

Ant Colony Algorithm based Optimization Methodology for Product Family Redesign

Kwang-Kyu Seo*

*Dept. of Management Engineering, Sangmyung University

Ant Colony 알고리즘 기반의 Product Family 재설계를 위한 최적화 방법론

서 광 규*

*상명대학교 경영공학과

Abstract

고객의 요구에 대한 빠른 대응과 유연하고 효율적으로 새로운 제품을 적기에 개발하기 위해서는 제품 플랫폼에 기초한 대량 맞춤이 절실히 요구된다. 이러한 목적을 달성하기 위하여 기업들은 상대적으로 생산비용을 낮게 유지 하면서 대량생산의 이점을 유지하고 동시에 고객의 요구사항을 만족시키기 위해, product family를 도입하고 가능 하면 작은 변화를 통하여 제품의 다양성을 유지하고자 한다. Product family를 설계할 때 중요한 이슈 중에 하나는 제품의 공통성과 차별성간의 절충점을 찾아내는 것인데, 본 연구에서는 설계자들이 product family 재설계를 용이 하게 하기 위한 방법론을 제안한다. 이를 위하여 본 연구에서는 ant colony 알고리즘과 product family의 공통성 평 가지수를 이용하여 product family 재설계 방법론을 개발한다. 제안한 방법론은 복잡하고 반복적인 많은 계산과정을 가지고 있는 다른 방법과 달리 메타 휴리스틱 알고리즘을 적용하여 인간의 간섭을 줄이고, 실험결과와 정확도, 반복성 및 강건성을 향상시킨다. 본 연구에서는 컴퓨터 마우스 제품군을 대상으로 제안한 방법의 타당성을 검증하였고, 추가적으로 product family 레벨과 부품 레벨의 product family 재설계 추천방안도 제시하였다.

Keywords : Product Family, Commonality Indices, Ant Colony

1. Introduction

To survive in global competition, companies need to develop a wide range of products to fit several market segments with different quality levels. At the same time, a new methodology for product variety is required to optimize the product development efforts across product families and generation. Companies are faced with the challenge of providing as much variety as possible for the market with as little variety as possible between products. In order to

achieve this, product families have been developed, allowing the development of a sufficient variety of products to meet the customers' demands while keeping costs relatively low [7].

A product family is defined as a group of related products that share common features, components, and subsystems to satisfy a variety of market niches. A product platform is the set of features, components or subsystems that remain constant from product to product, within a given product family. The challenge when designing a family of

† 교신저자: 서광규, 충남 천안시 동남구 안서동 300 상명대학교 경영공학과

M · P: 016-718-2682, E-mail: kwangkyu@smu.ac.kr

2011년 1월 20일 접수; 2011년 2월 23일 수정본 접수; 2011년 2월 25일 게재확정

products is in resolving the tradeoff between product commonality and distinctiveness. Toward this end, some commonality indices to evaluate component commonality in a product family have been developed by design researchers and these indices are to measure the amount of commonality within a product family.

There are two common approaches to product family redesign such as commonality and modularity.

To assess the degree of commonality within a product family, several commonality indices have been developed as mentioned above. An extensive comparison between many of these commonality indices and their usefulness for product family design or redesign can be found in previous works [6, 7, 9]. Modularity arises from the decomposition of a product family into modules. Several studies described the measure of product modularity and methods to achieve modularity in product redesign.

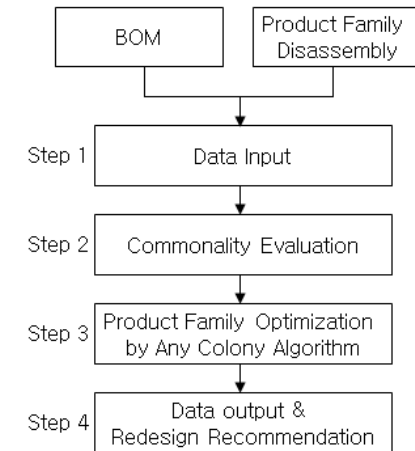
But there is a lack of previous researches to evaluate the impact of each component within a product family on the degree of commonality within the family or to determine the optimal level of commonality. Consequently, there is a need for less information-intensive measures that are useful during concept design and development [4].

