International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 52, No. 5, October, 2019, pp. 439-448
Journal homepage: http://iieta.org/journals/jesa

Sustainable Product Design Through Non-dominated Sorting Cuckoo Search

Hayam G. Wahdan[1*], Hisham E. Abdelslam[1], Tarek H. M. Abou-El-Enien[1], Sally S. Kassem[1,2]

[1] Faculty of computers and Artificial Intelligence, Cairo University, Egypt
[2] Smart Engineering Systems Research Centre, Nile University, Egypt

Corresponding Author Email: Hayam@fci-cu.edu.eg

https://doi.org/10.18280/jesa.520502

Received: 19 July 2019
Accepted: 8 October 2019

Keywords:
modular design, design structure matrix (DSM), clustering, non-dominated sorting, cuckoo search, multi-objective optimization

ABSTRACT

Sustainability is an important consideration in product design. The sustainable design should fully consider the environmental, social, and economic factors of the product. However, the three factors are often conflicting with each other. This paper aims to strike a balance between these factors and achieve sustainable product design through multi-objective optimization. The three influencing factors of sustainability, namely, the environmental factor, social factor and economic factor, were respectively defined as environmental impact, labor time and labor cost. Then, the product to be designed was represented as a design structure matrix (DSM), a list of all product components and the dependency patterns among these components. On this basis, the non-dominated sorting and cuckoo search were combined into a multi-objective optimization technique to optimize the product functionality. This technique looks for a set of Pareto optimal solutions, each of which represents the structure of modules and the number of modules. The effectiveness of the proposed technique was verified through a case study on a coffee maker. The results show that our technique outperformed the previous optimization methods.

1. INTRODUCTION

Modular design involves dividing product's component into set of modules these modules are important for the company. An ideal architecture is one that partitions the product into practical and useful modules. Modular design can be important tool in achieving sustainability because some successfully designed modules can be easily updated on regular time cycles, some can add in specific production stage to offer wide market variety, some can be easily removed and some can be easily swapped to gain more function [1].

Sustainability term is attracting the attention of many researchers. According to the United Nation's Brundtland commission (WBCD, 1987), sustainable development was defined as "meeting the needs of the present without compromising the ability of future generations to meet their own needs". As responsible citizens, we must try to conserve our resources to provide for use by future generations to meet their needs and this adds pressure for OEMs (Original Equipment Manufacturers) to be cautious when designing and manufacturing products so that these products do not harm the environment, society or the economy [2].

The aim of modular design is not only performed modularity form functionality factors but also product life cycle factors which affected the product sustainability factors economic, environmental and social. A functionality factor means function and structure of the product, sustainably factors labor time as social factor, environmental impact as environmental factor, and labor cost as economical factor as shown in Figure 1.

There is importance for achieving sustainable development of economy, society, and environment because of several causes: decreasing non-renewable resources, energy mass consumption in manufacturing, stricter regulations related to environment, increasing consumer consciousness for environmental issue, etc. Consequently, product design is faced with the challenge to contribute to the transition towards sustainable development. Sustainable design (SD) is a design taking into environmental, social, and economic factors in the design process [3].

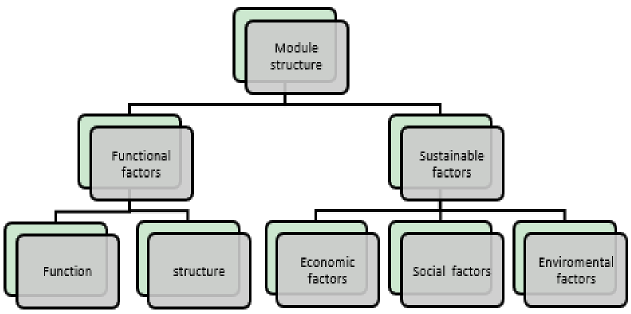

Figure 1. Hierarchy of module structure [2]

In this research we provide multi-objective optimization clustering algorithm, these algorithms take four DSMs as input, the first DSM represent the relationship between components as functionality representation of the product, this matrix is represented by binary matrix. The remaining three matrices represent the sustainability factors this represented by scores depending on the factor the matrix represent. Multi-objective cuckoo search is used to find s set of Pareto optimal solutions; each solution represents the structure of modules and the number of modules in the product which optimize functionality and sustainability objectives. This research is the first one considering multi-objective optimization problem in functionality and sustainability product design problem.

Following the introduction, the rest of the paper is structured as follows. Section 2 provides a brief introduction about DSMs, followed by a review of related literature in Section 3. Problem definition and proposed solution algorithms are provided in Sections 4 and 5, respectively. Section 6 includes numerical experimentation and analysis of the algorithm and, finally, Section 7 provides the paper conclusion and points for future research.

2. DESIGN STRUCTURE MATRIX

Design Structure Matrix (DSM) is general tool used to analysis complex system; it can cluster product components into set of modules with minimum interfaces externally and maximum internal integration between components. The matrix contains a list of all subsystems and the corresponding information exchange and dependency patterns. The DSM provides insights about how to manage a complex system [4].

The basic DSM is a simple square matrix, of size *n*, where *n* is the number of system elements. An example of a DSM is shown in Figure 2. Element names are placed on the left hand side of the matrix as row headings and across the top row as column headings in the same order. If an element *i* depends on element *j*, then the matrix element *i j* ($\text{row}_{i,}$ column_{j}) contains "1" or "x" otherwise the cell contains "0" or empty cell [5].

Once the DSM for a product is constructed, it can be analyzed for identifying modules, a process referred to as clustering. The goal of DSM clustering is to find a clustering arrangement where modules minimally interact with each other, while components within a module maximally interact with each other [6].

