A smart decision making tool for cleaning process planning in remanufacturing

Juan Carlos Martinez

Manufacturing and Industrial Engineering,
The University of Texas-Rio Grande Valley,
Edinburg, TX 78539, USA
Email: jcm251087@gmail.com

Zhenhua Wu*

Manufacturing Engineering,
Virginia State University,
Petersburg, VA 23806, USA
Email: zwu@vsu.edu
*Corresponding author

Jianzhi Li and Miguel Gonzalez

Manufacturing and Industrial Engineering,
The University of Texas-Rio Grande Valley,
Edinburg, TX 78539, USA
Email: jianzhi.li@utrgv.edu
Email: miguel.gonzalez@utrgv.edu

Abstract: Equipping stakeholders with advanced tools to make better decisions for sustainable production is a key to research in smart manufacturing in the 21st century. A smart decision tool to select the optimal cleaning processes for remanufacturing is presented in this paper. The approach started from formulating the process selection problem to a linear programming model to minimise the cost while observing the constraints of part cleaning level, processing time, and energy consumption. In order to model the vague and uncertain information associated with contamination, cost, time and energy consumption, fuzzy sets were applied. Finally, a genetic algorithm was proposed to search for the optimal solution to the mathematical model. Further, a software prototype was coded in MATLAB® to validate the proposed approach. Two case study results show that the proposed approach can overcome the deficiency on handling information vagueness and multiple objectives when searching for optimal cleaning solutions in remanufacturing. The proposed approach is systematic; it can be integrated into process planning in remanufacturing.

Keywords: smart decision; cleaning; process planning; remanufacturing.

Reference to this paper should be made as follows: Martinez, J.C., Wu, Z., Li, J. and Gonzalez, M. (2020) 'A smart decision making tool for cleaning process planning in remanufacturing', *Int. J. Rapid Manufacturing*, Vol. 9, Nos. 2/3, pp.167–193.

Biographical notes: Juan Carlos Martinez is currently an Industrial Engineer. He received his Master's degree from the University of Texas Pan American, currently University of Texas-Rio Grande Valley (UTRGV). He is currently working in the automotive industry in charge of decision making of business allocation to suppliers and program management.

Zhenhua Wu is currently an Associate Professor in Manufacturing Engineering at the Virginia State University. He received his PhD in Mechanical Engineering from the Texas A&M University at College Station, Texas in 2012. His current research focuses on smart manufacturing, sustainable manufacturing, and manufacturing automation.

Jianzhi Li received his PhD in Industrial Engineering from the Texas Tech University, Lubbock, in 2003. Currently, he is a Professor of Manufacturing & Industrial Engineering at University of Texas-Rio Grande Valley. He is a Faculty Fellow of Bentsen Endowed Chair in Engineering. His research focuses on laser material processing, additive manufacturing, remanufacturing, and smart manufacturing.

Miguel Gonzalez is a Professor of Manufacturing Engineering in the UTRGV College of Engineering and Computer Science. He received his PhD from the University of Houston. His current research interests include advanced manufacturing systems, integrated logistics support, simulation, work science and ergonomics.

1 Introduction

Smart manufacturing applies advanced cyber technologies such as digital manufacturing with data analytics for operations and businesses to emphasise product life cycle design and manufacturing innovations. In smart manufacturing applications, enterprises digitise every part of a manufacturing enterprise with interoperability and enhanced productivity, connect devices and distribute intelligence for real-time control and flexible production of small batch products, collaborate supply chain management with fast responsiveness to market changes and supplying chain disruption, integrate optimal decision making for energy and resources efficiency, and apply sensors and big data analytics through product lifecycle to achieve fast innovation cycle (Lu et al., 2016 NIST report). The eight priority areas suggested by NIST to advance smart manufacturing include:

1 smart manufacturing system reference model and reference architecture
2 internet of things (IoT) reference architecture for manufacturing
3 manufacturing service models
4 machine to machine communication
5 PLM/MES/ERP/SCM/CRM integration
6 cloud manufacturing
7 manufacturing sustainability
8 manufacturing cybersecurity (Lu et al., 2016 NIST report).

Table 1 Summarisation of cleaning processes in remanufacturing

Method	*Approach*	*Contamination to be removed*	*Typical work part*	*Cost per part*	*Energy consumption*
Immersion cleaning	Uses convection currents and vibrations to remove the surface contamination. The approaches to use immersion cleaning include belt conveyors and rotary drums where the pieces are put inside the media. Mechanical agitation in the aqueous media can be used to improve results. Another alternative is to use high pressure pumps to generate a flow in the media to clean the piece.	Soil particles, films and coating, oils, soils, carbon, rust, dirt and gaskets from solid surfaces	Regular and complex shapes, pieces with holes and parts hard to reach	\$0.06 to \$0.15	0.18 Kwh
Ultrasonic cleaning	This method consists of a tank filled with aqueous media that may or may not contain chemicals. The tank is connected to a motor that generates frequencies. These frequencies create bubble inside the tank that impacts the surface of the piece removing the contaminant.	Paint, oil, grease, carbon, rust and oxidation.	Regular and irregular shapes. Shapes with many holes or hidden chambers may be difficult to clean.	\$0.035 to \$0.45	0.86 Kwh
Molten salt cleaning	Using the same principle as immersion cleaning, molten salt uses a bath of salt combinations and different temperatures to clean the surface. There are three types of molten salt: molten alkali metal nitrates or a mixture of nitrate ions, molten cyanide baths, and molten chloride salts.	Organic soils that forms in cars, trucks and plane's engines	Regular and irregular shapes and it is good cleaning pieces with small holes	\$0.6 to \$0.8	0.1Kwh to 0.2 Kwh per cycle
Laser cleaning	Uses a laser beam to remove contaminant from the surface. The laser is directed by a mirror that gives the necessary direction to the beam. The contamination can be remove layer by layer in a controlled basis.	Any type of contaminant at any layer	Regular and irregular shapes, irregular shapes may not be clean, especially pieces with holes	\$2 to \$3	2Kwh to 12 Kwh per cycle

Source: Yagar (2012)

Table 1 Summarisation of cleaning processes in remanufacturing (continued)

Method	*Approach*	*Contamination to be removed*	*Typical work part*	*Cost per part*	*Energy consumption*
Vibratory cleaning	Consists of a container filled with media that uses a device to apply time variable forces to the container to develop a periodic motion. Based on the size and material of the particles, the media can be changed to provide different results. If the contamination is thick, then a bigger and harder particle is used. If the contamination is thin, fine and soft particles may be used. Moreover, the type of material in the piece to clean dictates the type of media to use to avoid damages.		Pieces with regular shapes. It is not suitable for irregular shapes if they have small holes in them.	\$0.04 to \$0.07	0.1 Kwh to 0.2 Kwh per cycle
Abrasive cleaning	Shoots particles into the piece to remove the contaminants in the surface. The process can be dry or wet. The dry process does not use liquid or chemicals, just the dry particles. Dry abrasive cleaning uses sand, slags (copper, nickel, iron), minerals, glass, ceramic, sponges, pellets, natural products, carbon oxide or aluminium oxide grit. Wet blasting uses water with chemicals (sand, mild alkaline cleaners, detergents, diluted acids, baking soda granules and other more) to remove the contaminants. The abrasive cleaning may be adapted to different needs by changing the nozzles through which the particles are shot. Bigger nozzles have more shotgun effect while a smaller nozzle is used for more detailed cleaning.	Dirt, soluble salt, carbon, oxidation, paint, gaskets, rust, ash, or even a layer of the part's surface	Good for regular and irregular shapes that do not have hidden chambers. Small holes may be hard to clean.	\$0.2 to \$0.45, but it can go to \$10 if using expensive chemical, or if a big piece needs more process time	

Source: Yagar (2012)

Table 1 Summarisation of cleaning processes in remanufacturing (continued)

Method	*Approach*	*Contamination to be removed*	*Typical work part*	*Cost per part*	*Energy consumption*
Thermal cleaning	Uses high temperatures in ovens to burn the contaminants and convert them into ashes or gases. A convection oven is used when direct flames cannot be used. The bottom part of the oven is heated and the radiated heat is what makes contact with the piece. Another oven is the open flames oven. This type can reach higher temperatures because of the exposure of the flames but can harm the piece. Due to high temperatures, the piece can melt, the material property may be changed or the piece can be damaged and not usable in the next process.	Organic contaminants, gasket material, rubber seals and heavy grease		\$0.08 to \$1.55	0.3 Kwh to 0.6 Kwh
Minor cleaning processes	These kinds of processes are used to perform the initial cleaning or to finalise cleaning from the surface of the piece. Spray wash, rinse, brush cleaning and any other that prepares the piece either to initial cleaning or finish it for the next step in the remanufacturing process.	Last part of the contaminants, clean residues, clean chemicals	Used on past cleaning method and/or perform the final details of the cleaning		

Source: Yagar (2012)

Equipping stakeholders with advanced tools for better decision-making for environmentally sustainable production is a key research area for smart manufacturing (Edgar et al., 2015, NSF smart manufacturing workshop report; Bernstein et al., 2018).

