

# PRODUCT MODULARIZATION CONSIDERING COST AND MANUFACTURABILITY OF MODULES

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It is argued that modular architecture allows us to create large product variety at lower cost, and in a shorter development cycle time. While it has been widely recognized that modular design improves assemblability, the manufacturability of modules themselves have rarely been considered during modularization. This paper presents a formal and integrated framework for product modularization by optimizing manufacturability of modules and costs of modularization during the earlier stages of product development. A fuzzy logic approach is used to handle the vague and imprecise product information available during the concept development phase of product development. The framework also facilitates sensitivity analysis to provide design engineers and managers with deeper insights on tradeoffs among conflicting design objectives. The methodology is validated through a case study on the modularization of an automotive climate control system.

**Significance:** This paper emphasizes manufacturability and the cost of modularizations while determining optimal modules; it is a newer approach to modularization that is validated through a case study from the automotive industry.

**Keywords:** Goal Programming, Product Modularization, Manufacturability, Costs of Modularization.

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## 1. INTRODUCTION

Among others, architectural selection decisions are the key decisions made during the early stage of development that have profound impact on the product costs, quality, and manufacturability (Robertson, and Ulrich, 2001; Nepal, 2005). Poor architecture increases costs by forcing companies to pay for launch difficulties, late engineering modifications, difficult part fabrication, inefficient assembly, and excessive part proliferation (Anderson, 2001; Ulrich, 1995).

Modular design strategy allows us to efficiently manage and develop complex products and systems by decomposing them into simpler subsystems without compromising the system's integrity (Baldwin and Clark, 1997; Fujita, 2002). It is also considered as an enabling technology for developing a large variety of products at reduced cost and development time (Muffato, 1999; Fujita, 2002). This type of design helps to improve the reliability and maintainability of the product due to standardized modules and the simple product architecture. Various industries have benefited from modular products strategy. In the early nineties, modular design and flexible manufacturing allowed Sony to produce a wide variety of Walkman® models, maintaining both high quality and low cost, which enabled the company to capture nearly 50% of the world market (Sanderson and Uzmeri, 1995). Another study shows that Volkswagen had been able to save \$1.7 billion annually on development and production costs through effective product architecture and a component commonality strategy among its four brands, VW, Audi, Skoda, and Seat (Dahmus et al., 2001). A number of analytical models for product family design have been developed and tested successfully (Kim and Chhajed, 2000; Simson et al., 2001; Simpson and D'Souza, 2004). However, unlike product family design limited attempts have been made in developing such approaches for module identifications.

Over the years, while many studies have focused on possible approaches for product modularization, researchers differed in their module selection criteria and methods. Pahl and Beitz (1984) consider the manufacturing and assembly costs for modularizing the product. Pimpler and Eppinger (1994) select the modules by prioritizing the functional interactions between the components using swapping heuristics. Salhieh and Kamrani (1999) have employed a group technology approach (P-median model) to maximize the similarity index between the components in a module. Erixon and Ericsson (1999) present “modular function deployment” heuristics to identify the modules.

Gu and Sosale (1999) suggest consideration of various aspects of a product's lifecycle, such as recyclability or serviceability while identifying the modules. Tsai and Wang (1999) use a fuzzy cluster identification method by considering correlation in design of components. Similarly, Huang and Kusiak (1999) develop the modular architecture for electronic products considering the testability issues. In contrast to these (quantitative) models, Stone et al. (2000) present three heuristics (called “dominant flow”, “branching flow”, and “conversion-transmission flow”) for identifying modules from a functional model according to the material, signal, and energy flow patterns shown in the product functional structure diagram. Gershenson et al. (2004) provide a comprehensive review of modular design methods and measures of product modularity. More recently, Nepal et al. (2005) present a fuzzy logic based optimization model to identify modules by minimizing the total cost of modularization. In the subsequent year, the authors extend their earlier work and integrate design for quality issues in modular design (Nepal et al., 2006).