In this paper, ant colony based optimization methodology with commonality indices for product family redesign is introduced. The proposed methodology uses simple data as inputs. The list of components is either obtained from a bill of materials, or a disassembly of the product family is performed. Using this data, commonality indices are evaluated to assess the commonality of the whole family, and ant colony algorithm is then implemented to maximize the value of these commonality indices. The proposed methodology provides recommendations on how to improve the redesign of a product family.

2. The Proposed Methodology

2.1 An Overview of the Methodology

The proposed methodology is shown in <Fig. 1>. Details of the proposed methodology are as follow.



<Fig. 1> The proposed methodology

The first step is to ask the user to enter basic information about the product family being studied.

Either the information is readily available, or the designer can disassembly the products in the family to obtain the necessary data. In the second step, the evaluation of the level of commonality in the family is realized through the computation of commonality indices. The third step is the use of ant colony algorithm to maximize the level of commonality in the family subject to specific constraints. The fourth step is the generation of recommendations based on experimental results.

2.2 Step 1: Data Input

The first step in the proposed methodology is to obtain the necessary data for the product family concerned. If the information is already available through a bill of materials, we use it. If the information is not available, a disassembly of the product family is required. To ensure consistency in the disassembly, each product within the family is disassembled to the lowest level possible. For each part, the data collected are the following:

- Size and geometry: this information is used to compare which parts are common, variant or unique throughout the product family.
- Material: the material of each part is stored.
- Manufacturing process: the way the part is produced is also recorded, to see if manufacturing processes can be standardized between the variant parts in a product.

- Assembly and fastening scheme: the way the parts are assembled and fastened together is stored.

2.3 Step 2: Commonality Evaluation

To measure the commonality within a product family, several commonality indices have been proposed in the literature [6, 9]. A commonality index is a metric to evaluate the degree of commonality within a product family. It is based on different parameters such as the number of common components, the component costs, the manufacturing processes, etc. These indices are often the starting point when designing a new family of products or when analyzing an existing family. They are intended to provide valuable information about the degree of commonality achieved within a family and how to improve a product's design to increase commonality in the family and reduce costs [6]. In this work, we use the Comprehensive Metric for Commonality (CMC) to evaluate the commonality of product family [9].

2.4 Step 3: Ant Colony Algorithm based Product Family Design Optimization

In this work, ant colony algorithm is used to maximize the CMC. Ant colony optimization (ACO) algorithm is a metaheuristic in which a colony of artificial ants cooperates in finding good solutions to difficult optimization problems [2, 5]. The ACO is based on agents that simulate the natural behaviour of ants, develop mechanisms for cooperation, and assist them in using experience [1] to find the shortest path between a food source and the nest.

ACO is a population-based heuristic that exploits something similar to the positive feedback that takes place when ants are able to communicate information concerning food sources via pheromone, in a process of indirect communication that is called stigmergy in both ant and technological contexts. Ants lay a pheromone and heuristic information to mark trails.

As the paths are visited by other ants, some of the trails may be reinforced and other paths may be allowed to evaporate. Pheromone trails can be

observed via the number of ants passing through the trail. When there are more pheromone on a path, there is larger probability that other ants will use that path and therefore, the pheromone trail on such a path will grow faster and attract more ants to follow. An iterative local search algorithm tries to search the current paths to neighboring paths until a better solution is found [3].

As mentioned above, The ACO maximizes the CMC, subject to the following additional constraints to facilitate the selection of components to be redesigned.

- Constraint 1: External/differentiating components. The components that are external

on a product usually differentiate the product; these components should not be modified during redesign.