Remanufacturing is a vital component for sustainable manufacturing because of many new opportunities that are provided such as: sustainability, job creation, and affordable prices, etc. The remanufacturing process receives used/retired products and puts in processes to deliver 'like-new' products with increased life-cycles and better reliability (Junior and Filho, 2012). In general remanufacturing processes the used products go through a series of steps including inspection, disassembly, cleaning, recondition/replenish, and re-assembly. Tests and inspections are done throughout the remanufacturing to achieve the quality desired. When parts are received for remanufacturing, its surfaces are covered with contamination that may decrease the performance of the product or that should not be on the surface. For example, the piston of the engine needs oil and grease to avoid high temperatures and wear due to friction. But as time passes using the engine, oil and grease start to stick on the walls of the piston chamber that mixed with the combustion and high temperature creating soot. Another example is painting and coating. Even though they are used to protect for the original product, when it comes to remanufacturing, those protections are considered contamination because a new paint and coat will be applied.

The cleaning process is critical to remanufacturing in that it delivers products which are ready for reprocessing. The main purpose of cleaning in remanufacturing is to facilitate inspection and damage correction, and thus make the parts like new in condition. However, it is difficult to measure the level of cleaning irrespectively as there is no standard available. In practice, it is mostly done by visual inspection and then determining which is good enough by experience of the workers. This also causes a difference in cleaning efforts and costs for each remanufacturer (Gamage et al., 2013). A survey ranks the cleaning process among the most costly process in remanufacturing (Hammond et al., 1998). It is ranked second (29%) just after part replacement (43%). While parts cleaning in regular manufacturing productions is serving as a prelude to surface finishing or protecting sensitive components. The cleaning level in regular manufacturing is measurable. For example, using procedures recommended by ASTM B322.

The contaminants are categorised as organic or inorganic. Organic contaminants include: organic particles, paints, lubricants, oils, grease, coatings, bacteria and fungi. Inorganic contaminants include: oxide scale, wear debris, dust, moisture and inorganic lubricants (Long et al., 2014). Cleaning processes to contaminants are generally classified into the following groups based on the technology or clean media used: immersion cleaning, ultrasonic cleaning, abrasive cleaning, laser cleaning, thermal cleaning, chemical cleaning, etc. Not all the cleaning processes can clean all the different contaminations at the same rate of time and cost. Table 1 summarises the cleaning approach, contamination to be removed, typical workpiece, cost, and energy consumption for each cleaning process. Different cleaning processes produce different cleaning results depending on the initial condition. Due to the uncertainty of the product condition and product usage condition at the moment of reception, the same cleaning method cannot be used all the time. Many evaluations on the cleaning methods need to be performed to decide which one can be used to achieve a desired cleanness level demanded by the remanufacturing process. The remanufacturers have to comprehensively understand the different decision parameters and performance measures in order to select the best cleaning processes. The decision parameters of a cleaning process generally involve: contamination level, contamination type, cleaning system type, material type, cleaning chemicals, temperature, and process cycle time. Performance measures may include: efficiency, system energy consumption, operating cost per part, system cost, emission levels, and cleaning effectiveness. Other factors that may also affect the performance and adoption of cleaning method include condition and geometry of the parts, clean media restriction, energy consumption, environment impact, quantity and types of contaminants, material resistance, etc. Further, most information available for the cleaning processes is vague and is only provided in ranges for equipment cost, energy consumption, cost per piece, etc.

Given all the issues discussed, it is difficult for the remanufacturers to choose the best processes that reduce cost and time meanwhile achieving maximum cleanliness level. A literature search has revealed a lack of rigorous models to select optimised cleaning processes that can relate input conditions with the outputs such as cost, cleaning performance, and energy consumption. Initiated by this, a smart decision making tool that helps the remanufacturers develop process planning with their desired goal is proposed in this paper. The overall methodology is based on mathematical programming model (PM) with fuzzy sets (FS) and genetic algorithm (GA) as the solution approach. The PM is used to model the objective function with the constraints and decisions variables. The FS are used to deal with the different uncertainties and lack of 'exact' information that exists in remanufacturing. FS help to work with ranges that the remanufacturer can establish depending on their need and knowledge of the process. The GA is used to find the best possible solution (close to optimal) that subjects to different constraints.

The rest of the paper is organised into the following sections. Section 2 reviews the related literature on intelligent decision making in process planning for remanufacturing. A research gap is identified at the end of this section. Section 3 covers the proposed approach on PM model, FS, membership functions, fuzzy inference and the input/output of the model and the GA. Section 4 presents a prototype software and case studies to validate the proposed approach. Section 5 concludes the paper and presents outlooks on the future research.

2 Literature review

The related literature was searched on artificial intelligence in remanufacturing process planning.

The stochastic and sporadic nature of the condition and quantity of the returned products impacts many levels of process planning and control for remanufacturing. NIST has investigated the sustainable process analytics formalism (SPAF) for "formal modelling of modular, extensible and reusable process components and enables the optimization of sustainability performance based on mathematical programming" (Brodsky et al., 2016). Based on the SPAF, they further developed a decision support system (DSS) that enables manufacturers to formulate optimisation problems at multiple manufacturing levels, to represent various manufacturing data, to create compatible and reusable models and to derive easily optimal solutions for improving sustainability performance (Shin et al., 2017). Kernbaum et al. (2009) presented an approach for the design and evaluation of the remanufacturing processes for a facility. A mixed integer programming (MIP) approach is used for the optimisation of a remanufacturing process plan from cleaning to reassembly by considering all the relevant costs. Jiang et al. (2011) defined reconditioning system planning as being made up of three closely related aspects, namely, restoration planning, process planning and technology planning. Assuming that the restoration and process planning have already been performed, a multi-criteria decision-making method was formulated to consider the economic and environmental aspects for the selection of the manufacturing technology portfolio. The analytical hierarchy process (AHP) was used to assign weights to the various criteria and capture the singular and synergistic benefits of each technology for decision making. Wang et al. (2008) presented a method to solve disassembly sequence planning problem. They proposed a disassembly feasibility information graph (DFIG) to describe the product disassembly sequence and operation information. Then, disassembly sequence planning problem was formulated onto the DFIG as an optimal path-searching problem, a GA was applied to find out feasible and optimal disassembly solutions efficiently. Gao et al. (2004) proposed a fuzzy reasoning Petri net (FRPN) model to represent related decision making rules in disassembly process. Using the proposed fuzzy reasoning algorithm based on the FRPN model, the multi-criterion disassembly rules can be considered in the parallel way to make the decision automatically and quickly. Instead of producing the disassembly sequences before disassembling a whole product, the proposed method makes intelligent decisions based on dynamically updated status of components in the product at each disassembly step. A fuzzy logic-genetic algorithm (FL-GA) methodology was proposed to the automatic assembly and disassembly sequence planning of products (Galantucci et al., 2004). The GA-fuzzy logic approach was implemented in two levels. The first level was to develop a Fuzzy controller for the parameters of an assembly or disassembly planner based on GAs. This controller acted on mutation probability and crossover rate in order to adapt their values dynamically while the algorithm was running. The second level was identified as the optimal assembly or disassembly sequence by a fuzzy function, in order to obtain a closer control of the technological knowledge of the assembly and disassembly processes. A fuzzy multi-criteria decision making algorithm was developed to evaluate alternative recycling activities of an e-waste recycling job under of the sustainability criteria on the environmental, economic, and social dimensions (Yeh and Xu, 2013). This decision making model meets the best sustainability interests for sustainable planning of e-waste recycling activities. A series of optimal weighting models are developed to determine the optimal weights for the three sustainability dimensions and their associated criteria. It contributes to the methodological development of weighting the three corporate sustainability dimensions for planning decisions. Researchers designed a remanufacturing cell for the automated rework of fine pitch components for electronics manufacturing. This remanufacturing cell can finish the processes of: component removal, solder cleaning, solder paste dispensing, pick and place components, solder reflow, and laser soldering (Fidan et al., 1998). They further developed a computer aided process planning (CAPP) tool (Fidan et al., 2003) and an intelligent simulation environment (Fidan et al., 2004) for electronics remanufacturing systems. According to recent research (Liu et al., 2013), the availability, quality, remanufacturing cost and the remaining life of the remanufactured product are directly influenced by various cleaning methods and the corresponding cleaning quality. They also pointed that unified standards for cleanliness judgment and the knowledge base of remanufacturing cleaning are insufficient in spite of simplification and effectiveness of present remanufacturing cleaning process. This gap is complemented with an existing problem in cleaning efficiency due to the low level of process automation. Additionally, the cleaning needs to have many important quality measures to assure the overall cleaning of the product/piece. One of the challenges to the remanufacturing industry is the lack of decision making tools that helps the remanufacturers decide which cleaning method will achieve the desired level of cleanliness at lower cost/time possible. This knowledge gap needs to be filled in order to contribute to the cleaning processes for remanufacturing.