Generally speaking the prior modularization methods either use heuristics or a single-objective optimization (for example, maximization of similarity index or minimization of modularization cost) approach to identify the modules. In reality, product development decisions are always involved with conflicting objectives and tradeoffs. More importantly, while it has been widely recognized that the modular design reduces the development time by improving the assemblability, the manufacturability of modules themselves have rarely been considered during modularization.

The objective of this paper is to present an integrated framework for product modularization by maximizing the manufacturability of modules while minimizing the total cost of modularization. It presents a multi-objective optimization model for module identification and allows design engineer/manager to conduct what-if analysis for studying the tradeoffs between the conflicting design objectives. A fuzzy logic approach is employed to handle imprecise and ambiguous product information available during early stages of development. The methodology is validated through an automotive industry application. The remaining sections of the paper are organized as follows. Section 2 describes the three different phases of the proposed methodology. Section 3 presents a case study on automotive climate control system architecture. Finally, section 4 summarizes the results of this research and identifies potential areas for future work. The above statistics indicate the disparity that exists in employment rates between the disabled and non-disabled and also within the various groups among the disabled. Further, from figures 2 and 3, it can be also inferred that there exists a strong relationship between the employment of an individual and his reliance on disability benefits via SSDI and/or SSI, his/her economic well-being (in terms of each group's annual median earnings). This has been observed particularly in the case of individuals with sensory disabilities who had higher employment rates, better economic well-being and higher median earnings (shown in figures 1, 2, and 3), compared to the other groups and hence lesser reliance on the disability benefits through SSDI and/or SSI. This implies that individuals with disabilities can function better in the society when they can make avail of the employment opportunities.

## 2. METHODOLOGY

The proposed methodology for product modularization during the conceptual stage follows a systems engineering approach that consists of three phases as shown in Figure 1. The following sections describe each phase in details.

### 2.1. Phase 1: Product Decomposition and Requirements Definition

The first step in this phase is functional and physical decomposition analyses of a product or system. The decomposition process helps in mapping out a gross relationship between product functionalities and its physical components. At the end of physical decomposition analysis, a list of basic components is identified from which a number of candidate modules are constituted in pairs. Thus, the performance evaluation will be centered on pair wise interaction between components. The next step is to identify performance attributes of interest or design objectives of modularization. In this paper we consider two objectives: maximization of the manufacturability of modules and minimization of total cost of modularization.

The most critical task in this phase is to identify an appropriate set of metrics to measure the earlier-defined product design or performance attributes. In this paper, as a working definition, a metric of a performance attribute is defined as the factor that influences it significantly. Traditionally, in modular design the primary objective has been to cluster the components into modules by localizing the functional interaction within each module and minimizing them between the modules (Ulrich and Eppinger, 2003). Modular design offers a loosely coupled production system in which different subassemblies can be made independently and then rapidly assembled to build the final product (Salhieh and Kamarani, 1999). However, to improve the overall manufacturability of the product, the modules themselves must be easy to

manufacture. Therefore, this paper focuses on manufacturability of the module in addition to traditional functional interactions between the components to identify the optimal modules for a product or system.