- Constraint 2: The components that are unique to one product will not be modified. The unique components provide a specific function that is present in only one product. These components are used to keep each product different aesthetically and functionally. Hence, it is desired not to modify these unique components.

- Constraint 3: If a component is already common throughout the whole family, the optimizer should not modify the component. The degree of commonality within a product family only is considered here. Other parameters, such as the performance of each product, are not considered. Hence, the components that are common through the whole are considered 'best' for the commonality and should not be modified, although the individual performance of each product may not be optimized.

- Constraint 4: maximum number of attributes allowed to change. There is a restriction on the number of parameters to change between the original design and the redesigned family. If this constraint is not added, the optimizer will find the "best" commonality when all the components are common.

By adding this constraint, the designer specifies a maximum number of allowable changes. Hence the ACO provides recommendations that most influence the commonality, helping the designer focus on the critical components to redesign. There are currently no guidelines to choose the appropriate value for this constraint. However, designers may want to take a

specific percentage of the total number of parameters for this constraint.

Based on these four constraints, the design variables are chosen: only the non-differentiating components are considered. Within this set of components, four attributes are considered: (1) size and geometry, (2) material, (3) manufacturing process, and (4) assembly. For a given component, if an attribute is common between all the products using this component, then this attribute is not considered during optimization.

2.5 Step 4: Data Output and Redesign Recommendations

Once the optimization is complete, the ACO proposes a redesign sequence that can be compared to the original redesign. The ACO does not currently check the feasibility of the solution into account; rather, the ACO provides the designer with a ranked list of parameters that most influences the degree of commonality in the product family. This can be viewed as a reduction of the redesign space, where the designer checks the feasibility of the solution a posteriori in the list of proposed recommendations, rather than checking the feasibility of a redesign solution a priori in a much wider space.

There are two main types of information given by the ACO: (1) at the product family level, if there exists more than one design for a particular family, then the algorithm assesses each design and classifies them; (2) at the component level, a list of components to redesign is proposed to achieve the highest commonality with a minimum number of changes.

- Recommendations at the product family level: if the designer wishes to assess more than one design for a product family, the algorithm is also run without the fourth constraint proposed in section 2.4; hence, once the design is optimized, the “ideal” commonality is reached, i.e., all the parts are common in the product family. An offline analysis of the values obtained after optimization enables the assessment of the different design strategies.

- Recommendations at the component level: the algorithm provides a set of possible changes that

could be implemented to maximize the commonality of the product family for a given number of changes. The best combination(s) of parts to redesign is proposed; additionally, the algorithm provides a ranked list of possible combinations. For a given number of changes, the designer can then choose the feasible combination of parameters that results in the highest CMC (highest increase in commonality).

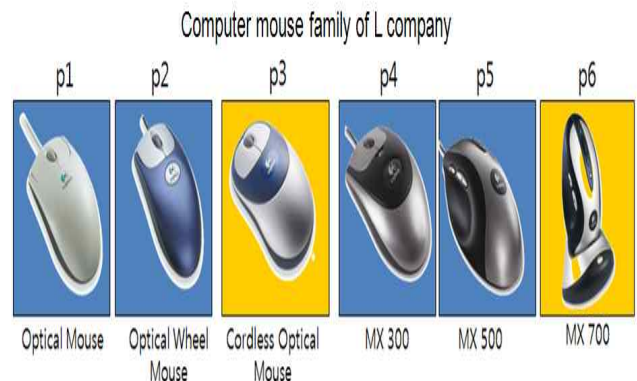
3. A Case Study

A complete example of the redesign of a product family is provided by using computer mice.

3.1 Step 1: Data Input

The product family analyzed consists of a set of six computer mice, all from the same manufacturer, as shown in <Fig. 2>. The BOM were not available for these products; hence, a disassembly was performed.