	1	2	3	4	5	6	7	8	9	10	11
1		1	0	0	0	0	0	0	0	0	0
2	1		0	0	1	0	0	0	0	0	0
3	0	0		0	1	0	0	0	0	0	0
4	0	0	0		1	1	1	0	0	0	0
5	0	1	1	1		1	0	0	1	1	1
6	0	0	0	1	1		0	0	0	0	1
7	0	0	0	1	0	0		1	0	0	0
8	0	0	0	0	0	0	1		0	0	0
9	0	0	0	0	1	0	0	0		0	0
10	0	0	0	0	1	0	0	0	0		1
11	0	0	0	0	1	1	0	0	0	1	

Figure 2. Design structure matrix [7]

	1	2	3	4	5	6	7	8	9	10	11
1		2	0	0	0	0	0	0	0	0	0
2	2		0	0	5	0	0	0	0	0	0
3	0	0		0	3	0	0	0	0	0	0
4	0	0	0		2	19	2	0	0	0	0
5	0	5	3	2		28	0	0	53	2	25
6	0	0	0	19	28		0	0	0	0	5
7	0	0	0	2	0	0		22	0	0	0
8	0	0	0	0	0	0	22		0	0	0
9	0	0	0	0	53	0	0	0		0	0
10	0	0	0	0	2	0	0	0	0		9
11	0	0	0	0	25	5	0	0	0	9	

Figure 3. Example of weighted DSM

Binary DSM is not enough to describe the nature of our problem; in this problem we have four DSMs. first one represented by binary DSM, the matrix represents in interactions between the product elements to achieve a specific function, Second DSM represents the weight dependency from social point of view, third DSM represents the weight dependency from environment point of view, and fourth DSM represents the weight dependency from economic point of view. Example of weighted DSMs is shown in Figure 3. This weight is represented the assembly labor time of coffee maker product in unit of seconds; labor time is considering one of social factor in sustainability design process. Let for example if element 1 assembly with element 2 it takes 2 seconds and if element 2 assembly with element 5 it takes 5 seconds and so on.

3. RELATED WORK

3.1 Modular designs with functionality objective

In this section we get quick look about the related work on modular design using DSM tool, DSM working as product representation tool, provide graphical representation of interaction between system element using binary representations. This representation provides the functionality of the product.

Main idea of clustering process firstly proposed by Eppinger et al. [8], this idea aims to maximize interaction within modules and minimized the dependency between different modules. Developed next by Idicula [9] which provide stochastic clustering algorithm using specific tool named DSM. Subsequent improvements on Idicula [9] were introduced by Gutierrez and Carlos Iñaki [10] in which a mathematical model was proposed to minimize the coordination cost, and hence, find the optimal solution for a given number of clusters. A Stochastic hill-climbing algorithm was performed by Thebeau [11] to find clustered DSM with cost minimization as the objective.

A genetic algorithm is developed; this algorithm aims to find the order of components within DSM which minimized the Module Strength Indicator' (MSI) [12]. A 'Module Strength Indicator' (MSI) function was utilized to determine a value representative of the degree of modularity of the components' groupings.

New developed method by Sosa et al. [13] used to differentiate between designing modular systems and integrating systems Fabrice [14] provided a study that focuses on the specification of modules, their architecture, and their interfaces. Design Structure Matrix (DSM) was used and extended to represent more accurately the studied model. Yassine et al. [7] provided clustering algorithm to find the optimal structure of overlapped modules within DSM. Minimum description length (MDL) working as clustering objective and GA is an optimization technique. DSM is used as system analysis tools to represent the interdependency between system elements.

Borjesson [15] proposed a method for promoting better output from the clustering algorithm used in the conceptual module generation phase by adding convergence properties, a collective reference to data identified as option properties, geometrical information, flow heuristics, and module driver compatibility. Van Beek et al. [16] developed a modularization scheme based on the functional model of a system. The k-means clustering was adopted for DSM based modularization by defining a proper entity representation, a relation measure and an objective function. A clustering method utilizing Neural Network algorithms and Design Structure Matrices (DSMs) was introduced by Pandremenos, and Chryssolouris [17]. The algorithm aimed to cluster components in DSM with predetermined number of clusters and clustering efficiency as an objective function.

Borjesson and Hölttä [18] used IGTA (Idicula-Gutierrez-Thebeau Algorithm) for clustering Component-DSM as the basis for their work. They provided some improvement named IGTA-plus. IGTA-plus represented a significant improvement in the speed and quality of the solution obtained. Borjesson and Sellgren [19] provided efficient clustering algorithm using GA and Minimum Description Length clustering objective. This algorithm is tested using four case studies.

Yang et al. [20] provided a systematic clustering method for organizational DSM. The proposed clustering algorithm was able to evaluate the clustering structure based on the interaction strength. Jung and Simpson [21] introduced simple new metrics that can be used as modularity indices bounded between 0 and 1, and also utilized as the objective functions to obtain the optimal DSM. The optimum DSM was the one with the maximized interactions within modules and the minimized interactions between modules. Kim et al. [22] provided a new approach for product design by integrating assembly and disassembly sequence structure planning.

A hybrid approach is developed, based on multidimensional scaling (MDS) and clustering methods. This approach is applied on DSM to provide product architecting [23]. Cuckoo Search clustering algorithm is used to find the optimal number of clusters and the optimal assignment of components to clusters with total coordination cost as objective [24-25]. A new practical method is proposed, it is supports designers to create service modules by extending the DSM [26] developed reseach suggested a tradeoff between commonality and the quality of the modular architecture in product design platform selection also introduced a method for designers to identify multiple component sharing options that lie along a Pareto front of maximum commonality and strategic [27]. A New research focused on the answering the questions, how modularity used in product design, how it is helped in product Varity and how modularity increased the organization performance [28].

We can conclude from the review above, there are many researchers working in product design using modularity concept. These researches are mainly different in clustering objective and solutions methods. Clustering efficiency is one of the clustering objectives as declared reference [17], also assuming predefined number of clusters. Total coordination cost is another objective. This objective consists of two parts intra cost (interaction within cluster) and extra cost (interactions outside cluster). Intra cost want to be maximized and extra cost want to be minimized. Total coordination minimized the summation of these two components [11]. DSM is compared to another one to be clustered using Minimal Description Length (MDL) objective [7], also assuming predefined number of clusters and allow overlapping between clusters.

From the solution method point of view, stochastic hill-climbing algorithm is one of the clustering solution methods [11], Genetic Algorithm [7] and reference [12], and neural networks [17]. This research is the first one using multi-objective Meta heuristic techniques to optimize the product functionality and sustainability in solving product design problem under modularity.