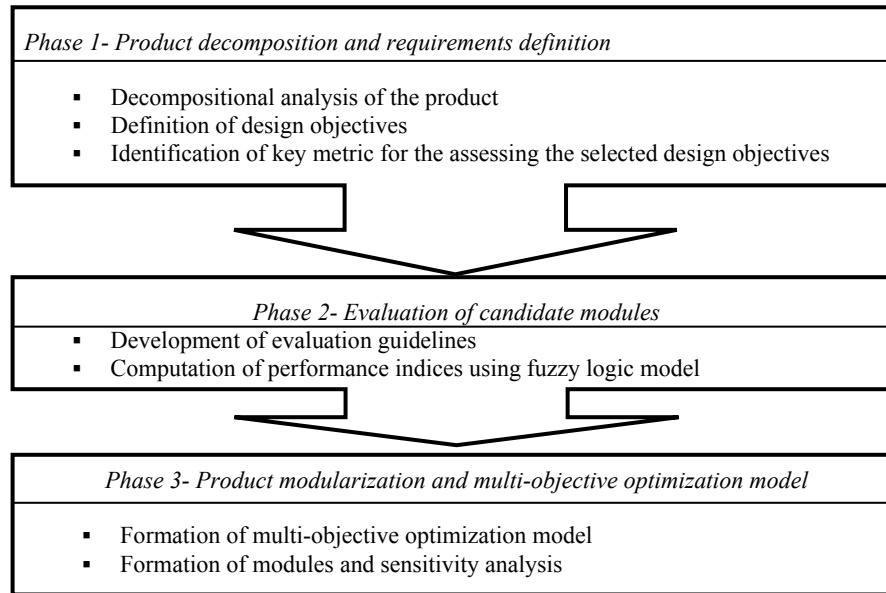


Figure 1: Flow diagram of proposed methodology

Similarly, the bottom line for any improvement in design depends on the cost or investment; and modularization is no exception to that either. Therefore, cost factor is another main criterion for product modularization in this paper. We consider two main categories of modularization costs: manufacturing and product variety (Nepal et al., 2005). In order to refine the evaluation process, the manufacturing cost is broken down into two sub-metrics: cost of interface and requirements of assembly resource, such as time and skills set. Finally, we consider the product variety or reusability cost of a module as the third metric for measuring the cost of modularization.

## 2.2. Phase 2: Evaluation of Candidate Modules

This phase also consists of two tasks. The first task focuses primarily on developing a formal and structured process for engineering judgment of candidate modules with respect to the selected design objective metrics. The second task involves a fuzzy logic model for transforming these subjective judgments into a set of crisp performance indices.

Table 1. Evaluation guidelines for manufacturability of a candidate module

Rating	Manufacturability level	Description of joining and fastening method
5	Very High	Simple snap/slide fitting (without nuts and bolts, etc.) is possible. Chances of assembly-related errors are almost none.
4	High	Minor assembly direction or reorientation of component is needed during assembly process. Chances of assembly-related errors are low.
3	Moderate	Moderate assembly direction or reorientation of component is needed during assembly process. Chances of assembly-related errors are medium.
2	Low	Highly skilled resource or advance facility is required to accomplish the assembly. Yet chances of assembly-related errors are medium.
1	Very Low	An external/internal interface is required in addition to the machining requirements on both the mating parts. Chances of assembly-related errors are very high.

### 2.2.1 Development of evaluation guidelines

Since the architectural analysis at early stages involves subjective information, detailed and well structured evaluation guidelines should be developed to formalize the evaluation process. Building on the prior work and in consultations with practicing design engineers, we have developed the guidelines for assessing the cost (Nepal et al., 2005) and manufacturability metrics (Pahl and Beitz, 1984; Gu and Sosale, 1999; Boothroyd *et al.*, 2002) are developed in the paper.

The evaluation guidelines for manufacturability metrics are given in Tables 1 and 2, and that for cost metrics can be found in Nepal et al. (2005). Each metric is assessed in a rating scale of 1-5 (1- *Very Low*, 5- *Very High*).

Table 2. Evaluation guidelines for functional interactions between components of a candidate module

Rating	Interaction Level	Description of functional interaction
5	Very High	There is significant exchange of material between the components. In other words, the components are functionally inseparable.
4	High	There is very high exchange of torque/ energy between the components and the components are not easily separable.
3	Moderate	There is an exchange of displacement between the components in such a way that the two components need alignment with each other. There is no material flow between them.
2	Low	There is an exchange of force between the components, meaning that one component is aligned with a fixed component. But they are easily separable and there is no material flow between them.
1	Very Low	There may or may not be signal flow between the components. But there are no flows of material and energy between them.

