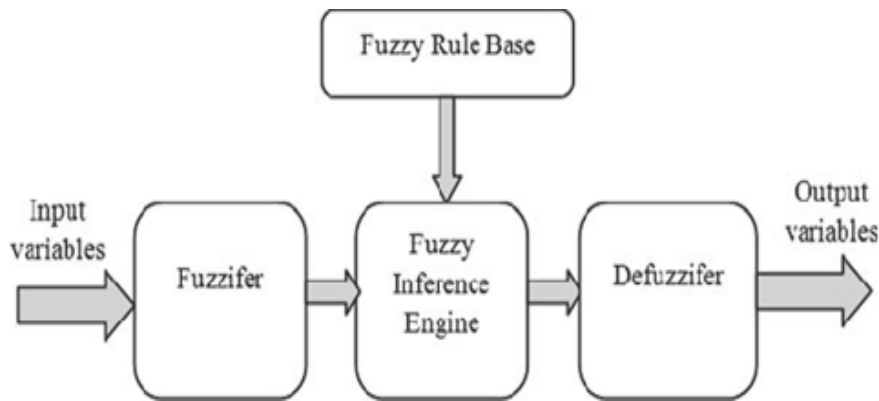


FIGURE 1. Fuzzy logic system (Africa et al. 2020)

Thereafter, Mamdani model was used to evaluate the rules in the rule base and sum up the results. Eventually, the Fuzzy values were changed to non-Fuzzy values

through the defuzzification process in order to make the best decision whether it was to repair or replace (output variables) as shown in Table 2 (Africa et al. 2020).

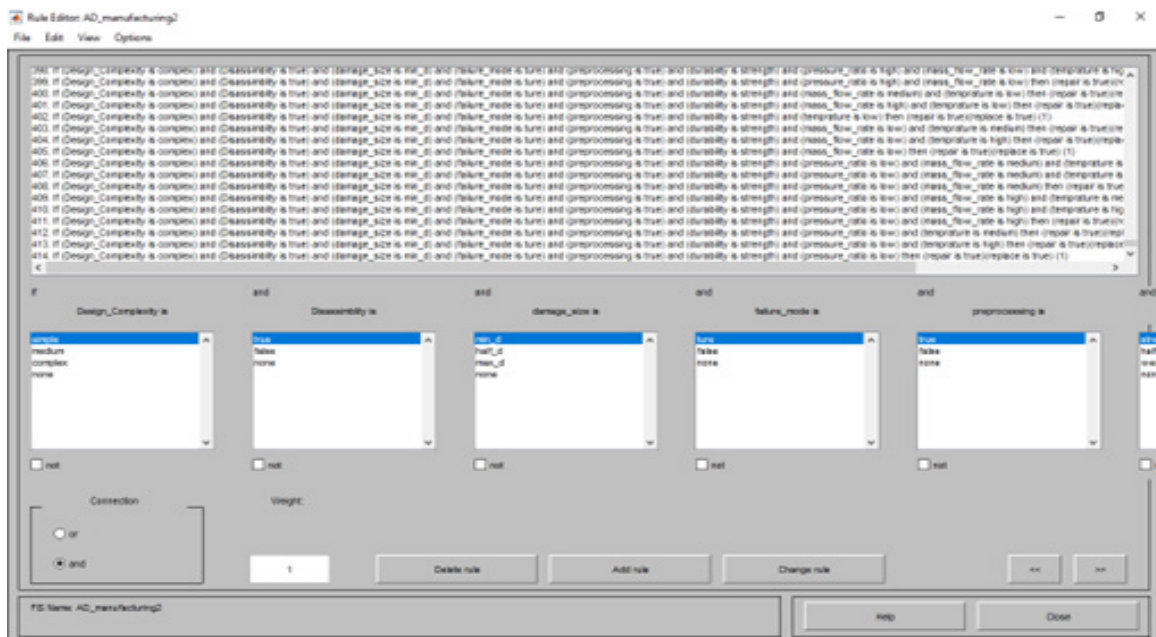


FIGURE 2. Matlab Fuzzy logic rule viewer

TABLE 2. Output variables

Output variables	Range
Repair	True: 0%-60%, False: 50%-100%
Replacement	True: 0%-60%, False: 50%-100%