A review of literature identifies that current research lacks enough consideration on the questions below for selecting the optimal cleaning processes in remanufacturing:

1 Can the factors, including contamination, work piece material and shape, processing time, cleanliness level, and cost etc., be incorporated into the cleaning process selection model?

2 Can the process vagueness and uncertainties on the decision variables be processed in the selection modelling?

3 Can an efficient optimisation algorithm to properly select the cleaning process be developed that considers the multiple objectives including cost, cleaning effect, process time, involved in cleaning for remanufacturing while subjecting to constraints?

These three issues form our research questions to be solved in the following sections.

3 Smart decision support model for process planning in remanufacturing

The proposed model of smart decision making for optimal cleaning process planning in remanufacturing is presented in this section. First, the mathematical PM with decision variables, objective function and constraints are formed. Second, the FS with the membership functions are illustrated. Third, the GA is explained on searching optimal solution to the proposed model; and fourth, the decision support model is explained in a flowchart. It is important to note that every remanufacture process has different criteria, different measurements, and different needs. Thus these FS and membership functions need to be implemented to better understand the current knowledge. Also, the proposed decision support model should be generic to help the remanufacturer make a good decision; however, the technical information should be modified according to their own process.

The following terms are used throughout the model.

- Sequence of cleaning processes (Y_i). This refers to the cleaning chosen to perform the study. The index 'i' is used to differentiate from other sequence. It is modelled as an array of processes that contains the sequence. $Y_i = [y_1 \ldots y_j]$. For example, $Y_1 = [1\ 2\ 3\ 4]$, in which the sequence is ultrasonic, abrasive, laser and thermal. Each j^{th} term represents one cleaning method and the i^{th} array represents the sequence in which will be performed. This variable is randomly created.
- Process cycle time (T_i). Similar to Y_i, it refers to the time in which each cleaning process will be used. It is also an array and each position refers to the time that a process of the array Y_i will be used. $T_i = [t_1 \ldots t_j]$. For example, $T_1 = [15\ 20\ 25\ 30]$ refers to process time of the cleaning processes. Also, the index T_i has a relationship to the index Y_i. Each j^{th} term represents the time of each method and the i^{th} array represents the process time.
- Acceptable process time (Tw). This is the maximum process time allowed for the combination of cleaning process. It is given by the user with a number or by a subset of the set time. It serves as the upper limit.
- Acceptable clean level (CLp). This is the minimum cleaning level that the piece should meet in order to be suitable for the next processes. It is given by the user by a number or by a subset of the set cleanliness level. It serves as the lower limit.
- Acceptable energy consumption (Ev). Similar to time Tw, Ev is the maximum energy consumption that can be used in the cleaning process. It is given by the user.
- Fuzzy inference output (P_i). This refers to the results given the fuzzy inference after evaluating the necessary rules. The output is cleaning result (CL), energy

consumption result (EC) and cost result (CR). Later in the process, the Y_i and T_i are combined to check the constraints with the input given by the user.

- $\bar{y}_j$, represents the binary element for the array Y_i. If an element of the array is bigger than zero, the $\bar{y}_j = 1$. Otherwise, $\bar{y}_j = 0$.
- Contamination type (*CT*). It is a user input that refers to the type of contaminant that is located on the surface of the piece. May be organic, inorganic, mixed, etc.
- Contamination level (*CTh*). It is a user input that refers to the amount of contaminant located in the surface of the piece.
- Material type (*MT*). It is a user input that describes the type of material that is contained in the piece. The material may be metal, ceramic, polymer, and composite, etc. For the study, the material type may be metal or non-metal.
- Piece shape (*PS*). It is a user input that gives information about the form of the piece. It may be flat, round, may contain holes. For the study, *PS* is used as a fuzzy set with sub-sets of simple, complex and very complex.
- Feasible solutions (Q_i). This term is an output after checking the constraints. It contains information about the inputs of the user, sequence of cleaning processes, processing time and output of the fuzzy inference. This array is built each generation with the processes that only met the constraints.
- Best solution (s_i). This refers to the best solution of each generation that is contained in Q_i.

3.1 The model

3.1.1 Decision variables

The decision variables are Y_i and T_i. These two variables give the sequence of process and the time in which processing of the sequence is performed. They will initiate the model to evaluate cleaning processes in terms of cleanliness level, energy consumption and cost. After the evaluation, it is important to calculate the cleanness level achieved, the energy consumed and the cost incurred. The first two and the T_i are used in the constraints checking to assure that the sequences of processes are suitable.

3.1.2 Constraints

The constraints serve as the filter to disregard any options that do not meet user expectation (given in the input). *CLp*, *Tw*, and *Ev* are limits that need to be met. The user implements the constraints on the inputs of the acceptable process time, Acceptable cleaning level, and acceptable energy consumption. The output P_i = [CL, EC, CR] given by the fuzzy inference is used to check the constraints. CR is not part of the constraints, but it is part of the array. The time constraint is checked with the array T_i.

As explained before, CL is the cleaning level achieved by the sequence of process. The cleaning output has to be higher than the user input *CLp*. The output EC and the process time generated T_i are needed to be lower than the user input *Tw* and *Ev*. The constraints are set as follows:

$$CL \geq CLp \tag{1}$$

$$T_i \leq Tw \rightarrow \sum_{j=1}^{j=n} \overline{y}_j t_j = R_i \leq Tw \tag{2}$$

$$EC \leq Ev \rightarrow \sum_{j=1}^{j=n} \overline{y}_j E_j \leq Ev \tag{3}$$

3.1.3 Objective function

The objective function is to minimise the cost given by the function:

$$Min(Z) = \sum_{j=1}^{j=n} \overline{y}_j C_j \rightarrow Min(Z) = CR \tag{4}$$

3.2 FS and membership functions

Because of the imprecise and vague information involved with input variables, FS and membership functions are used to explain first a variable and to convert a crisp value to a specific degree of membership (Chen and Pham, 2000).

The sets used for the decision model are:

- *Contamination type (CT)*. There are three categories of contamination type in the model: organic, inorganic, and mixed, which were modelled with discrete values as Table 2 shows.

Table 2 Description of contamination types

Contamination type	*Description*
1	Organic only (oil, grease, organic paints, etc.)
2	Inorganic only (oxidation, rust, dust, etc)
3	Mixed contaminations – organic and inorganic

- *Contamination levels (CTh)*. For the model, the set has five subsets as Table 3 describing the amount of contaminant on work piece surface. The membership function is as Figure 1.