2.2.2 Computation of performance indices using fuzzy logic model

To help capture the uncertainties associated with both input and output variables and the imprecise knowledge about their relationship, fuzzy set theory has been used in this paper. It provides a scientific way to map the approximate relationship between fuzzy variables (Bellman and Zadeh, 1995). The fuzzy variables are also known as linguistic variables in fuzzy set theory and their measure levels are called linguistic levels. Fuzzy variables and their values (measure levels) are characterized by membership functions. Five trapezoidal membership functions used for each input and output variable are defined as ‘very low,’ ‘low,’ ‘moderate,’ ‘high,’ and ‘very high’. Mathematically, the trapezoidal membership function is specified by four parameters (*a, b, c, d*) as given below (Jung et al., 1997):

$$\text{Trapezoidal } (X; a, b, c, d) = \left\{ \begin{array}{ll} 0, & x \leq a \\ (x-a)/(b-a), & a \leq x \leq b \\ 1, & b \leq x \leq c \\ (d-x)/(d-c), & c \leq x \leq d \\ 0, & d \leq x \end{array} \right\} \dots \dots (1)$$

In fuzzy logic, the ‘if-then’ rules are developed to relate inputs to output variable. These rules represent the expert’s knowledge about the interactions between input variables and their effects on the output. A fuzzy rule is expressed as ‘if *x* is *A* then *y* is *B*’. Here, *A* and *B* are the linguistic values defined by fuzzy sets on universe of discourse *X* and *Y*. The ‘if’ part of the rule ‘*x* is *A*’ is called the antecedent or premise, while the ‘then’ part of the rule ‘*y* is *B*’ is called the consequent or conclusion. All the rules that have any truth in their antecedent will fire and contribute to the fuzzy conclusion set. In order to avoid the redundancies and improve the efficiency of the fuzzy logic model, this research develops a few general and specific rules as opposed to a full set of rules. As suggested by Isibuchi and Nakasima (2001), specific rules are given a higher certainty factor (CF) than general rules to balance the decision space for each rule. Below are a few examples of rules developed for estimating the MFIs and CPIs:

Specific rule:

**If (Manufacturability Is High) AND (Functional Interaction is High) THEN (MFI Is High) with C.F. =1**  
**If Interface Cost Is Very Low AND Assembly Resources Required Is High AND Reusability Cost Is High THEN CPI is Very High with CF =1.**

General rule:

**If Interface Cost Is High AND Assembly Resources Required Is High THEN CPI is High with CF =0.75.**

For more than one input, the T-norm operator is used to combine the IF-part of each input variable. It is a conjunctive or AND operator. The minimum T-norm or pair-wise minimum operator is given as (Jang et al., 1997).

$$\mu_B^l = \min \{ \mu_{A_1}^l(x), \mu_{A_2}^l(x), \dots, \mu_{A_n}^l(x) \} = \mu_{A_1}^l(x) \wedge \mu_{A_2}^l(x) \wedge \dots \wedge \mu_{A_n}^l(x) \dots \dots (2)$$

where  $n$  is the number of inputs and  $l$  represents the rule number. Similarly,  $\mu_B$  is the membership functions for the “combined If-part” and  $\mu_{An}$  is that for an individual input represented in the  $n^{\text{th}}$  rule. The outputs of each fuzzy rule that is fired are aggregated to get a fuzzy output. This paper uses the Mamdani fuzzy inference logic, which employs compositional max–min rules for aggregation. This means that the aggregation process utilizes the max-operator (S-norm operator) or the extension principle. The membership function of the output fuzzy set is given by

$$\mu_B(y) = \max \{ \mu_B^1(y), \mu_B^2(y), \dots, \mu_B^m(y) \} \quad \dots \quad \dots(3)$$

where  $\mu_B^m(y)$  is the output membership function of  $m^{\text{th}}$  fired rule. After we get a fuzzy output, we defuzzify it to get a crisp performance index (modularity or cost) by using a “centroid of area” defuzzification technique. The centroid of area ( $Z_{COA}$ ) defuzzifier is expressed mathematically as

$$Z_{COA} = \frac{\int \mu_B(Z) Z dZ}{\int \mu_B(Z) dZ} \quad \dots \quad \dots(4)$$

where  $\mu_B(Z)$  is the aggregated output membership function (MF). However, some fuzzy systems such as the Mamdani fuzzy inference system have a built-in defuzzification technique. In that case, there is no need for defuzzification as a separate step (see Nepal *et al.* (2005) for details about the application of a fuzzy logic model in modularization).