GENETIC ALGORITHM

Genetic algorithm (GA) is an optimization method based on heuristic search invented by Charles Darwin's theory of natural selection (Katoch et al.2020). GA process is inspired by the natural selection process: the qualified individuals are selected to produce better offspring for the next generation. GA was applied to optimize the repair process using the Fuzzy model on design settings, such as rules, method, inputs and outputs. Consequently, GA is a search algorithm used in artificial intelligence to find the optimum parameters (Leirno et al. 2019). GA, like other optimization algorithms, has optimization settings, such as number of populations, selection, crossover, and

mutation. These settings are represented using a string of alphabets, meaning that these strings are encoded to the values of 1s and 0s (Castillo et al. 2020). In GA, every chromosome gives a possible solution. Therefore, the number of populations is a combination of chromosomes. In addition, the objective function represents each individual chromosome in the population and the chosen objective function is the one converged to zero. Moreover, the best individuals are isolated to reproduce the offspring. Therefore, the produced offspring will have the best features of both parents called a mutation. Table 3 includes the GA phases used to optimize the repair process after the decision on repair is made by the Fuzzy model (Andriushchenko et al. 2021).

TABLE 3. GA optimization phases

No.	Phases	Description
1	Initialization	In this phase, the optimization settings are initialized, including the number of population (chromosomes), iterations, crossover percent, mutation percent, ..., etc. as shown in Table (3) related to turbocharger.
2	Objective function (fitness) selection	A function that helps the selection of the individuals to produce the next generation as selected for turbocharger in Eq (1).
3	Selection (pairing)	Is the key phase used to select the best region that gives the best solution.
4	Mating	Is the process of creating new offspring from the parent individuals selected in the pairing phase as shown in Table (5) for turbocharger.
5	Crossover	In this phase, a random number is selected in the encoded chromosomes during mating process to generate new offspring. In addition, there are three types of crossover: single point crossover, two-point crossover, uniform crossover. This can be seen in Table (4) for turbocharger.
6	Mutation	In this phase, some of the chromosomes have bits that are flipped in order to create the diversity in the population and it is a criterion to stop the convergence.
7	Convergence	Every optimization algorithm has a criterion to stop iteration, such as the best solution and the end of number of iterations.

In the next section, the hybrid method of FGA is introduced and its implementation in repair and replacement of a turbocharger using additive manufacturing is discussed.

FUZZY-GENETIC ALGORITHM

In this section, the FGA is introduced to demonstrate its principal operation in the application of repair using

additive manufacturing. The Fuzzy part was used to model the relationship between the design parameters (inputs) and the outputs (repair and replace) in order to make a decision whether the turbocharger needed to be repaired or replaced. Thereby, if the decision is replacement, then the damaged part of the turbocharger will be replaced. Else, the turbocharger needs to be repaired. Then, the repair process was initiated by using the following objective function used to minimize the whole cost of the repair

operation, including the material cost, labors cost and operation cost. It also depended on the volume support, volume of the part (turbocharger) and height (Liu et al. 2019):

$$C_{AM} = 65.36 + 0.0288V_{part}(\varphi) + 0.0116V_{support}(\varphi) + 5.1283h(\varphi) \tag{1}$$

where $V_{support}(\varphi)$ can be found by subtracting $V_{part}(\varphi)$ from its bounding-box volume and optionally multiplying the result by a factor lower than 1.

where C_{AM} is the cost (objective) function of the turbocharger; $V_{part}(\varphi)$ is the volume of the part (turbocharger); $V_{support}(\varphi)$ is the volume support; and $h(\varphi)$ is the height.

In this work, a Fuzzy model identified the relationship between the inputs and outputs with the aid of GA. The following is the procedure of the FGA:

1. Step 1: Initialization of the turbocharger design parameters (inputs) to FL model.

2. Step 2: Assign membership functions to the inputs and outputs.

3. Step 3: Assign Fuzzy model type (Mamdani).

4. Step 4: Write the rules in the Fuzzy Inference System (FIS) to describe the decision-making model.

5. Step 5: Export the FIS results to the Genetic Algorithm.

6. Step 6: Use the FIS parameters and initialize the GA optimization settings.

7. Step 7: Define the objective function (equation 1).

8. Step 8: Implement the GA optimization using the Fuzzy model outstep 9puts.

9. Step 9: Record the results from the Fuzzy model and Genetic Algorithm.

Figure 3 shows the general flow chart for the FGA method adopted in this work.