3.2 Modular designs with sustainability objective

From the previous literature, a lot of methods are interesting on satisfying product functions, using DSM with zeros and ones representation; designing process not take into consideration the environmental, social and economic impact on the design of the product. In this section we provide a review on modular design with sustainability factors into consideration.

There is great attention on sustainable development in design; Sustainability principle is very important during new product development. Therefore, sustainable design considering environmental, social, and economic feasibility has been widely considered as a main transition toward sustainable development [29].

Kimura et al. [30] provide a method aims to reduce the environmental waste, by performing reuse and recycling to product components, which perform commonality analysis to identify the modules shared by different product. A multi-viewpoint modular design method for engineering design reuse is developed to response to market requirements quickly for the designed product [31]. Modular design method for supporting green life cycle engineering focuses on green material, which identifies modules by component-to-component relationships of combination type, tool type, and accessed direction [32]. Eight criteria such as life compatibility, material compatibility, and maintainability are presented to reduce the potential environmental burden through modular design [33].

A modularization scheme is proposed for mechatronic systems using function-behavior-state to satisfy the customers' requirements [16]. Huang et al. [34] integrate 3R abilities into product modularity to reduce waste of electrical and electronic equipment and considered product disassembly pattern. They took designer's preferences into account during module formation. Key components could then be identified and handled as designer's preferences.

Yan et al. [3] integrated 6R concept into module clustering criteria such as function, manufacturability, and end-of-life (EOL) options to achieve objective of sustainable design. DSM is tool used to identify the interactions and interdependency between system elements. A fuzzy logic is employed to handle uncertainty. The probability of each EOL option is determined by aggregating fuzzy set operations and left-right hand fuzzy rank method [35].

Ma et al. [36] developed research aimed to develop a Modular Product Design (MPD) approach to improve the product life cycle performance for dimensions of sustainability. Focused on two current research gaps: (1) how to best handle key components and (2) taking into account life cycle uncertainty at the component or product end-of-life (EOL) stage. Key components represent core techniques and can have the highest sustainability impact. Ma et al. [37] provided research aimed to improve products environmental performance, in this research environmental impact from Eco-99 tool is adopted as an environment indicator. A heuristic clustering algorithm with environmental impact optimization and key component specification consideration is offered to generate module. Ma et al. [38] Provided literature review of about 100 papers are working in modular product design with sustainability point of view.

4. PROBLEM DEFINITION

The problem under study has four of DSMs like one shown in Figure 2, these DSMs are considered system inputs. First DSM represent interaction between product components, this interaction is represented as zeros and ones Matrix, if component i is dependent on component j, then the matrix element $i\ j$ (row_i, $column_j$) contains "1" or "x" otherwise it contains "0" or remains empty. this first matrix represent functionality objective, Second DSM represent social matrix, this matrix contains score from specific range depend on the sustainability factor we interest, in our problem we focus on labor time as social factor represent scores by unit of seconds, the third represent environment matrix, in our problem we focus on environmental impact as environmental factor, this matrix represented by scores measured from Eco-99 tool, this tool is adopted as an environment indicator. Finally, fourth DSM represent economic matrix, this matrix contains score from specific range depend on the sustainability factor we interest, in our problem we focus on labor cost as economic factor, this score represented by dollar unit.

The objective is to cluster these components in such a way that minimizes the total coordination cost. Minimized the total coordination cost guarantee achieving the four objectives, functionality objective and three sustainability factors. Minimizing the total coordination cost to this problem ensure minimizing functionality objective and maximizing sustainability objective, this sustainability objective represented in the three factors we interest. Accordingly, two sets of decisions are to be considered; (1) the number of clusters to form, and (2) the optimal assignment of components to cluster.

For each one the given DSMs, the total coordination cost consists of two parts; IntraClusterCost and Extraclustercost. if elements i and k belong to cluster j, then coordination of IntraClusterCost is calculated as shown in Equation 1, otherwise no cluster contains i and k, then coordination ExtraClusterCost is calculated as shown in Equations 2,

$$intraClusterCost = \sum_{i,k \in Cluster\,j}(DSMik + DSMki) * \sum_{j=1}^{ncluster}(ClusterSize\ j)^{powcc} \quad (1)$$

$$ExtraClusterCost = \sum_{i,k \notin cluster\,j}(DSMik + DSMki)DSMSize^{powcc}\ ,\ j = 1 \dots ncluster \quad (2)$$

where, DSM_{ik} is the interactions between elements i and k, DSM can be one represent functionality objective (zeros and ones), can be one represent social objective, can be one represent environment objective and can be one represent economic objective. DSMSize is the number of elements (rows) in the matrix, powcc is the exponent used to penalize the size of clusters, and n cluster is the total number of clusters. Cluster size is the number of elements in cluster j [39], and the total cost represents the summation of IntraClusterCost and ExtraClusterCost.

Total coordination Cost = IntraClusterCost + ExtraClusterCost

The problem under consideration involves one key constraint, that is, each element is assigned only to one cluster; in other words, overlapping between clusters is not allowed. Prohibiting overlapping, or multi-cluster elements, is important as in the case of allowing elements to be assigned in multiple clusters, the importance and usefulness of the clustering algorithm will be diminished or eliminated. If elements exist in more than one cluster, this forces interactions between these clusters on multi levels. It is advantageous that elements placed in the same cluster are very similar. Modularity affects both the profit and the sustainability of the product. A modular product contains modules that can be removed and replaced.

The manufacturer can develop new modules instead of entirely new products. Therefore, customers buying upgraded modules only dispose of a portion of the product, thus reducing the total amount of waste. Hence, a customer upgrading a module does not have an entirely new product [3].

This problem has four objectives, these objectives are conflicting. Three objectives provide sustainability objective and one provide functionality objective. Product sustainability factors are economic, environmental and social. A sustainably factors assumes labor time as social factor, environmental impact as environmental factor, and labor cost as economical factor.