### 2.3. Phase 3: Product Modularization and Multi-Objective Optimization Model

We use Chebychev goal programming (CGP) model for optimizing multiple objectives- namely maximization of modules manufacturability and minimization of cost of modularization. The CGP model does not require estimating aspiration levels subjectively, nor does it require any ranking or weighting procedures (Ignizio and Cavalier, 1994). For modularization purpose, clustering constraints are embedded on the CGP model. This paper modifies the traditional Group Technology (GT) P-median algorithm (Salhieh and Kamarani, 1999) and uses the number of median components as decision variable to determine the optimal number of modules. The details of the mathematical model are as follows:

#### Decision Variables and Parameters

- $X_{ij}$  =  $\begin{cases} 1, & \text{If component } i \text{ belong to component family (module) } j \\ 0, & \text{Otherwise} \end{cases}$
- $\delta$  = Worst unwanted deviation from design goals
- $N$  = Number of modules for a product (or, in other words, # of median components)
- $M_{ij}$  = MFI index w.r.t. Components  $i$  and  $j$  when both of them are in the same module
- $C_{ij}$  = CPI index w.r.t. Components  $i$  and  $j$  when both of them are in the same module

#### Objective Function

Minimize  $\delta$

Subject to:

$$\sum_{j=1}^n X_{ij} = 1 \quad \forall i \quad (\text{One component –one module constraint}) \quad \dots \quad \dots(5)$$

$$X_{ij} \leq X_{ji} \quad \forall i, \forall j \quad (\text{Median component constraint}) \quad \dots \quad \dots(6)$$

$$\sum_{j=1}^n \sum_{i=1}^n M_{ij} * X_{ij} + \delta \geq a_1 (\text{Manufacturability goal constraint}) \quad \dots \quad \dots(7)$$

$$\sum_{j=1}^n \sum_{i=1}^n C_{ij} * X_{ij} + \delta \leq a_2 (\text{Cost of modularization goal constraint}) \quad \dots \quad \dots(8)$$

$$X_{ij} = 0/1 \quad \forall i, \forall j \quad (\text{Binary constraints}) \quad \dots \quad \dots(9)$$

Upon finding optimal modules, we next perform the sensitivity analysis by varying the cost of modularizations and study its impact on the manufacturability of the modules. Also, during the design review, the modules are checked for the feasibility for other reasons such as supplier’s capability and available technology. If the modules are satisfactory, they will pass the design review, otherwise we rerun post optimality analysis after making necessary adjustment in the model parameters such as MFIs and CPIs.

### 3. AUTOMOTIVE CASE STUDY

We piloted this product modularization methodology considering manufacturability and cost metrics on an automotive climate control system. A group of senior climate control system design engineers from a Tier 1 Automotive Supplier Corporation located in Southeastern Michigan (USA) were interviewed for this case study. To protect confidentiality, the name of the company is not disclosed. The functions of the automotive climate control system are to heat and cool passenger compartment in a vehicle. Heating is done by circulating the hot engine coolant via the heater hoses through the heater core, whereas cooling is achieved with a refrigerant loop consisting of compressor, condenser, evaporator, expansion valve, and accumulator. More details about the climate control components including a schematic diagram can be found in Pimpler and Eppinger (1994).

#### 3.1 Product Analysis

Since the objective of this case study was to develop an alternative (modular) architecture for climate control system through incremental design in order to enhance its manufacturability, we have considered only physical decomposition. The following sixteen basic components were identified during the physical decomposition analysis: air controls, refrigeration controls, sensors, heater hoses, command distribution, radiator, engine fan, condenser, compressor, accumulator, evaporator core, heater core, blower motor, blower controller, evaporator case, and actuator. Out of 16 basic components, 120 (= 16C<sub>2</sub>) candidate modules were formed for evaluation purposes.