The computer mice family is disassembled, and the data is stored in an Excel spreadsheet, as shown in <Table 1>. And then the data is rearranged to calculate the CMC as shown <Table 2>. The first two columns in <Table 2> are the name of the parts, and the corresponding product (p1, ..., p6), as shown in <Fig. 2>. In the next column, Size and Geometry, the designer enters a number indicating if the part is common between different products. In the next three columns, the designer enters a number corresponding to the material, the manufacturing process, and the assembly/fastening scheme.



<Fig. 2> The computer mice family

<Table 1> Storage of product family data

Module	Module type	Optical mouse	Optical Wheel mouse	Cordless Optical Wheel Mouse...	MX300	MX500	MX700
Back cover	Unique						
Back panel	Variant						

<Table 2> Sample data for product family

Parts	Size & Geometry	Material	Manufacturing process	Assembly & fastening scheme
Back cover	in p1	1	11	13
	in p2			
	in p3			
	in p4			
	in p5			
	in p6			
Back panel	in p1	1	31	11
	in p2	1	31	11
	in p3	2	31	11
	in p4	3	31	11
	in p5	4	31	11
	in p6	5	31	11

3.2 Step 2: Commonality Evaluation

As mention before, we use the CMC to calculate commonality of product family. The CMC is component-based commonality metric, and the following information is needed for each component in each product in the product family being analyzed: manufacturing process, material, assembly scheme, production volume, and initial cost. The CMC is given by:

$$CMC = \frac{\sum_{i=1}^p n_i * f_{1i} * f_{2i} * f_{3i} * f_{4i} * (C_i^{max} - C_i)}{\sum_{i=1}^p n_i * f_{1i}^{max} * f_{2i}^{max} * f_{3i}^{max} * f_{4i}^{max} * (C_i^{max} - C_i^{min})} \quad (1)$$

The more details of equation (1) can be found in Ref. [9] and we don't describes the details in here.

Using Microsoft Excel, the computation of the CMC is automated: more details on the computation can be found in Ref. [6].

When CMC = 0, either none of the The CMC ranges from 0 to 1. The highest value of the CMC (= 1) is obtained when all the non-differentiating components are common between all the products, and they use the cheapest variant available. The lowest value of the index (= 0) is obtained when all the components are different (size, geometry, manufacturing process, assembly, material) between all the products. The CMC value obtained for the

family of computer mice is 0.563, on a 0-1 scale. This value provides the baseline for comparison after redesign.

3.3 Step 3: Ant Colony Algorithm based Product Family Design Optimization

The proposed ACO follows the classical ACO algorithmic scheme and improves its efficiency by incorporating a constraint propagation procedure for solving the problem, as follows in <Table 3>.

Based on the above four constraints in section 2.4, the design variables are chosen: only the non-differentiating components are considered. Within this set of components, four attributes are considered: (1) size and geometry, (2) material, (3) manufacturing process, and (4) assembly. For a given component, if an attribute is common between all the products using this component, then this attribute is not considered during optimization.

<Table 3> The proposed ACO algorithm

```

Begin
Set parameters and initialize pheromone trails
Sort variables by the most constrained variable rule.
Repeat
  For c from 1 to MaxCycle
    For n from 1 to N_ants
      A ← ϕ
      While |A| < |X| Do
        Select a variable x_j ∈ X that is not
        assigned in A
        Choose a value v ∈ D(x_j) with probability
        P_A((x_j,v)) using the repair mechanism to guarantee all
        solutions are feasible;
        A ← A ∪ {(x_j,v)}
      End While
    End For
  Update pheromone trails using the best ant of cycles
  (the cycle best) {A_k}
  If (several cycles pass by) then reinforce
  pheromone trails using the best ant trial (the global
  best) {A_j}
  End For
Until max trials reached
End
    
```

The mathematical formulation of the optimization problem is shown in Eq. (2):

Maximize CMC

Subject to $C_{ijk} \in (V_l)_{ijk}$

$$\sum_{i=1}^p \sum_{j=1}^n \sum_{k=1}^4 \Pi(C_{ijk} \neq C_{ijk}^{initial}) \leq m \quad (2)$$

$$i = 1, \dots, p$$

$$j = 1, \dots, n$$

$$k = 1, \dots, 4$$

where:

C_{ijk} = value of parameter k for component i in product j .