Sustainability objectives are achieved when grouping the most similar elements in the same cluster and not allowing overlapping between clusters. Not allowing overlapping or multi-cluster elements is important for the following reasons: When allowing elements to be assigned in multiple clusters, the importance and usefulness of the clustering algorithm will be diminished or eliminated. Also, Modularity affects both the profit and the sustainability of the product. A modular product contains modules that can be removed and replaced. The manufacturer can develop new modules rather than entirely new products. Therefore, customers buying upgraded modules only dispose of a portion of the product, thus reducing the total amount of waste. Hence, a customer upgrading a module does not have an entirely new product. Functionality objective provide the function and structure of the product.

5. PROPOSED ALGORITHM

Most of engineering problems is classified as multi-objective optimization problems. Multi-objective means the existence of conflicting objectives. Algorithms used in solving single objective optimization are different from algorithms used in solving multi-objective optimization problems. In single objective optimization problem, we search for one single optimal solution. In multi-objective optimization problem we search for set (subset) of Pareto optimal solutions, In order to get the sense of the unknown Pareto optimal solutions or Pareto front, we have to generate many different solution points, and therefore computational effort will increase depending on the number of approximate points, complexity of the problem and the way of handling solution diversity [40].

5.1 Multi-objective cuckoo search

Cuckoo search is one of the meta heuristics techniques developed by Yang and Deb [41], algorithm originally based on optimizing single objective and three mainly rules.

1. Each cuckoo lay only one egg and randomly drums it in a nest.
2. The best nests with high quality solution will be kept to next generation.
3. The number of available host nests is fixed, and a host

can discover an alien egg with a probability $pa \in [0, 1]$.

For multi-objective optimization problems with K different objectives, set of modification can be one to the first and the last rules [42]:

1. Each cuckoo lays K eggs, and randomly dumps chosen nest. Egg k corresponds to the solution to the kth objective.
2. Each nest will be abandoned with a probability pa and a new nest with K eggs will be built, according to the similarities differences of the eggs. Some random mixing can be used to generate diversity.

For simplicity, this last assumption can be approximated by a fraction pa of the n nests being replaced by new nests (with new random solutions at new locations). For the maximization of objectives, the quality or fitness of a solution can simply be proportional to each objective function, and a non-dominated solution should be sought. The basic steps of the multi-objective CS algorithm are summarized in the pseudo code in Figure 4.

```
Initialize Objective functions f1(x),…,fk(x), x = (x1, ..., xd)T ;
Generate an Initial population of n host nests xi and each of K eggs (i = 1, 2, ..., n);
while (t <MaxGeneration);
    Get a cuckoo (i) randomly using Levy flights;
    Evaluate and check if it is pareto optimal;
    Choose a nest among n (j) randomly;
    Evaluate K solutions for nest j;
      if (new solution of nest j dominate those of nest i);
       Replace nest i by new solution set of nest j;
      end
    Abandon a fraction (pa) of worse nests;
    Keep the best solutions (or nests with non-dominated sets);
    Sort and find the current Pareto optimal solutions;
 end while
Post process results and visualization;
```

Figure 4. Pseudo code of multi-objective Cuckoo Search (MOCS) [42]

5.2 Implementation

5.2.1 Solution representation

Cuckoo search is mainly designed to solve continuous optimization problem. The problem under study is considered discrete optimization problem because a solution (nest) is represented by a vector of length that is equal to the number of elements in DSM. This DSM can be represented functionality, social, environmental and economic objectives. Each cell in the vector can assume take values from 1 to number of elements in DSM, as shown in Figure 5. This vector represents one of the problem solutions, where the DSM contains 10 elements with specific interaction between each other, these elements want to be assigned in specific cluster, the vector in Figure 4 shows that we have three clusters. Cluster number one contain elements 1, 2, 10, cluster two contains elements 3, 5, 6, 7 and finally the third cluster contains elements 4, 8, 9. Assume that we start with the maximum possible number of clusters, which equals to the number of elements in the DSM. The next step is to try to find the optimal number of clusters after deleting empty clusters. Such representation ensures avoiding multi-clustering; in other words, each element will be assigned to only one cluster.

The algorithm starts with a randomly generated set of nests. Real random values are generated and converted to nearest integer by simply rounding, trancating up, or trancatingdown [43]. Through iterations, nests are updated according to Lévy flights and the updating role, upper and lower function keeps the solution in the problem boundaries.

1	**1**	**2**	**3**	**2**	**2**	**2**	**3**	**3**	**1**

Figure 5. Example of Solution representation vector

5.2.2 Solution evaluation

In this problem we have four objectives evaluated separately, these four objectives are based mainly on the total coordination cost objective, and the total coordination cost of the DSM is based on *IntraClusterCost* and *ExtraClusterCost*. Regarding *intracluster* cost, if interaction *DSMik* belongs to cluster j, then intra cluster cost is calculated. On the other hand, if interaction *DSMik* does not belong to cluster j, then the extra cluster cost is calculated.

In this problem we have four DSMs each one represents problem objective, zeros-ones matrix represent functionality objective, One provides social factor (labor time DSM), one provides environmental factor (environmental impact DSM) and the last provides the economic factor (labor cost). These are the three legs of sustainability objective.

At the beginning of the algorithm, an Initial population of n host nests is randomly generated, and the total coordination cost is calculated depends on the input matrix, if zeros - ones input, then functionality objective value is calculated, if labor time DSM input, then the social objective is calculated, if environmental impact DSM input, then the environment objective is calculated, if labor cost DSM input, then the economic objective is calculated. Details of calculating the total coordination cost, IntraClusterCost, and ExtraClusterCost, are given in Section 4. Evaluation of the solutions is performed, and then the algorithm check if it is Pareto optimal and a new iteration begins. The algorithm selects the best solution and moves to the next solution; (1) using Levy flight, carrying the best nests with high quality eggs (solutions) over to the next generations in MOCS. Sort and find the current Pareto optimal solution using Non-dominated sort method to provide the set of Pareto of optimal set of solutions. Optimization process continues till the stopping condition is reached.

6. ILLUSTRATIVE CASE STUDY

We use a coffee maker to show the implementation of this methodology. Coffee maker includes eleven components, components attributes shown in Table 1, each component interacts with other components in the product in order to generate primary product functions as shown in Figure 6, Labor time DSM shown in Figure 7, environmental impact DSM shown in Figure 8 and labor cost DSM shown in Figure 9. Each one of these matrix represent model input. So we have 4 inputs in our model, we represent the four objectives which want to optimize. The first DSM represents the functionality objective and the remaining three DSMs represent the sustainability objective. Each one of the three matrices represent factor affecting the sustainability objective. One provides social factor (labor time DSM), one provides environmental factor (environmental impact DSM) and the last provides the economic factor (labor cost). These are the three legs of sustainability objective.