#### 3.2 Evaluation of Candidate Modules- A Survey of Real World Automotive Climate Control System

Each candidate module was evaluated against all of the five metrics (two for manufacturability and three for cost of modularization) using engineering judgments and the guidelines provided in the section 2.2. A web-based survey was conducted with five senior climate control engineers with combined experience of 41 years in various departments of climate control subsystems. The survey consisted of both open and close ended questions. A snapshot of a typical close ended question asked during the survey is shown in Figure 2. A 5-point scale was chosen to evaluate the candidate modules by considering the human ability for subjective judgments (Schwartz et al, 1990) In order to avoid flaws in the survey instrument, a series of pre-testing was conducted before the actual launching of the survey. Even though the survey was conducted online, follow-up meetings were held with the subject matter experts (SMEs) to clarify the suspicious data.

1 \*How would it affect the following performance metrics if I combined RADIATOR and ENGINE FAN into one module?

	1	2	3	4	5
	Very Low	Low	Moderate	High	Very High
Manufacturability	<input type="button" value="1"/>	<input type="button" value="2"/>	<input type="button" value="3"/>	<input type="button" value="4"/>	<input type="button" value="5"/>
Functional Interaction	<input type="button" value="1"/>	<input type="button" value="2"/>	<input type="button" value="3"/>	<input type="button" value="4"/>	<input type="button" value="5"/>
Cost of Interface	<input type="button" value="1"/>	<input type="button" value="2"/>	<input type="button" value="3"/>	<input type="button" value="4"/>	<input type="button" value="5"/>
Assembly Time	<input type="button" value="1"/>	<input type="button" value="2"/>	<input type="button" value="3"/>	<input type="button" value="4"/>	<input type="button" value="5"/>
Cost of Reusability	<input type="button" value="1"/>	<input type="button" value="2"/>	<input type="button" value="3"/>	<input type="button" value="4"/>	<input type="button" value="5"/>

Figure 2. A snapshot of questionnaire used in the survey of automotive climate control system architecture

#### 3.3 Computation of Design Objective Indices

Since multiple climate control engineers were involved in the evaluation process, the original survey data was normalized in order to minimize the variability due to personal biases. Table 3 shows the selected samples of original (or raw) data and the corresponding normalized data. For example, it shows that the raw rating for ‘manufacturability’ for a candidate module consisting of components ‘radiator’ and ‘engine fan’ is ‘4,’ which means this candidate module has ‘high’ manufacturability. Similarly, there is ‘moderate’ (3 on a rating scale of 1-5) functional interaction between the ‘radiator’ and ‘engine fan.’ The ratings for the cost metrics for the same candidate module were assigned as

$$\{Cost\ of\ Interface,\ Assembly\ Resource\ Requirements,\ Cost\ of\ reusability\} = \{2,\ 2,\ 3\}$$

This means that the aforementioned candidate module would incur ‘low’ costs in terms of interface and assembly resources requirements but needs ‘moderate’ amount of design modifications (costs) if we were to reuse it across other vehicle programs.

Table 3. Selected samples of raw normal data for candidate modules

Component 'I'	Component 'J'	Cost of Modularization						Manufacturability			
		cost of interface		Assembly Resource Requirement		Cost of reusability		Manufacturability		Interaction between components	
		Raw	Norm.	Raw	Norm.	Raw	Norm.	Raw	Norm.	Raw	Norm.
Radiator	Engine Fan	2	-0.91	2	-0.86	3	-0.40	4	0.93	3	1.06
Air controls	Radiator	5	0.97	5	1.16	3	-0.40	1	-0.89	1	-0.92
	Engine Fan	5	0.97	5	1.16	3	-0.40	1	-0.89	2	-0.26
Refrigerant controls	Compressor	5	0.97	5	1.16	5	1.10	1	-0.89	2	-0.26
	Sensors	3	-0.28	3	-0.19	3	1.10	3	0.32	4	1.06
	Heater hoses	5	0.97	5	1.16	5	1.10	1	-0.89	1	-0.92
	Heater Core	2	-0.91	2	-0.86	2	-1.15	4	0.93	4	1.06
	Blower Motor	2	-0.91	2	-0.86	3	-0.40	4	0.93	4	0.40

3.3.1 Computation of CPI and MFI using Fuzzy logic model

The normalized data shown in Table 3 were plugged into the fuzzy logic model to get the crisp sets of CPI and MFI. For example, upon substituting the values of 0.93 and 1.06, respectively, for ‘manufacturability’ and ‘functional interaction,’ the MFI for the candidate module consisting of components ‘Radiator’ and ‘Engine fan’ was found to be 3.84. Similarly, the CPI of the same candidate module was found to be 2.39.