$C_{ijk}^{initial}$ = initial value of parameter k component i in product j .

V_1 = possible value 1.

$(V_l)_{ijk}$ = set of possible values allowed for parameter k for component i in product j .

p = total number of components in all the products in the product family.

n = total number of products in product family.

m = maximum number of parameters allowed to change.

$$\Pi(C_{ijk} \neq C_{ijk}^{initial}) = 0 \text{ if } C_{ijk} = C_{ijk}^{initial} \text{ and } 1 \text{ otherwise}$$

To understand the formulation, let's consider the follows. For a given product family with n products, a list of p components is established. For each component i in each product j , four parameters are considered: C_{ij1} , C_{ij2} , C_{ij3} and C_{ij4} , respectively corresponding to the values for Size and Geometry, Manufacturing Process, Materials and Assembly. The ACO maximizes the CMC by modifying the values of these C_{ijk} under the constraint specified above (i.e., the C_{ijk} can take a particular set of values $(V_l)_{ijk}$ out of all the possible values V_1).

As mentioned before, the objective function is the CMC, and the objective is to maximize it. The parameters of the proposed ACO algorithm were carefully investigated and tuned in a sensitivity analysis. Major parameters include the evaporation rate (ρ, γ), the number of artificial ant (N_{ants}), the number of reinforcement cycles (RF) and the number of cycles in a trial (C). This setting is determined by a 2^6 full factorial design of experiments approach on the six parameters. <Table 4> presents the resulting setting of the parameters.

<Table 4> Setting parameters

Parameters	Values
α	1(fixed)
ρ, γ	0.001, 0.01
N_{ants}	100, 200
C	1000, 2000
RF	25, 50

Note that the derived constraints proposed in section 2.4 are taken into account: the results are used to (1) choose the appropriate parameters for the ACO and (2) evaluate the design of the product family.

To show the utility of the proposed ACO, we compare the ACO with genetic algorithms (GAs).

Gas are optimization techniques based on the mechanism of natural selection. They used operations found in natural genetics to guide itself through the paths in the search space [8]. Because of their advantages, recently, GAs have been widely used as a tool to optimize existing designs.

Various values were tested for the parameters of the GAs and the ACO. The results show that the highest performance is achieved by setting the parameters to values shown in <Table 5>. The experimental results are shown in <Table 6> which shows the best performance by GAs and the ACO.

<Table 5> GA and ACO parameters setting with the highest performance

GA		ACO	
Population	0.6	α	1
Crossover Prob.	0.01	ρ, γ	0.001
Mutation Prob.	2000	N_{ants}	100
Iteration	100	C	2000
		RF	50

<Table 6> The performance (CMC improvement rate) by the GA and the ACO

	CMC(Best Value)	Improvement(%)
GA	0.819	45.5%
ACO	0.884	52.4%

We find that the ACO obtained a higher CMC than that of the GA. The best result by the ACO is the CMC value of 0.858, an increase of more than 52% compared to the original value (0.563) whereas the best CMC value by GA is 0.819, an increase of more than 45% compared to the original value. The values by the ACO and the GA are far from the "ideal" value of 100, obtained only when all the non-unique parts are used in all the products in the product family, and these parts have the same size and geometry, same material, same manufacturing processes, and same fastening and assembly schemes.

3.4 Step 4: Data Output and Redesign Recommendations

Once the optimization is complete, the ACO optimizer proposes a redesign sequence that can be compared to the original redesign. Two main types of information are given using the algorithm: (1) at the product family level, if there exists more than one design for a particular family, then the algorithm assesses each design and classifies it; (2) at the component level, a list of components to redesign is proposed to achieve the highest commonality for a given number of changes.