All previous works considered the single objective clustering problem, by taking one of the sustainability factors and find the optimal modules with respect this objective. In this research we take the decaled four matrices as input and evaluated separately and find the optimal number of cluster and the optimal structure of modules which optimize the functionality and sustainability objective.

When running the optimizations model of multi-objective cuckoo search with population size of 100 nests and probability of discovering 0.25, sets of 100 solutions are appeared in Pareto front, these solutions are sorted using the non-dominated sort algorithm. sample of these solutions are shown in Table 1 in appendix, each solution provides the optimal assignment of each element in specific cluster and the optimal number of clusters formed. 13% solutions are found in rank 1, 16% are found in rank 2, 25% solutions are found in rank 3, 15% solutions are found in rank4, and so o for the remaining ranks. Figure 10 provides Distribution of solutions through ranks of domination.

Table 1. Components attributes of coffee maker [44]

No.	Component	Material	Weight(g)	price($)	Mfg. Environmental Impact (mPt)
1	Filter Basket	Plastic	90.8	3	35.41
2	Filter Basket Holder	Plastic	101.696	3	39.66
3	Lid	Plastic	52.664	2	20.54
4	Warming Plate	Steel	63.56	5	5.47
5	Main housing	Plastic	1273.016	4	496.48
6	Heating Pipe	Steel	227	8	19.52
7	Carafe	Glass	348.672	10	20.22
8	Carafe Handle	Plastic/Steel	84.444	3	27.8
9	Bottom Plate	Steel	214.288	3	18.43
10	Power Cord	Copper/Plastic	60.836	2	24.34
11	Switch	Plastic/Metal	7.264	5	2.39

	1	2	3	4	5	6	7	8	9	10	11
1		1	0	0	0	0	0	0	0	0	0
2	1		0	0	1	0	0	0	0	0	0
3	0	0		0	1	0	0	0	0	0	0
4	0	0	0		1	1	1	0	0	0	0
5	0	1	1	1		1	0	0	1	1	1
6	0	0	0	1	1		0	0	0	0	1
7	0	0	0	1	0	0		1	0	0	0
8	0	0	0	0	0	0	1		0	0	0
9	0	0	0	0	1	0	0	0		0	0
10	0	0	0	0	1	0	0	0	0		1
11	0	0	0	0	1	1	0	0	0	1	

Figure 6. Coffee maker connection DSM [37]

	1	2	3	4	5	6	7	8	9	10	11
1		1.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.23		0.00	0.00	8.80	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00		0.00	8.48	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00		24.09	6.68	21.75	0.00	0.00	0.00	0.00
5	0.00	8.80	8.48	24.09		27.03	0.00	0.00	26.80	59.46	23.07
6	0.00	0.00	0.00	6.68	27.03		0.00	0.00	0.00	0.00	4.22
7	0.00	0.00	0.00	21.75	0.00	0.00		12.93	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	12.93		0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	26.80	0.00	0.00	0.00		0.00	0.00
10	0.00	0.00	0.00	0.00	59.46	0.00	0.00	0.00	0.00		1.52
11	0.00	0.00	0.00	0.00	23.07	4.22	0.00	0.00	0.00	1.52	

Figure 8. Assembly environment impact DSM (unit: mPt, found in Ref. [37])

	1	2	3	4	5	6	7	8	9	10	11
1		2	0	0	0	0	0	0	0	0	0
2	2		0	0	5	0	0	0	0	0	0
3	0	0		0	3	0	0	0	0	0	0
4	0	0	0		2	19	2	0	0	0	0
5	0	5	3	2		28	0	0	53	2	25
6	0	0	0	19	28		0	0	0	0	5
7	0	0	0	2	0	0		22	0	0	0
8	0	0	0	0	0	0	22		0	0	0
9	0	0	0	0	53	0	0	0		0	0
10	0	0	0	0	2	0	0	0	0		9
11	0	0	0	0	25	5	0	0	0	9	

Figure 7. Assembly labor time DSM (unit: s, found in Ref. [36])

	1	2	3	4	5	6	7	8	9	10	11
1		0.01	0	0	0	0	0	0	0	0	0
2	0.01		0	0	0.03	0	0	0	0	0	0
3	0	0		0	0.02	0	0	0	0	0	0
4	0	0	0		0.01	0.1	0.01	0	0	0	0
5	0	0.03	0.02	0.01		0.14	0	0	0.43	0.01	0.13
6	0	0	0	0.1	0.14		0	0	0	0	0.03
7	0	0	0	0.01	0	0		0.15	0	0	0
8	0	0	0	0	0	0	0.15		0	0	0
9	0	0	0	0	0.43	0	0	0		0	0
10	0	0	0	0	0.01	0	0	0	0		0.05
11	0	0	0	0	0.13	0.03	0	0	0	0.05	

Figure 9. Assembly cost DSM (unit: $ found in [36])

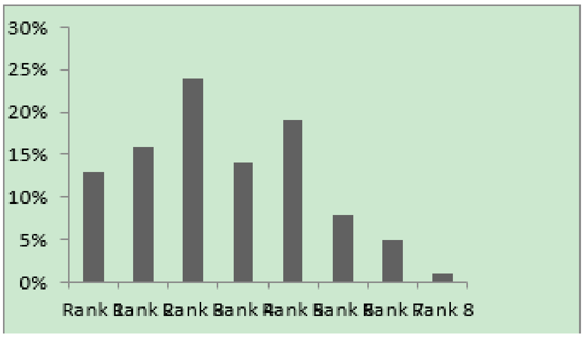

Figure 10. Distribution of solutions through ranks of domination

We noticed from the previous work on sustainability, all works deal with each objective as single objective. The solution obtained is the worse than we obtained in multi-objective work. For example, Ma and Kremer [37] provide heuristics algorithm to find the optimal module structure to optimize environmental objective, this module structure provides objective function value obtained in the higher ranks in our multi-objective model. When comparing our work with Ma et al. [38], seven solutions are found in different papers with different objective sorted with solution obtained from this problem. Figure 11 provide Percentage of solutions obtained compared to solution found in literature in each rank separately, we can conclude from this figure that solution found in literature start appear in rank 3 one solution appear, one appear in rank 4,one solution appears in rank 6, two solutions appears in rank 7and two solutions appears in rank 8.