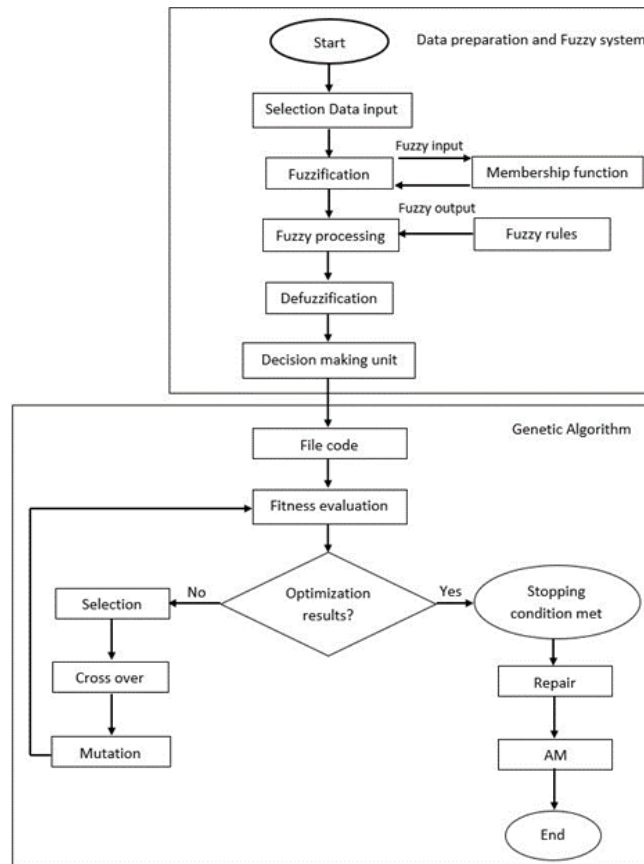


FIGURE 3. General flow chart of the FGA hybrid approach

RESULTS

In the fuzzy model, the effects of the design parameters are interpreted into rules in the FIS to obtain the best decision by relating the inputs to the repair output. Consequently, the results of the FGA hybrid method have shown the effectiveness of its implementation of repairing and replacing turbocharger using AM technology. The followings are the simulation results of both repair and replacement using Fuzzy model and the repair process using GA.

REPAIR

Figure 4(a) shows the effects of both design complexity and damage size together on the repair decision-making. The magnitude of the damage that requires a 50% more extensive repair increases as part complexity increases. Meanwhile, Figure 4(b), shows the when the durability is low the turbocharger does not need to be repaired whatever the design complexity value is. If the turbocharger's durability is lower than 40%, no repairs are necessary, durability of turbocharger is good. Figure 4(c) explains that if the mass flow rate through the turbocharger is higher than 68 kg/sec and the design is complicated, then the

turbocharger will need to be repaired. Figure 4(d) shows the durability and damage size of the turbocharger. If they are above 30%, then the turbocharger will need to be repaired. The functional parts are not affected by the defect. Figure 4(e) shows that no matter the pressure ratio on the turbocharger, if the damage size is lower than 35%, then the turbocharger will not need to be repaired. Else, it will be repaired. Consequently, Figure 4(f) illustrates the temperature impact on the damage size turbocharger. There is no need to repair a turbocharger if the temperature and damage level are less than 250°C and 20%, respectively. Then if this is above 300°C, then the turbocharger will need to be repaired.

On the other hand, Figure 5(a) shows that if the complexity of the design has increased the turbocharger need to be replaced. Figure 5(b) views the impact of the durability and complexity of the turbocharger on the repair action. Figure 5(c) explains mass flow rate and design complexity to the replace decision. Figure 5(d) presents the durability and the damage size effects on the replace decision. Figure 5(e) shows the pressure ration and damage size impacts on taking replace decision. Figure 5(f) presents that whenever the temperature increased with the damage size the replace decision should be taken to replace the turbocharger .