Table 4. CPI matrix for given climate control candidate modules

	Air Controls	Refrigerant controls	Sensors	Heater hoses	Command Distribution	Radiator	Engine Fan	Condenser	Compressor	Accumulator	Evaporator Core	Heater Core	Blower Motor	Blower Controller	Evaporator case
Air Controls	1.98	1.03	1.03	4.5	1.02	3.95	3.95	3.95	4.5	4.5	2.97	2.97	1.45	1.03	1.53
Refrigerant controls	1.98	2.97	2.97	4.5	1.02	4.5	4.5	4.5	3.9	1.98	1.98	1.98	2.39	2.39	1.54
Sensors	1.03	2.97	4.5	4.5	2.39	4.5	4.48	3.31	3.31	2.53	1.98	3.31	3.96	1.98	3.27
Heater hoses	4.5	4.5	4.5	4.48	4.48	1.96	4.48	4.48	4.48	4.5	4.49	1.53	3.95	4.5	3.95
Command Distribution	1.02	1.02	2.39	4.48	3.95	3.4	3.95	4.5	3.94	3.95	3.95	2.98	1.98	4.49	
Radiator	3.95	4.5	4.5	1.96	3.95	2.39	1.98	4.5	1.98	4.5	4.5	4.5	4.5	4.5	
Engine Fan	3.95	4.5	4.48	4.48	3.4	2.39	2.98	4.48	1.98	4.5	4.5	4.5	4.5	3.27	
Condenser	3.95	4.5	3.31	4.48	3.95	1.98	2.98	3.9	2.49	4.5	4.5	4.48	3.84	4.48	
Compressor	4.5	3.9	3.31	4.48	4.5	4.5	4.48	3.9	3.96	4.48	3.33	4.5	2.39	3.9	
Accumulator	4.5	1.98	2.53	4.5	3.94	1.98	1.98	2.49	3.96	2.4	3.95	3.94	2.39	1.98	
Evaporator Core	2.97	1.98	1.98	4.49	3.95	4.5	4.5	4.5	4.48	2.4	1.98	1.98	2.39	2.53	
Heater Core	2.97	1.98	3.31	1.53	3.95	4.5	4.5	4.5	3.33	3.95	1.98	1.03	1.03	1.03	
Blower Motor	1.45	2.39	3.96	3.95	2.98	4.5	4.5	4.48	4.5	3.94	2.39	1.03	2.51	1.41	
Blower Controller	1.03	2.39	1.98	4.5	1.98	4.5	3.27	3.84	2.39	2.39	2.53	1.03	2.51	1.41	
Evaporator case	1.53	1.54	3.27	3.95	4.49	4.5	4.5	4.48	3.9	1.98	1.03	1.03	1.41	1.41	
Actuator	2.4	4.5	3.96	4.5	3.95	4.5	3.98	4.48	3.96	3.95	1.03	1.03	1.03	1.03	

Tables 4 and 5 illustrate the cost performance index and MFI matrices respectively. The fuzzy outputs of all four fuzzy sets were aggregated into a single fuzzy set with the help of a max S-norm operator. A surface plot of the Mamdani fuzzy inference model with two inputs and one output is shown in Figure 3.