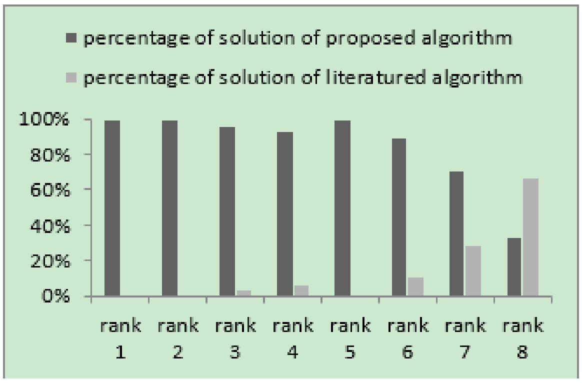

Figure 11. Percentage of solutions obtained compared to solution found in literature in each rank

For each module structure, sustainability index (SI) was calculated as shown in equation this index is depending on the value obtained from the three objectives which represent the three sustainability factors, labor time (LT), environmental impact (EI) and labor cost (LC) environmental objectives. Each objective is normalized to be the same unit; the normalization step is done after dividing the objective value for each module structure by the minimum objective value, the index calculated using sum product of each normalized objective value and corresponding objective weight [3]. These weights are depending on decision making preferences. In this problem we assume AHP model weights, which assume 0.66 for economic and 0.21 for environment and 0.13 for social, the best solution is the one which provide the minimum sustainability index, and this solution is one of solutions obtained in rank1.

$$SI = W1 * \frac{LT_i}{LT_{min}} + W2 * \frac{EI_i}{EI_{min}} + W3 * \frac{LC_i}{LC_{min}}$$

where, W1, W2, W3 are weights and determined by customers or manufactures, Lt_i, EI_i, and LC_i are ith module structure's functional, life cycle cost, environmental impact, and labor time; LT_{min}, EI_{min}, and LC_{min} are optimal sustainability value w.r.t. functional, economic, environmental, and social sustainability.

7. CONCLUSION AND FUTURE WORK

Sustainability plays an important role in product design, sustainability aims to produce product protect the environment. Sustainability is based on three factors: economic factors, environmental factors and social factors. In addition to these factors functionality factors, each product has specific function to achieve. In this research we try to find the optimal number of modules in product and the optimal assignment of each component in specific module to achieve these objectives; functionality objectives and sustainability objectives. Multi-objective cuckoo search is used to achieve these objectives. Non-dominated sort algorithm is used to sort set of solution in Pareto set. Product is represented in the form of DSM, DSM provide clear visualization of product elements and provide the interaction between product components. In the future, we will apply the design for variety (DFV) concept to determine set of standard components (components not changed through the product design generation), set of modular components (components can be changed and replaced through product design generation) , and set of blocked components (set of components form the modules in the product). A fuzzy logic approach is adapted in designing sustainability matrix and more sustainability factors are added in product development design.

REFERENCES

[1] Aguwa, C.C., Leslie, M., Sylajakumari, P.A. (2012). Effect of rating modification on a fuzzy-based modular architecture for medical device design and development. Advances in Fuzzy Systems, 2012: 14 pages. http://dx.doi.org/10.1155/2012/106354

[2] Yan, J.H., Feng, C.H., Cheng, K. (2011). Sustainability-oriented product modular design using kernel-based fuzzy C-means clustering and genetic algorithm. Engineering Manufacture, 226(10): 1-13. https://doi.org/10.1177/0954405412446283

[3] Yan, J.H., Feng, C.H. (2014). Sustainable design-oriented product modularity combined with 6R concept: a case study of rotor laboratory bench. Clean Technologies and Environmental Policy, 16(1): 95-109. http://dx.doi.org/10.1007/s10098-013-0602-x

[4] Abdelsalam, H.M., Rasmy, M.H., Mohamed, H.G. (2014). A simulation-based time reduction approach for resource constrained design structure matrix. International Journal of Modeling and Optimization, 4(1): 51-55. http//doi.org/10.7763/IJMO.2014.V4.346

[5] Steward, D.V. (1981). The design structure system: A method for managing the design of complex systems. IEEE Transactions on Engineering Management, 28(3): 71-74. http://dx.doi.org/10.1109/TEM.1981.6448589