Table 3 Description of contamination levels

Contamination level	*Description*
0	Contamination cannot be seen by the human eye
1	Very thin layers of contaminants
2	Thin layers of contaminants
3	Medium layer of contaminants
4	High presence of contaminants. Very thick layers

- *Product shape (PS) and material type (MT)*. This relates to product properties. It is important to understand the shape/size of the product and also the material on which was built. The main reason is because different cleaning methods support different kind of materials and shapes (explained in Table 1). Product shape is a set of three subsets: simple, complex, and very complex as illustrated in Figure 2. The material types are discrete values: 1 = metal and 2 = non-metal.

Figure 1 Contamination levels membership function (see online version for colours)

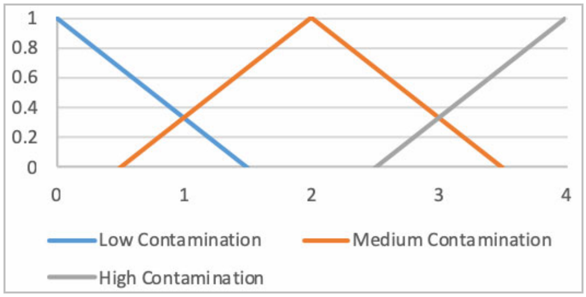
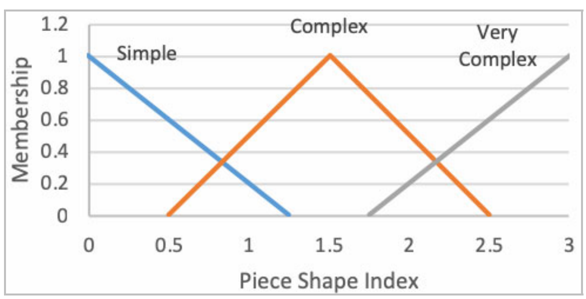


Table 4 Description of piece shape index

Piece shape index	*Description*
0	Very simple shape, i.e., sheet of metal, plane.
1	Some presence of complicated part, i.e., curves, depth, spikes
2	Presence of complicated shapes and holes
3	Very complicated shape – many holes, spikes, lack of support.

Figure 2 Piece shape membership function (see online version for colours)



- *Time*. This set is used for process time and acceptable process time defined by the user. Both use the same membership function. The difference between the two times is that the time given by the user is for constraints purposes (total process time) and the time used for the cleaning method is for 'cleaning processing' time. The set time has membership function as Figure 3.
- *Cleanliness level*. This set refers to the overall cleaning output after a cleaning method is used. The cleanliness level is measured by how clean the surface of piece is. Less contaminants or undesired components are on the surface, the cleaner the piece is. The range for the model is between 0 and 10 as Table 5, where 0 is not cleaned at all and 10 is completely clean. The numbers in between refers to partial cleaning in which some contaminants were removed but unwanted components are still in the surface. This set is used to evaluate the user input to the model and then used as constraint in order to evaluate the cleaning performance of the different

cleaning methods. The set of cleanliness level has the membership function as Figure 4.

Figure 3 Time membership function (see online version for colours)

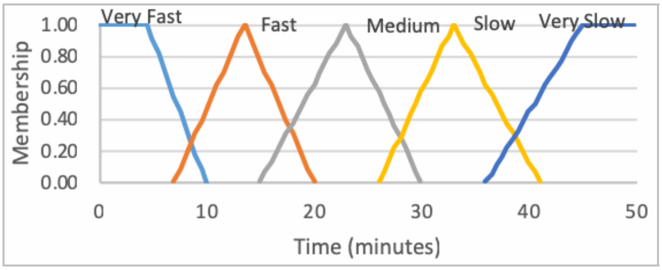
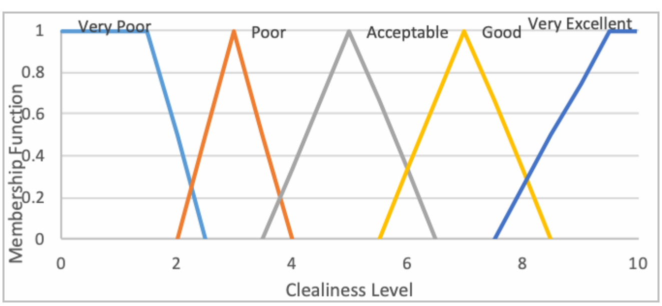


Table 5 Cleaning level index

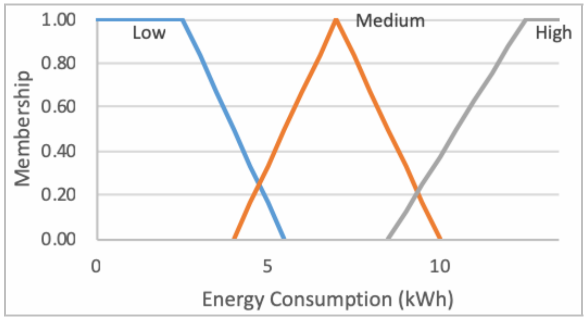
Cleaning level index	*Description*
0	High presence of contaminants
1	Super minor removal of contaminants
2	Minor removal of contaminants
3	Minor cleaning – presence of cleaned spots starts to appear
4	Minor cleaning – small presence of cleaned spots
5	Medium cleaning – still many contaminants
6	Medium cleaning – spots with contaminants
7	Good cleaning – some major spot with contaminants
8	Very good cleaning – still some spots with contaminants
9	Excellent cleaning – contaminant cannot be seen by human eye
10	Very excellent cleaning – no contamination at any level

Figure 4 Cleanliness level membership function (see online version for colours)



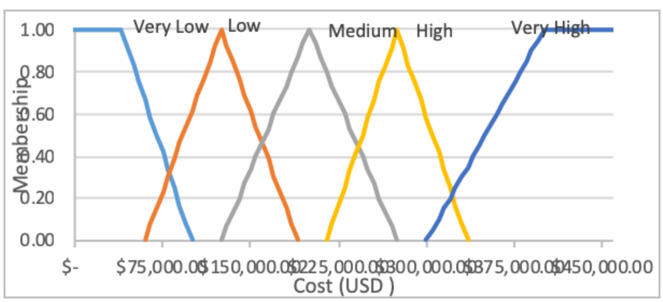
- *Energy consumption*. This set refers to the energy consumed by the different cleaning methods in process. Also, it refers to the user input for the expected energy consumption that wants to be consumed. The user input is used to evaluate the energy consumption constraint (explained later in the PM) with the energy consumed by the cleaning processes. The energy is measured in kWh. It has the membership function as Figure 5.

Figure 5 Energy consumption membership function (see online version for colours)



- *Cost*. This set refers to the cost per cleaning process and the overall cost. The cost includes designs, machines, implementation of the process and every cost that is incurs when implementing the cleaning process. It can be refer as 'system cost' also. It does not include the cost per piece. It will be used to build the objective function in the model. The set is divided into five subsets: very low, low, medium, high, and very high. It ranges from \$10,000 to \$460,000. The set cost has the membership function as Figure 6.

Figure 6 Cost membership function (see online version for colours)



3.3 GA and genetic operators

The GA serves as the optimisation tool in the proposed DSS. It goes through the steps of:

1 input

2 seeds generation

3 process evaluation

4 constraint checking

5 crossover and mutation

6 stopping.

3.3.1 Inputs

The user input is an array named as $I = [CT, CTh, MT, PS, T_w, CL_p, E_v]$ which consists of contaminant type, contaminant thickness, material type, shape of the piece, expected process time, expected cleaning level and expected energy consumption. The first four elements of the array are used to perform the fuzzy inference. The last three are to evaluate the constraints. The user needs to input this information in order to calculate the best possible combination of cleaning processes that results in the possibly lower cost.

3.3.2 Generation of seeds

The seeds are generated randomly for Y_i and T_i. Each element of the array is random integer number between 0 and n, representing the different cleaning processes available to choose from. If the remanufacturer has four cleaning processes available, then $n = 4$. The zero should be included to represent that 'no cleaning process' is used. Similarly, T_i has random numbers between 0 and m, where 'm' represents the upper limit for the time range. Later, this number is turn to linguistic terms with the fuzzy inference rules.