- Recommendations at the product family level: If the designer wishes to evaluate more than one design for a product family, the algorithm is also run without the fourth constraint proposed in section 2.4; hence, once the design is optimized, the "ideal" commonality is reached, i.e., all non-differentiating components are made common in the product family.

- Recommendations at the component level: The ACO algorithm provides a set of possible changes that could be implemented to maximize the commonality of the product family (maximization of the commonality index) for a given number of changes. In this case, the fourth constraint explained in the previous section is implemented, and the best combination of components to redesign is obtained. The values for the ACO algorithm in this work are chosen as one example in run 13 or 15. By specifying the maximum number of changes desired, the optimizer gives the best CMC that is achieved

with this particular number of changes, as well as the corresponding changes. The feasibility of the proposed solutions is not checked as discussed previously, but a ranked list of suggested recommendations is provided, helping designers choose the components that influence commonality the most.

4. Conclusion

In this paper, a novel ant colony algorithm based optimization methodology with commonality indices to support component redesign within a product family was introduced. We compare its performance with GAs. ACO has the higher performance than GA and experimental results demonstrate competitive performance of ACO. The combined use of ACO and the CMC to support product family redesign provides useful information for the redesign of a product family, both at the product family level (assessment of the overall design of a product family) and at the component level (which components to redesign, how to redesign them). The reduction of the redesign space by providing a ranked list of components to modify during product family redesign helps the designers focus on critical components that they may not have easily identified without such a systematic approach. In future, we'll need to use the more detailed commonality indices to evaluate the commonality within the family as well as apply the more product families.

5. References

- [1] Dorigo, M., Maniezzo, V., & Colomi, A., "Ant system: Optimization by a colony of cooperating agents", *IEEE Transactions on System, Man, and Cybernetics - Part B*, 26(1) (1996): 29 - 41
- [2] Dorigo, M., & Di Caro, G., *The ant colony optimization metaheuristic*, New ideas in optimization, McGraw-Hill, (1999)
- [3] Dorigo, M., & Stutzle, T., *The ant colony optimization metaheuristic: Algorithms applications and advances*. Technical Report IRIDIA/2000-32, IRIDIA, Universite Libre de Bruxelles, Belgium, (2000)

- [4] Gershenson, J. K., Prasad, G. J. and Zhang, Y., "Product Modularity: Measures and Design Methods," *Journal of Engineering Design*, 15(1), (2004): 33-51
- [5] Gravel, M., Price, W. L., & Gagn, C., "Scheduling continuous casting of aluminum using a multiple objective ant colony optimization metaheuristic", *European Journal of Operational Research*, 143(1) (2002): 218 - 229
- [6] Kwang Kyu Seo, "A comparison study on the evaluating methods of component commonality in a product family", *Journal of the Society of Korea Industrial and Systems Engineering*, 33(4) (2010): 23-27
- [7] Simpson, T. W., Siddique, S., and Jiao, J., *Product Platform and Product Family Design : Methods and Applications*, Springer, NY, (2005)
- [8] Srinivas, M., & Patnik, L. M., *Genetic algorithms: A survey*. Los lamitos: IEEE Computer Society Press, (1994)
- [9] Thevenot, H. J. and Simpson, T. W., "A Comprehensive

Metric for Evaluating Commonality in a Product Family," *Journal of Engineering Design*, 17(2) (2006): 99-119

Author

Kwang-Kyu Seo



Kwang-Kyu Seo is a professor of Management Engineering at Sangmyung University. Dr. Seo received a Ph.D. degree in industrial engineering from Korea University and worked as a research scientist at KIST. He is interested in production/operation management, Information system, Data mining and CRM, e-business and so on.

Address: Dept. of Management Engineering, Sangmyung University, 300, Anso-Dong, Dongnam-Gu, Cheonan-Si, Chungnam