[6] Wahdan, H.G., Kassem, S.S., Abdelsalam, H.M. (2016). A cuckoo search clustering algorithm for design structure matrix. Italy-Rome: s. n., 2016. 5th the International Conference on Operations Research and Enterprise Systems (ICORES 2016), pp. 36-43. http//doi.org/10.5220/0005693000360043
[7] Yassine, A.A., Yu, T.L., Goldberg, D.E. (2007). An information theoretic method for developing modular architectures using genetic algorithms. Research in Product Design, 18(2): 91-109. http//doi.org/10.1007/s00163-007-0030-1
[8] Eppinger, S.D., Whitney, D.E., Smith, R.P., Gebala, D.A. (1994). A model based method for organizing tasks in product development. Research in Engineering Design, 6(1): 1-13. https://doi.org/10.1007/BF01588087
[9] Idicula, J. (1995). Planning for concurrent engineering. Singapore: Gintic Institute Research.
[10] Gutierrez, Iñaki, C. (1998). Integration analysis of product architecture to support effective team co-location. Cambridge: Masters. Thesis, Massachusetts Institute of Technology.
[11] Thebeau, R.E. (2001). Knowledge management of system interfaces and interactions for product development process. Massachusetts Institute of Technology, Thesis (S.M.)-Massachusetts Institute of Technology, System Design & Management Program.
[12] Whitfield, R.L., Smith, J.S., Duffy, A.H. (2002). Identifying component modules. Cambridge, United Kingdom: the 7th International Conference on Artificial Intelligence in Design AID'02, pp. 571-592.
[13] Sosa, M.E., Rowles, C.M. (2003). Identifying modular and integrative systems and their impact on design team interactions. ASME J Mech Des, 125(2): 240-252. https://doi.org/10.1115/1.1564074
[14] Fabrice, A., Shooter, S.B., Thevenot, H.J. (2006). Design structure matrix flow for improving identification and specification of modules. Philadelphia, Pennsylvania, USA: ASME 2006, International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, pp. 399-411. https://doi.org/10.1115/DETC2006-99524
[15] Borjesson, F. (2009). Improved output in modular function deployment using heuristics. Stanford, USA: International Conference on Engineering Design, pp. 24-27.
[16] Van, B., Thom, J., Erden, M.S., Tomiyama, T. (2010). Modular design of mechatronic systems with function modeling. Mechatronics, 20(8): 850-863. https://doi.org/10.1016/j.mechatronics.2010.02.002
[17] Pandremenos, J. Chryssolouris, G. (2012). A neural network approach for the development of modular product architectures. International Journal of Computer Integrated Manufacturing, 24(10): 879-887. https://doi.org/10.1080/0951192X.2011.602361
[18] Borjesson, F., Hölttä-Otto, K. (2012). Improved clustering algolrithm for design structure matrix. Chicago, IL, USA: IDETC/CIE 2012, 2012. ASME 2012 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference. https://doi.org/10.1115/DETC2012-70076
[19] Borjesson, F., Sellgren, U. (2013). Fast hybrid genetic clustering algorithm for design structure matrix. Portland, Oregon, USA: ASME 2013, 25th International Conference on Design Theory and Methodology. https://doi.org/10.1115/DETC2013-12041
[20] Yang, Q., Yao, T., Lu, T., Zhang, B. (2014). An overlapping-based design structure matrix for measuring interaction strength and clustering analysis in product development project. IEEE Transactions on Engineering Management, 61(1): 159-170. http//doi.org/10.1109/TEM.2013.2267779
[21] Jung, S., Simpson, T.W. (2014). A clustering method using new modularity indices and genetic algorithm with extended chromosomes. DSM 14 Proceedings of the 16th International DSM Conference: Risk and Change Management in Complex Systems, 3(2): 167-176.
[22] Samyeon, K., Baek, J.W., Moon, S.K., Jeon, S.M. (2015). A new approach for product design by integrating assembly and disassembly sequence structure planning. Proceedings of the 18th Asia Pacific Symposium on Intelligent and Evolutionary Systems, 1: 247-257. http//doi.org/10.1007/978-3-319-13359-1_20
[23] Qiao, L., Efatmaneshnik, M., Ryan, M., Shoval, S. (2017). Product modular analysis with design structure matrix using a hybrid approach based on MDS and clustering. Journal of Engineering Design, 28(6): 433-456. http://dx.doi.org/10.1080/09544828.2017.1325858
[24] Wahdan, H., Kassem, S.S., Abdelsalam, H. (2016). A cuckoo search clustering algorithm for design structure matrix. 5th the International Conference on Operations Research and Enterprise Systems (ICORES 2016), Italy-Rome, pp. 36-43. https://doi.org/10.5220/0005693000360043
[25] Wahdan, H.G., Abdelsalam, H.M., Kassem, S.S. (2017). Product modularization using cuckoo search. In Operations Research and Enterprise Systems. http//doi.org/10.1007/978-3-319-53982-9_2
[26] Sakao, T., Song, W., Matschewsky, J. (2017). Creating service modules for customising product/service systems by extending DSM. CIRP Annals, 66(1): 21-24. https://doi.org/10.1016/j.cirp.2017.04.107
[27] Baylis, K., Zhang, G., McAdams, D. (2018). Product family platform selection using a Pareto front of maximum commonality and strategic modularity. Research in Engineering Design, 29(4): 547-563. https://doi.org/10.1007/s00163-018-0288-5
[28] Ezzat, O., Medini, K., Boucher, X., Delorme, X. (2019). Product and service modularization for variety management. Procedia Manufacturing, 28: 148-153. https://doi.org/10.1016/j.promfg.2018.12.024
[29] Jayal, A.D., Badurdeen, F., Dillon Jr., O.W., Jawahir, I.S. (2010). Sustainable manufacturing: modeling and optimization challenges at the product, process and system levels. CIRP J Manuf Sci Technol, 2(3): 144-152. http//doi.org/10.1016/j.cirpj.2010.03.006
[30] Kimura, F., Kato, S., Hata, T., Masuda, T. (2001). Product modularization for parts reuse in inverse manufacturing. CIRP Ann Manuf Technol, 50(1): 89-92. http//doi.org/10.1016/S0007-8506(07)62078-2
[31] Meehan, J.S., Duffy, A.H.B., Whitfield, R.I. (2007). Supporting 'design for re-use' with modular design. Concurrent Engineering, 15(2): 141-155. https://doi.org/10.1177/1063293X07079319
[32] Tseng, H.E., Chang, C.C., Li, J.D. (2008). Modular design to support green life-cycle engineering. Expert Systems with Applications, 34: 2524-2537. http//doi.org/10.1016/j.eswa.2007.04.018
[33] Qian, X.Q., Zhang, H. (2009). Design for environment:

An environmentally conscious analysis model for modular design., IEEE Transactions on Electronics Packaging Manufacturing, 32(3): 164-175. http//doi.org/10.1109/ISEE.2003.1208058

[34] Huanga, C.C., Liangb, W.Y., Chua, H.F. (2012). A novel approach to product modularity and product disassembly with the consideration of 3R-abilities. Computers & Industrial Engineering, 62(1): 96-107. http//doi.org/10.1016/j.cie.2011.08.021

[35] Ma, J.F., Kremer, G.E. (2014). A fuzzy logic-based approach for handling uncertain EOL options in product design stage. Proceedings of the 2014 Industrial and Systems Engineering Research Conference.