3.3.3 Process evaluation loop

After gathering all the inputs and generated seeds, it is necessary to evaluate the performance of sequence of the cleaning processes dictated by Y_i. The inputs to this operation are: CT, CTh, MT, PS, y_j and t_j. The fuzzy inference engine does the performance evaluation giving the result in terms of cleaning level, energy consumption, cost and a term called 'new contamination levels' with the name I_{nct}. This new term serve as an input for the next element in the Y_i. After the first element of the array is evaluated, the results need to be storage and evaluation of the next element of Y_i. The input for the evaluation of the next element are: CT, I_{nct}, MT, PS, y_{j+1} and t_{j+1}.

The increment 'j + 1' is to evaluate all the elements in the arrays Y_i and T_i. In the case than an element of the array is equal to zero, the solutions for that given iterations is going to be zero. After all the elements are evaluated, the final result for the array Y_i is storage in the array P_i that was explained before.

3.3.4 Constraints checking

After gathering all the results from the process evaluation loop, these results are checked to determine whether they satisfy the customer requirements.

As explained before, *CLp*, *Tw* and *Ev* are the user input and represent the limits of the user requirements. *CLp* is the lower boundary. *Tw* and *Ev* are the upper boundary. The constraints are checked by equations (1), (2) and (3). Any array Y_i that does not meet any of the constraint is disregarded and no longer taken in consideration as a feasible solution. This step of the model is to filter which solutions that are suitable from those that are not. Finally, the objective function is calculated and it is stored as part of the array 'Q_i'. At the end, this array has all the information from the user input to the overall results.

$$Q_i = [CT \ CTh \ MT \ PS \ Y_i \ T_i \ CR \ R_i \ CLp \ Ev]$$

3.3.5 Crossover and mutation

Crossover and mutation have a rate given by the term *Pc* and *Pm*. The first one is set around 0.7 and the second one around 0.1. In other words, 70% of the feasible solutions are going to be set for crossover operations and 10% of those are going to mutate. The mutation is set to be randomly to any j^{th} of the arrays Y_i and T_i. The crossover is performed between the best 's' solutions to generate new population. The term 's' stands for a number of best solutions. It may be 10, 20, 30 or any number that represents the best solutions. This is set by later in order to optimise the computation time. The crossover point is set randomly. Before performing any operations, the best 's' solutions are going to be saved. The best solutions may be contained in past generations. All new generations are entered in the loop to evaluate the process performance, the constraints and save the solutions of the feasible ones.

3.3.6 Stopping

All the solutions that are crossover and mutated are entered again in the model to evaluate the performance and check the constraints. The last part of the loop is to choose the best solution based on the stopping conditions. The GA has the stop conditions as following:

- The numbers of generations are met.
- The objective function has not improved in the past two generations or is between the +/– N%. The 'N' stands for the tolerance of the user.

When the stopping conditions are met, the best solution is chosen and given to the user.

3.4 Decision model flowchart

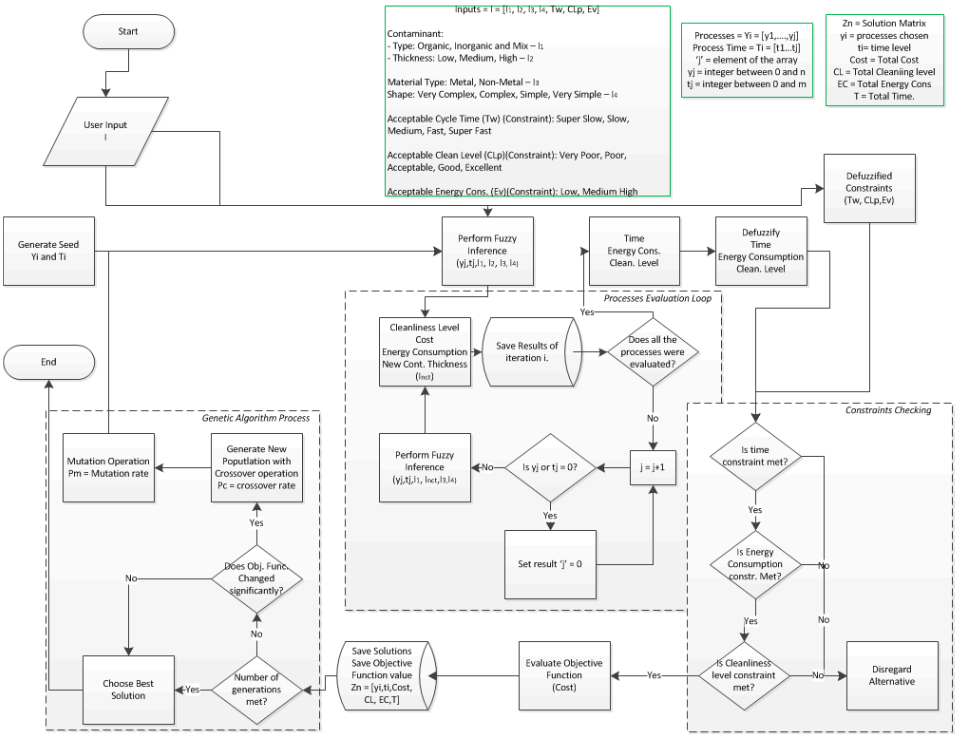
Finally the flowchart for the decision model is shown in Figure 7. In Figure 7, the process of the software is simple and includes the following function blocks:

1. User input and constraints.
2. Generation of first seed. The size can be changed inside the code.
3. Evaluation of the element of the seed with the fuzzy toolbox to predict cost, energy consumption and cleaning level achieved.
4. Performing evaluation of the different elements of the array to check which ones meets the constraints.
5. If a certain number of generations are created, then entering to the stop condition loop to check if the cost variance is significant enough to stop the solution.
6. If the stop conditions have not triggered, going to the GA process.
7. Performing the crossover and mutation operations. Checking that a solution it is not repeated inside the same generation.
8. Setting the new population of possible solutions.

9 Going to step 3 to begin the prediction of performance of the new population and evaluation. Stopping when the stop conditions are met.

Based on Figure 7, the software prototype and case studies were developed as in Section 4. The details of each function block in Figure 7 will be described in Section 4.

Figure 7 Decision model flowchart (see online version for colours)



4 Software, case study, and discussions

This section describes the development of a software to validate the proposed decision support model. Two case studies with results demonstrated how the smart decision making model works.

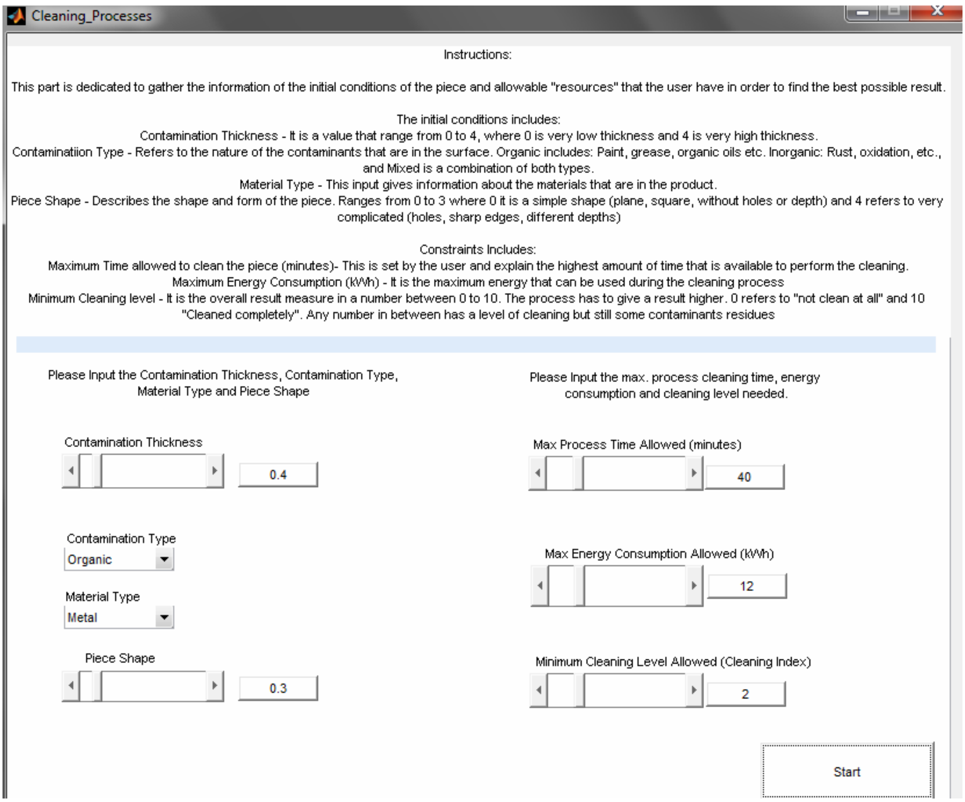
4.1 Prototype

The software was coded in MATLAB® with its 'fuzzy toolbox' and the GA functions in the 'optimisation toolbox'. The software consists of four main sections including: user inputs and first seed generation, FS, processes evaluation, crossover and mutation operations, and finally stop conditions.