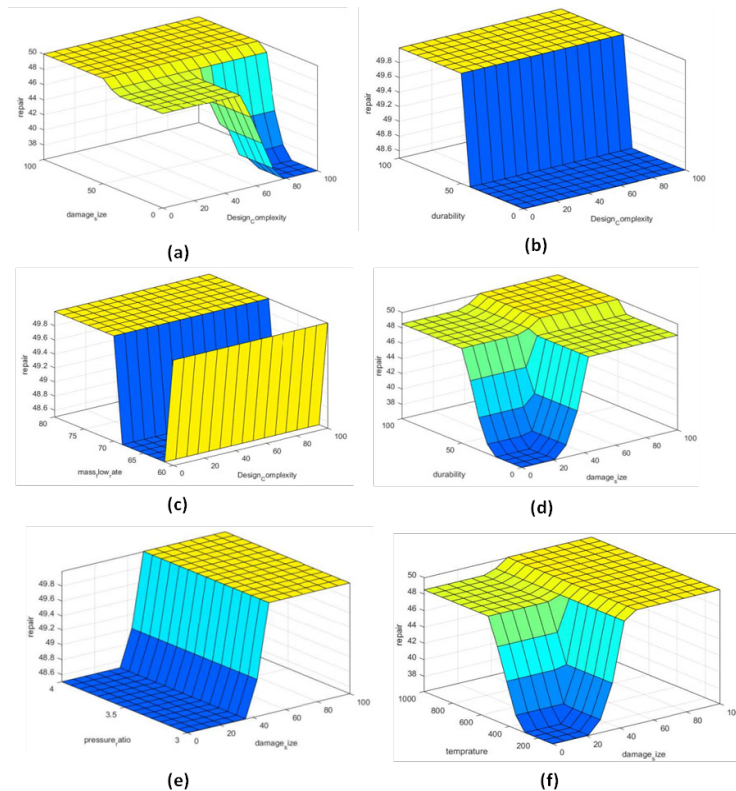


FIGURE 4. The relationship between input parameters with repair. (a) Design complexity and damage size. (b) Durability and design complexity. (c) Mass flow rate and design complexity. (d) Durability and damage size. (e) Pressure ratio and damage size. (f) Temperature and damage size

REPLACE

Figure 5(a) views the design complexity and the damage size of the turbocharger that impacts the replace decision after the value of 50% and 70%, respectively. In addition, Figure 5(b) shows the durability with the complexity of the turbocharger design. If they are below 50%, then the turbocharger will need to be replaced. Figure 5(c) illustrates the effects of both mass flow rate and design complexity factors on decision-making for replacement, with a 50% influence on replacement when both the mass flow rate and

design complexity are increased. Meanwhile, Figure 5(d) views the impact of the durability and the damage size, if the damage size increase above 35% the turbocharger on the replace action. Figure 5(e) explains that when the pressure ratio and the damage size of the turbocharger increase, the replace action will be the choice is 50% of the Fuzzy model. Moreover, the effects of both damage size and the temperature together on the replace decision-making as shown in Figure 5(f). The fuzzy model in Figures 4 and 5 shows the effect of parameter ratios on the repair and replacement process of turbochargers and when to make the decision to repair or replace.