[36] Ma, J.F., Kremer, G.E. (2016). A sustainable modular product design approach with key components and uncertain end-of-life strategy consideration. The International Journal of Advanced Manufacturing Technology, 85(1): 741-763. http//doi.org/10.1007/s00170-015-7979-0

[37] Ma, J.F., Kremer, G.E. (2016). A new design for environment tool: Key component-based modular product design approach. Proceedings of the 2016 Industrial and Systems Engineering Research Conference.

[38] Ma, J., Kremer, G. (2016). A systematic literature review of modular product design (MPD) from the perspective of sustainability. Int J Adv Manuf. Technol, 86: 1509-1539. http//doi.org/10.1007/s00170-015-8290-9

[39] Borjesson, F., ltta-Otto, K. (2014). A module generation algorithm for product architecture based on component interactions and strategic drivers. Research in Engineering Design, 25(1): 31-51. https://doi.org/10.1007/s00163-013-0164-2

[40] Gong, W.Y., Cai, Z.H., Zhu, L. (2009). An effective multi objective differential evolution algorithm for engineering design. Structural and Multidisciplinary Optimization, 38: 137-157. http//doi.org/10.1007/s00158-008-0269-9

[41] Yang, X., Deb, S. (2009). Cuckoo search via Levy flights. Coimbatore, IEEE, The World Congress on Nature and Biologically Inspired Computing. http//doi.org/10.1109/NABIC.2009.5393690

[42] Yang, X.S., Deb, S. (2013). Multi objective cuckoo search for design optimization. Computers & Operations Research, 40(6): 1616-1624. http//doi.org/10.1016/j.cor.2011.09.026

[43] Burnwal, S., Deb, S. (2012). Scheduling optimization of flexible manufacturing system using cuckoo search-based approach. International Journal of Advanced Manufacturing Technology, 64: 1-9. http//doi.org/10.1007/s00170-012-4061-z

[44] Chung, W.H., Okudan, G.E., Wysk, R.A. (2014). A modular design Approach to improve product life cycle performance based on the optimization of a closed-loop supply chain. Journal of Mechanical Design, 136(2): 021001. https://doi.org/10.1115/1.4025022

APPENDIX

Table 1. Pareto set of solutions from multi-objective cuckoo search

sequence										Function	Labor time	Environmental impact		Labor cost	Rank
7	7	3	6	8	1	8	8	3	10	8	94.40	1144.62	1452.95	6.94	1
4	10	8	5	2	6	7	8	10	6	4	94.33	1039.16	1639.85	6.49	1
6	8	2	10	7	8	2	7	10	8	3	94.40	1043.86	1589.12	6.43	1
3	1	9	3	9	7	7	9	6	9	7	94.40	1144.62	1452.95	6.94	1
7	10	5	6	7	9	4	5	3	6	8	91.50	1256.37	1555.68	8.26	1
10	3	6	9	4	8	6	8	6	10	9	97.09	1050.32	1756.53	6.40	1
7	2	8	10	2	6	7	7	4	6	9	94.29	1226.24	1538.22	8.04	1
5	5	9	11	7	10	9	2	4	1	8	99.99	998.55	1753.48	6.02	1
3	5	9	2	6	7	5	4	10	2	8	93.62	1033.22	1757.04	6.22	1
6	4	6	1	4	2	7	2	6	6	8	98.87	1033.88	1694.77	6.35	1
11	10	3	11	2	2	1	9	5	6	1	92.51	1062.36	1671.00	6.51	1
2	1	3	7	5	1	3	7	7	5	10	94.33	1077.27	1524.70	6.68	1
2	4	8	4	7	3	3	11	8	8	6	98.87	1033.88	1694.77	6.35	1
11	6	8	6	7	10	2	9	2	1	10	103.45	1162.12	1547.43	7.03	2
4	3	6	6	4	6	6	7	6	7	3	95.27	1059.98	1652.08	6.63	2
6	2	3	2	3	10	11	3	9	8	2	93.62	1199.60	1755.78	7.05	2
8	4	5	4	6	6	10	1	6	8	5	98.87	1261.96	1502.45	7.74	2
8	5	2	4	9	10	1	7	5	5	3	98.87	1261.96	1502.45	7.74	2
10	11	4	8	5	8	8	8	10	2	10	98.03	1059.14	1761.38	6.45	2
3	7	7	7	10	2	2	1	7	5	10	101.77	1032.48	1765.41	6.20	2
6	3	2	3	1	2	7	8	11	6	7	98.87	1134.64	1558.60	6.85	2
8	10	4	10	9	11	1	9	11	4	11	98.87	1134.64	1558.60	6.85	2
1	2	5	6	6	4	5	4	5	6	6	101.88	1254.14	1493.13	7.39	2
9	10	8	11	1	6	8	2	6	9	10	94.57	1226.18	1568.23	8.02	2
2	10	7	4	9	5	4	3	5	7	7	98.87	1261.96	1502.45	7.74	2
8	9	6	2	4	11	3	10	4	2	11	98.87	1075.10	1678.83	6.58	2
2	3	6	2	9	9	9	6	4	4	7	96.46	1134.91	1551.94	6.74	2
7	7	10	5	10	7	9	2	2	7	8	101.88	1254.14	1493.13	7.39	2

7	9	3	11	8	6	2	9	3	8	6	98.87	1134.64	1558.60	6.85	2
6	3	9	7	10	9	5	6	4	3	2	100.93	1144.02	1568.49	6.81	3
10	4	4	5	5	1	3	1	9	5	6	101.88	1037.35	1772.04	6.26	3
9	2	9	10	9	3	10	9	7	4	4	99.82	1095.92	1691.06	6.72	3
9	10	6	11	11	10	4	8	9	4	5	98.03	1270.36	1554.23	7.58	3
3	9	2	4	2	8	3	8	3	8	9	101.88	1113.23	1668.90	6.69	3
6	1	9	2	10	6	2	3	8	10	6	95.51	1191.43	1759.76	7.02	3
9	2	6	3	5	1	5	6	10	5	2	98.14	1155.06	1561.09	6.85	3
4	9	2	10	9	8	5	4	4	9	2	95.27	1397.06	1558.96	9.14	3
8	2	5	2	3	6	1	1	6	11	3	96.46	1373.38	1538.98	9.02	3
1	9	1	7	4	4	6	2	8	6	11	106.35	1371.49	1542.63	8.20	3