4.1.1 User inputs and first seed generation

Figure 8 is a graphical view of the user inputs of initial parameters and constraints in the software model. User inputs four initial condition parameters [contamination type, contamination level, material type, piece shape, cleanness level]. Also, the user gives the inputs for the constraints on: [total processing time allowed, minimum cleaning level needed, maximum energy consumption allowed]. Then, the fuzzy toolbox reads these inputs for next steps.

Figure 8 User input and constraints input GUI (see online version for colours)



4.1.2 Fuzzy sets

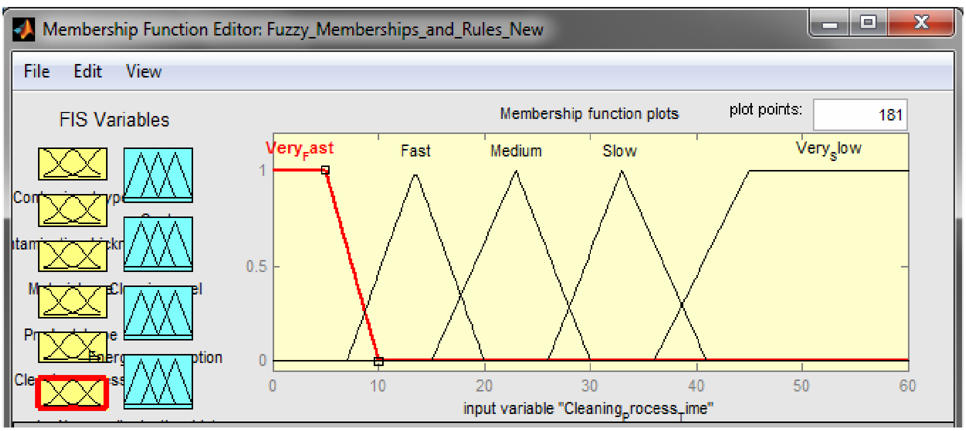
The user inputs and outs of [cost, cleanness level, energy consumption, and new contamination level] go through the steps of:

1 fuzzification of variables (membership function)
2 evaluation of rules
3 fuzzy inference
4 defuzzification of output.

The fuzzy inference is established by the 'If-Then' rules. Outputs are the final answer to the case evaluated. Also, the toolbox leaves the users to decide different parameters such as: defuzzification method, aggregation method, implication method, etc. For the software all the parameters are used in their default values. The membership function of the inputs and outputs are very easy to set up.

Figure 9 shows an example of membership functions and Figure 10 shows the fuzzy inference process. An example of fuzzy inference in the model is: 'IF contamination type is organic, and contamination level is low, and material type is metal, and piece shape is simple, and cleaning process is ultrasonic and is fast', THEN, 'cost is low, cleaning level is excellent, energy consumption is low and new contamination level is super low'.

Figure 9 Example of the membership function in the Fuzzy Toolbox® (see online version for colours)

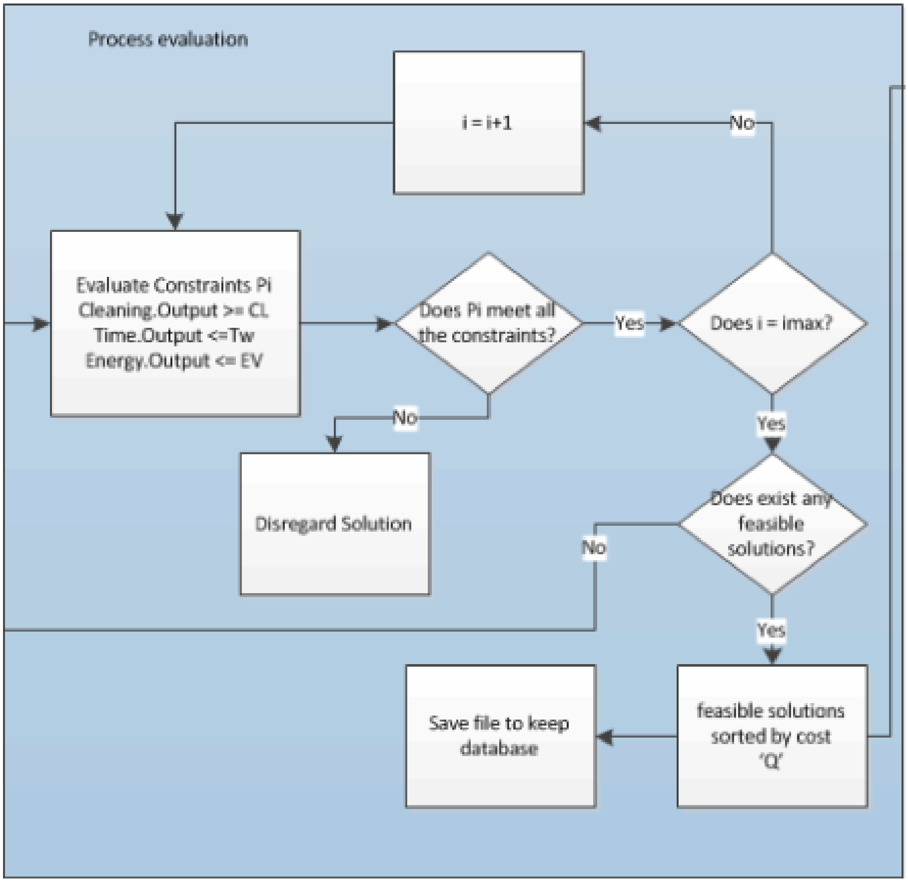


4.1.3 Process evaluation

The process evaluation consists of checking the seed generated to ensure that the sequence of cleaning processes associated with the seed meets the constraints set by the user. Figure 11 shows the flow of process evaluation in the software. Each element of the seed, with the results from the FS, is compared with the processing time constraint, minimum cleaning level constraint and maximum energy consumption constraint. The checking is performed by a binary operation. The constraint that is met is assigned a number '1'. If not, a number '0' is assigned. When all three constraints are check, it begins a multiplication between the binaries number. An element that has all the numbers as '1' will be considered as feasible solution. Those which has a '0' are disregarded. For example, constraint check 1 × constraint check 2 × constraint check 3 = 1 × 1 × 1 = 1 = feasible solution. In other case, constraint check 1 × constraint check 2 × constraint check 3 = 1 × 0 × 1 = 0 = non-feasible solution. At the end, the ones that meet all the necessary constraints are kept as a feasible solution. The elements that do not meet the constraints are disregarded.

Figure 10 Fuzzy inference example (see online version for colours)

Figure 11 Process evaluation loop (see online version for colours)



There are two options when there is no feasible solutions.