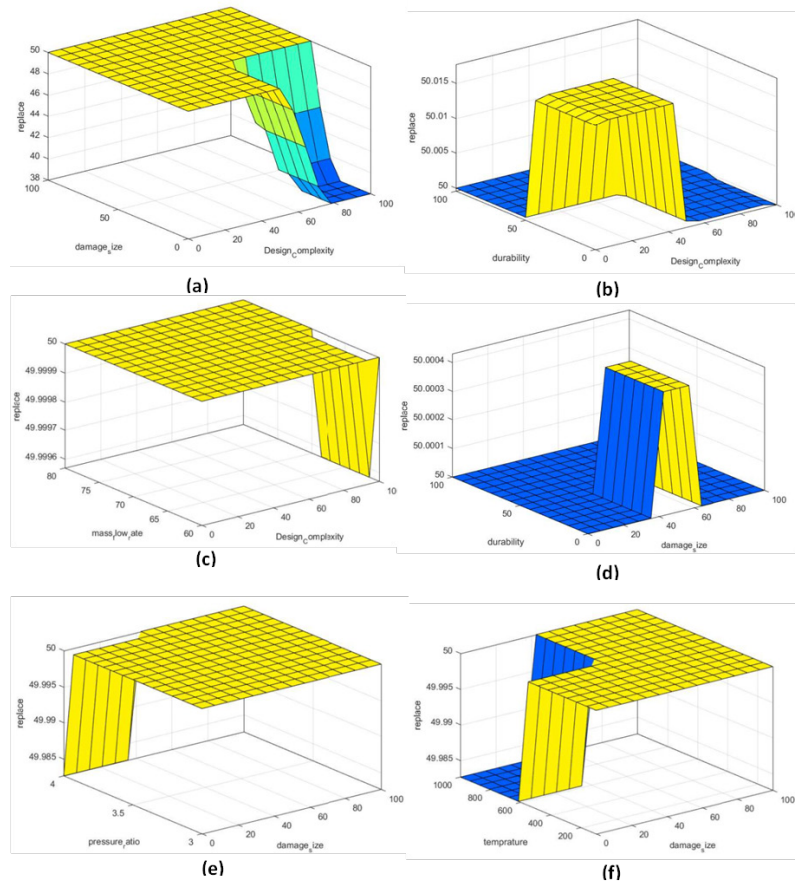


FIGURE 5. Relationship between input parameters and replacement. (a) Design complexity and damage size. (b) Durability and design complexity. (c) Mass flow rate and design complexity. (d) Durability and damage size. (e) Pressure ratio and damage size. (f) Temperature and damage size.

Next, the rules and settings of the FIS are used to trigger the GA optimization method for repair process in order to optimize the minimum cost for the overall process.

GA RESULTS FOR REPAIR PROCESS

After the decision is made using Fuzzy model and the decision is to repair the turbocharger, then the FIS settings are used as inputs to the GA in order to optimize this

process. After many tests, the GA had to be set up by initializing the optimization settings as shown in Table 4.

Table 5 shows samples of the crossover before the mutation of the GA after using FIS file settings as input to the GA file. These columns are samples of the crossover resulted in the GA as a preparation setup to the next step. Table 6 shows a sample of parents and offspring after the mutation phase in the GA to produce new generation. In this step the parents are selected to produce the next generation represented by the offspring

TABLE 4. GA optimization settings

Iterations	CrossPercent	MutatPercent	Dimension	VarMin	VarMax	No. of Pop.
10	70	20	30	1	30	100

TABLE 5. The samples crossover population array of the GA

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
34.543324	3.413486	33.434573	1.2343415	82.743469	53.53346	62.85734
4.38349	73.723332	45.62734	13.7224	85.70341	35.56324	24.07341
23.5322	4.45454	44.9544	3.52234	59.44234	43.98234	34.0417
5.693332	4.83993	23.3443	3.586585	3.44545	36.5344	1.34775
0.93196	43.8377	4.83993	24.1555	2.9749	29.221	27.14909
40.4739	2.34605	42.9761	26.7861	13.05913	12.2256	12.73323
0.93196	42.9761	29.2208	26.7860	12.2256	22.3656	23.7597

TABLE 6. Samples of parents and offspring of GA

Parents							
Parent1	4.9801	4.7842	4.6702	3.9882	5.1474	3.7481	3.9884
Parent2	5.3997	5.6471	3.6161	4.4657	4.7605	7.9381	3.9776
Offspring							
Offspring1	5.3531	5.5513	3.7331	4.4127	4.8035	7.4731	3.9788
Offspring2	5.0463	4.9204	4.5038	4.0636	5.0863	4.4097	3.9867

Table 7 views a sample of the top population and the best population. The top population is the best population in each column while the best population is the best amongst the bests (minimum value) in that column. In this step, best population have been selected from each iteration and yet the best one will be selected among them.