1 If the simulation has run for small amount of generations, then it should start over.

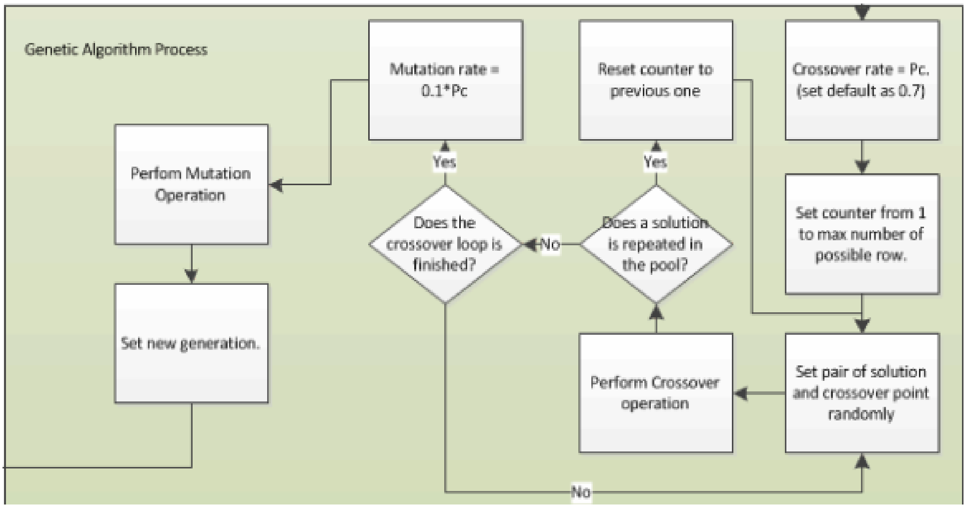
2 If the simulation has run for a specific number of generations and the user is satisfied, then the solutions should be used. At the end, the user can decide to run again the simulation or keep the solutions found.

4.1.4 Genetic algorithm

This GA intends to find better solutions generation by generation. The GA mixes the solutions obtained in the current generation to capture the best characteristic of each array. From here, a new generation of possible solutions is created and it is submitted to the fuzzy toolbox and the process evaluation. Figure 12 shows the GA process.

The crossover rate is set to 0.7. Many articles and previous studies has shown that the crossover rate should be around 0.6 to 0.75 of the population. The mutation rate is set up to 10% of the population that perform a crossover. It is important to mention that the crossover point is done randomly. Sometimes it is done at one position, sometimes in another. This helps to simulate the 'randomness' that exist in nature. Also, it helps to cover more possible solutions that may be a good fit. The GA also checks if a solution is repeated in the same generation. In case that happens, one of the elements repeated is eliminated and another is created using crossover operation.

Figure 12 Genetic algorithm (see online version for colours)



The user can decide how big the population is in each generation. This is to set the counter of the GA when creating the elements of the next generation. If the user decides that a population of 50 is wanted every generation, then the counter is set to 50. In case a solution is repeated when creating the generation, the counter returns to the previous value. The checking process of repeated solutions is performed after the second element of the generation is created and continues until the number of elements set by the user is met.

When performing the crossover operation, the software selects two populations of the solution, then sets the crossover point randomly and creates the new element of the population.

4.1.5 Stop condition

This part of the software is designed to stop simulation if the conditions are met. For this model, the stop conditions depend on the number of generations performed and variance of the cost. The stop condition is set up to meet both requirements. In case there is no feasible solution during any generation, a display is shown to let the user decide whether he will run the simulation again or use the feasible solutions found.

4.2 Case studies

Two case studies were developed to demonstrate the proposed DSS and software. Different inputs received from a remanufacturing company at Laredo TX (Long et al., 2014) were used in each case. At the end of each case, the best solutions of each generation are shown on a cost plot.

Case 1: The input from the Case 1 is as Table 6.

Table 6 Case 1 input

Inputs	*Index*	*Description*
Contamination type	1	Organic
Contamination levels	2.4	Medium
Material type	1	Metal
Piece shape	1.5	Complex
Cleaning level constraint	8	Min. allowed
Energy constraint (KWh)	20	Max. allowed
Time constraint (min)	80	Max. allowed

With this input to the decision model, stop condition was met at generation 9. From Figure 13, the best solution is located in generation 7. Table 7 illustrates the selection of cleaning process in each generation. In Table 7, the cell in black means that it did not select any cleaning process, generation 7 selected the best process of immersion cleaning, which will clean the part for 23 minutes to achieve the performance in generation 7, Table 8.

Figure 13 Case 1 cost plot of best solutions (see online version for colours)

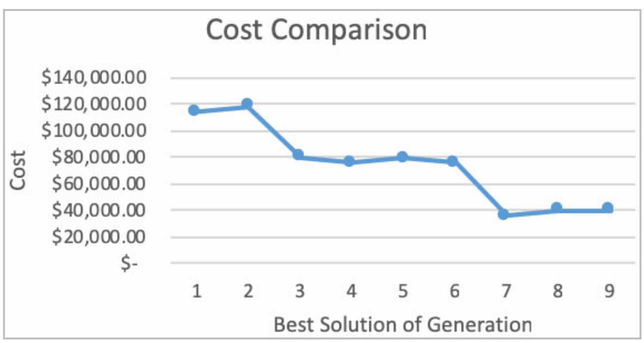


Table 7 Case 1 best solutions

Generation	*Cleaning process 1*	*Cleaning process 2*	*Cleaning process 3*	*Cleaning process 4*
1	No process	Thermal	Abrasive	Molten salt
2	Immersion	No process	Vibratory	Thermal
3	Immersion	Abrasive	No process	No process
4	No process	No process	Abrasive	Vibratory
5	Vibratory	Vibratory	No process	No process
6	No process	Abrasive	No process	Molten salt
7	No process	No process	No process	Immersion
8	No process	No process	No process	Immersion
9	No process	No process	No process	Immersion

Table 8 Case 1 results

Generation	*Cost ($)*	*Total time (min)*	*Cleaning level*	*Energy cons. (kWh)*
1	114,029.84	68.00	9.07	12.09
2	117,816.36	68.00	9.14	6.69
3	80,247.49	21.00	9.05	4.55
4	75,554.32	43.00	9.07	10.09
5	78,720.27	19.00	9.02	4.47
6	75,896.18	26.00	8.89	4.32
7	35,964.97	23.00	9.17	2.06
8	40,345.00	16.00	9.05	2.28
9	40,218.75	20.00	9.05	2.28

In Table 8, the optimised process gives a cleaning level of 9.17 (excellent cleaning) and energy consumption of 2.06 kWh. The system cost predicted is $35,964.97. It is important to mention that generation 8 and 9 have a little higher cost than generation 7, although the process time is a little shorter. The reason for this is that the software it is not entirely perfect and some solutions may be lost when performing the crossover and mutation operations. Also, the fuzzy inference is used to predict the result. Even though the best effort is done to have a consistent prediction, sometimes it may go just a little differently than expected. This is one of the risks taken when using fuzzy inference.

Case 2: The input to the second case study is as Table 9.

Table 9 Case 2 input

Inputs	*Index*	*Description*
Contamination type	3	Mixed
Contamination level	3.2	High
Material type	1	Metal
Piece shape	2.1	Complex
Cleaning level constraint	7	Minimum allowed
Energy constraint (KWh)	20	Max. allowed
Time constraint (min)	100	Max. allowed

Table 10 Case 2 best solutions

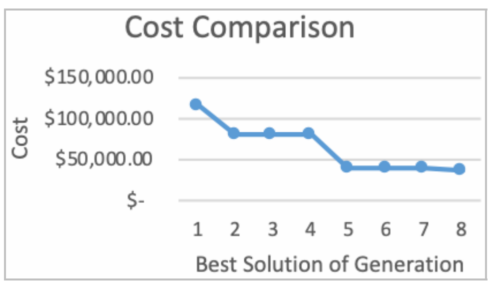
Generation	*Cleaning process 1*	*Cleaning process 2*	*Cleaning process 3*	*Cleaning process 4*
1	Abrasive	Thermal	No process	Molten salt
2	No process	Immersion	No process	Molten salt
3	No process	Immersion	No process	Vibratory
4	No process	Immersion	No process	Vibratory
5	No process	No process	No process	Vibratory
6	No process	No process	No process	Vibratory
7	No process	No process	No process	Vibratory
8	No process	No process	No process	Molten salt

Table 11 Case 2 results

Generation	*Cost ($)*	*Total time (min)*	*Cleaning level*	*Energy cons. (kWh)*
1	114,537.79	65.00	9.17	12.30
2	79,352.14	70.00	9.11	10.16
3	79,820.01	61.00	7.76	4.52
4	79,820.01	35.00	7.76	4.52
5	38,694.36	33.00	7.76	2.20
6	38,694.36	56.00	7.76	2.20
7	38,694.36	33.00	7.76	2.20
8	35,964.97	56.00	9.17	7.84

The stop condition was met at generation 8. From Figure 14, the best solution is located in generation 8, and Table 10 illustrated the best solutions of cleaning process is molten salt cleaning for 56 minutes. Table 11 shows it will achieve a cleaning level of 9.17 (excellent cleaning) and energy consumption of 2.06 kWh. The system cost predicted is $35,964.97. There is no increase between generations that happened in case 1.