Eventually, Figure 7 shows the cost convergence of the objective function in equation (1). Obviously, it indicated that the repair process had been successively optimized because after 10 iterations, the cost converged from almost 3000 and continued to be minimized to the lowest possible value.

TABLE 7. The top and best population in GA

Best population						
0.93196	0.345455	5.6672	1.251499	0.22345	2.9749	3.351494
Top population						
2.35149	7.34342	5.6672	1.35149	11.349396	50.6672	6.32349
1.3515	1.34939	50.6676	3.351499	0.22345	50.6672	3.351494
2.34605	4.4739	27.14909	4.1555	13.05913	2.9749	25.3656
0.93196	42.9761	29.221	26.7861	12.2256	4.83993	35.7597
4.33454	0.345455	50.6676	1.251499	0.343467	50.6672	8.33294

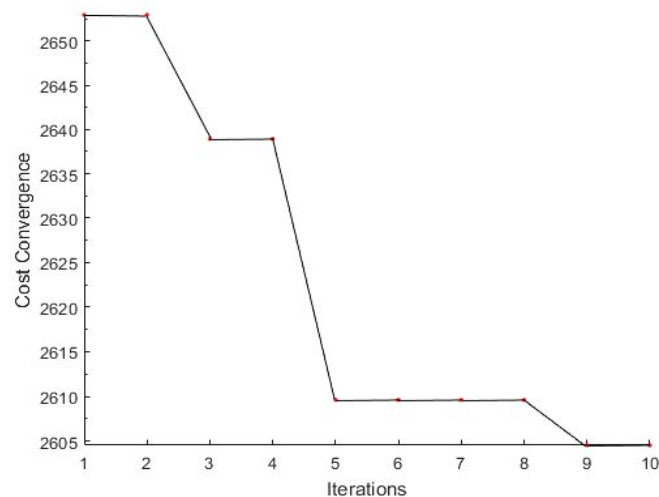


FIGURE 7. Cost convergence of the objective function

DISCUSSION

In the simulation results, the efficiency of the FGA hybrid method for repairing and replacing turbocharger using AM technology has been achieved. The Fuzzy model used the rules in FIS to obtain the relationship between each parameter input and the corresponding output. Thereby, these results showed the accuracy of the Fuzzy logic-based modeling to make the best decision on whether the turbocharger needed to be repaired or replaced. In the previous section, the results showed that there were some parameters that were more effective in turbocharger longevity than others, such as design complexity, damage size, durability, pressure ratio, mass flow rate and temperature. Figure 4(b) and Figure 5(b) have shown the high influence of both durability and design complexity on repair and replace process. Figure 4(d) and Figure 5(d) have shown the high influence of both durability and damage size on the repair and replace. Figure 4(e) and Figure 5(e) have shown the influence of both pressure ratio and damage size on the repair and replace. Figure 4(c) and Figure 5(c) have illustrated the influence of both mass flow rate and design complexity on the repair and replace. Figure 4(f) and Figure 5(f) have presented the influence of both temperature and damage size on the repair and replace. The mentioned figures proved the priorities or the dominance of these parameters over the others.

However, there are other parameters which have less impact on the decisions to repair or replace the turbocharger, such as preprocessing, disassembleability and failure modes, which may be effective in other components. However, the selected objective function is applicable to other components with modifications to the Fuzzy input parameters (Andriushchenko et al. 2021). In general, the

results have indicated the effectiveness of the FGA hybrid method in the decision-making for turbocharger repair or replacement.

CONCLUSION

This paper presents and discusses the application and efficiency of the FGA hybrid method for decision-making in repair and replacement of a turbocharger using AM. The design parameters that have been chosen in this work are not the only influential parameters on turbocharger; therefore, the work can be extended using other parameters and materials. The function is not limited with the one used in this work. It can also be any mathematical equation derived using the material characteristics that need to be remanufactured. Fuzzy logic was used to model the relation between the design parameters as input, and repair and replacement as outputs. Moreover, it can be used as a controller with GA as a hybrid method to control the process in AM technology. In conclusion, the results showed the successful implementation of the FGA method in repairing and replacing turbocharger through AM technology.

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DECLARATION OF COMPETING INTEREST

None

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