Figure 14 Case 2 cost plot of best solutions (see online version for colours)



In both cases, the cost was reducing during the simulation. The solution may have been repeated in terms of cleaning processes chosen, but processing time and cleanness level changed. The comparison is not only among different processes, but also in different processing times of a same cleaning process. The method and software give the users a better idea of which cleaning processes should be used when planning the processes.

5 Conclusions and future research

A smart decision making tool was presented in this paper to select optimal cleaning processes. A linear programming mathematical model on selecting cleaning process was first formulated. Fuzzy set theory was then applied to process the vague and uncertain decision variables in the mathematical model. In order to find the optimal solution in the decision making, a GA algorithm was proposed. Further, the proposed approach was prototyped in MATLAB®. Two case studies demonstrate that the combination of fuzzy set and GA is promising to make optimal decision for selecting the cleaning approach. This model could be used in the process planning to remanufacturing for 21st century. It will reduce process time and cost, achieving a desired level of cleanliness to remanufacture 'like new' products.

For future research, validation on physical experiments and more parameters will be investigated. The two case studies received initial inputs from remanufacturing industry, but did not validate in real productions. Physical experiments can help better understand the decision making process. Besides this, this decision mode has variables uncovered that are important for remanufacturing such as surface finish, batch sizes, measure of contamination layers, etc. For example, some cleaning processes may not be as incisive as others on the surface finish. An abrasive method may leave a bad surface, but the ultrasonic method leaves an untouched surface. This decides how much reprocessing of the workpiece would need after the cleaning. Further, the software calculates the cost based on the information from literature. The cost range may change depending on the size of returned product batches and the quality level of equipment.

To apply this approach to real production, the decision model focuses on implementing a completely new cleaning process. In case that the remanufacturer has some established cleaning processes or other processes not showing here, the user has to include those processes in the fuzzy toolbox and eliminate those that are not part of their process. Sometimes, cost is not the only important process performance; overall cleaning level may be important also. By setting the utility functions for cost and cleaning level, the user is going to look for the solution that has the better measure in terms of utility. The solution may not be the lower cost or the highest cleaning level, but the combination of both factors that the user feels good about it at the end.

Acknowledgements

We thank Caterpillar Reman Laredo for providing data amongst other support for this work. One of the authors (ZW) thanks National Science Foundation for partially support his research in this manuscript through the Grant No. 1818655, any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. The authors also would like to sincerely thank the anonymous reviewers for their many invaluable comments and suggestions, which have greatly improved the quality of this article.

References

Bernstein, W.Z., Subramaniyan, A.B., Brodsky, A., Garretson, I.C., Haapala, K., Libes, D.E., Morris, K.C., Pan, R., Prabhu, V., Sarkar, A., Raman, A.S. and Wu, Z. (2018) 'Research directions for an open unit manufacturing process repository: a collaborative vision', *Manufacturing Letters*, Vol. 15, *Part B: Special Issue-Industry 4.0 and Smart Manufacturing*, pp.71–75

Brodsky, A., Shao, G. and Riddick, F. (2016) 'Process analytics formalism for decision guidance in sustainable manufacturing', *Journal of Intelligent Manufacturing*, Vol. 27, No. 3, pp.561–580.

Chen, G. and Pham, T. (2000) *Introduction to Fuzzy Sets, Fuzzy Logic and Fuzzy Control Systems*, 1st ed., CRC Press LLC, 2000 N.W. Corporate Blvd., Boca Raton, Florida 33431.

Edgar, T., Davis, J. and Burka, M. (2015) *Report on NSF Workshop on Research Needs in advanced Sensors, Controls, Platforms and Modeling (ASCPM) for Smart Manufacturing*, Atlanta, Georgia.

Fidan, I., Kraft, R., Ruff, L. and Derby, S. (1998) 'Integration steps of a fully-automated remanufacturing cell system used for fine-pitch surface mounted devices', *IEEE Transactions on Components, Packaging and Manufacturing Technology*, Vol. 21, No. 1, pp.71–78.

Fidan, I., Roush, E.M., Tumkor, S. and Kraft, R.P. (2004) 'Intelligent simulation environment for electronics remanufacturing systems', *Proceedings of the 29th IEEE/CPMT/SEMI International Electronics Manufacturing Technology Symposium*, San Jose, CA, 14–16 July, pp.160–164.

Fidan, I., Tumkor, S. and Kraft, R.P. (2003) 'The development of a computer-aided process planning tool for electronics manufacturing education', *Proceedings of 2003 ASEE Annual Conference*, Nashville, TN, 22–25 June.

Galantucci, L.M., Percoco, G. and Spina, R. (2004) 'Assembly and disassembly by using fuzzy logic & genetic algorithms', *International Journal of Advanced Robotic Systems*, Vol. 1, No. 2, pp.67–74.

Gamage, J.R., Ijomah, W.L. and Windmill, J. (2013) 'What makes cleaning a costly operation in remanufacturing?', *Proceedings of 11th Global Conference on Sustainable Manufacturing*, Berlin, Germany.

Gao, M., Zhou, M-C. and Tang, Y. (2004) 'Intelligent decision making in disassembly process based on fuzzy reasoning Petri nets', *IEEE Transactions on Systems, Man and Cybernetics-Part B: Cybernetics*, Vol. 34, No. 5, pp.2029–2034.

Hammond, R., Amezquita, T. and Bras, B.A. (1998) 'Issues in the automotive parts remanufacturing industry-a discussion of results from surveys performed among remanufacturers', *International Journal of Engineering Design and Automation-Special Issue on Environmentally Conscious Design and Manufacturing*, Vol. 4, No. 1, pp.27–46.

Jiang, Z., Zhang, H. and Sutherland, J.W. (2011) 'Development of multicriteria decision making model for remanufacturing technology portfolio selection', *Journal of Cleaner Production*, Vol. 19, Nos. 17–18, pp.1939–1945.

Junior, M.L. and Filho, M.G. (2012) 'Production planning and control for remanufacturing: literature review and analysis', *Journal of Production Planning & Control*, Vol. 23, No. 6, pp.419–435.

Kernbaum, S., Heyer, S., Chiotellis, S. and Seliger, G. (2009) 'Process planning for IT-equipment remanufacturing', *CIRP Journal of Manufacturing Science and Technology*, Vol. 2, No. 1, pp.13–20.

Liu, W.W., Zhang, B., Li, M.Z., Li, Y.Z. and Zhang, H-C. (2013) 'Study on remanufacturing cleaning technology in mechanical equipment remanufacturing process', *20th CIRP International Conference on Life Cycle Engineering*, in Nee, A., Song, B. and Ong, S.K. (Eds.), Re-engineering Manufacturing for Sustainability, Springer, Singapore, pp.647–648.

Long, Y., Li, J., Timmer, D., Jones, R. and Gonzalez, M. (2014) 'Modelling and optimization of the molten salt cleaning process', *Journal of Cleaner Production*, 1 April, Vol. 68, pp.243–251.

Lu, Y., Morris, K.C. and Frechette, S. (2016) *Current Standards Landscape for Smart Manufacturing Systems*, NIST Technique report.

Shin, S.J., Kim, D.B., Shao, G., Brodsky, A. and Lechevalier, D. (2017) 'Developing a decision support system for improving sustainability performance of manufacturing processes', *Journal of Intelligent Manufacturing*, Vol. 28, No. 6, pp.1421–1440.

Wang, H., Xiang, D. and Duan, G.H. (2008) 'A genetic algorithm for product disassembly sequence planning', *Neurocomputing*, Vol. 71, Nos. 13–15, pp.2720–2726.

Yagar, O. (2012) *Remanufacturing Cleaning Process Evaluation, Comparison and Planning*, Master's thesis, the University of Texas Pan-American, pp.18–81, 122–125.

Yeh, C-H. and Xu, Y. (2013) 'Sustainable planning of e-waste recycling activities using fuzzy multicriteria decision making', *Journal of Cleaner Production*, 1 August, Vol. 52, pp.194–204.