3.4 Identification of Optimal Modules Using the CGP Model

The Premium Solver provided by Frontline Systems ® was used to solve the mathematical model. Figure 4 summarizes output of the Premium Solver and determines the optimal modules and their configurations. Those modules were compared with the existing modules and found that few common modules existed. For example, the existing “cooling module,” consisting of the radiator and condenser was same as module 2 in Figure 4. The other occasionally created (for few specific vehicle programs only) module was an HVAC (heating, ventilation, and air conditioning) module, which comprised the evaporator case, evaporator core, blower motor, heater core, actuator, accumulator, and blower controller. In reality, the current climate control system was not systematically modularized, hence very few modules existed. Even the existing module such as HVAC, according to the engineers surveyed, had NVH (noise, vibration, and harshness) concerns due to the positioning of the accumulator. On the contrary, the proposed six-module solution not only provided an opportunity for more modularity (as opposed to the existing two) but also offered an alternative solution to tackle the present NVH

concerns. In the new solution, the accumulator was in a separate module from the one with a blower motor, blower controller, and heater core. Also, having modules with well-defined interfaces and minimum reusability cost can help in reducing complexity by commonizing them across different vehicle programs. Improved manufacturability of the modules is certainly the major contribution of this approach. Further, this can also be a good document for technical design reviews.

Table 5. MFI matrix for the given climate control candidate modules

	Air Controls	Refrigerant controls	Sensors	Heater hoses	Command Distribution	Radiator	Engine Fan	Condenser	Compressor	Accumulator	Evaporator Core	Heater Core	Blower Motor	Blower Controller	Evaporator case	Actuator
Air Controls		4.47	3.86	1.03	4.5	1.03	1.09	1.03	1.09	1.03	3.84	3.84	3.84	4.5	3.84	4.5
Refrigerant controls	4.47		3.86	1.03	4.5	1.09	1.09	1.03	1.46	4.49	3.86	3.86	3.84	4.49	3.86	1.09
Sensors	3.86	3.86		1.03	3.36	1.03	1.09	1.99	2.35	2.99	3.86	3.86	1.09	3.84	2.99	1.04
Heater hoses	1.03	1.03	1.03		1.03	1.99	1.03	1.03	1.03	1.03	1.03	4.49	1.03	1.03	1.03	1.03
Command Distribution	4.5	4.5	3.36	1.03		1.03	1.03	1.03	1.03	1.03	1.03	1.99	4.5	1.09	1.46	
Radiator	1.03	1.09	1.03	1.99	1.03		3.84	3.86	1.03	3.85	1.03	1.03	1.03	1.03	1.03	1.03
Engine Fan	1.09	1.09	1.09	1.03	1.03	3.84		3.36	1.03	1.04	1.03	1.03	1.03	1.03	1.03	1.04
Condenser	1.03	1.03	1.99	1.03	1.03	3.86	3.36		2.62	3.86	1.03	1.03	1.03	1.03	1.03	1.03
Compressor	1.09	1.46	2.35	1.03	1.03	1.03	1.03	2.62		2.99	1.03	1.03	1.03	4.47	1.03	1.04
Accumulator	1.03	4.49	2.99	1.03	1.03	3.85	1.04	3.86	2.99		3.86	1.48	1.03	1.48	4.47	1.03
Evaporator Core	3.84	3.86	3.86	1.03	1.03	1.03	1.03	1.03	1.03	3.86		4.47	3.86	3.86	4.5	4.47
Heater Core	3.84	3.86	3.86	4.49	1.03	1.03	1.03	1.03	1.03	1.48	4.47		4.5	4.47	4.5	4.47
Blower Motor	3.84	3.84	1.09	1.03	1.99	1.03	1.03	1.03	1.03	1.03	3.86	4.5		3.36	3.86	4.47
Blower Controller	4.5	4.49	3.84	1.03	4.5	1.03	1.03	1.03	4.47	1.48	3.86	4.47	3.36		4.47	4.47
Evaporator case	3.84	3.86	2.99	1.03	1.09	1.03	1.03	1.03	1.03	4.47	4.5	4.5	3.86	4.47		4.47
Actuator	4.5	1.09	1.04	1.03	1.46	1.03	1.04	1.03	1.04	1.03	4.47	4.47	4.47	4.47	4.47	

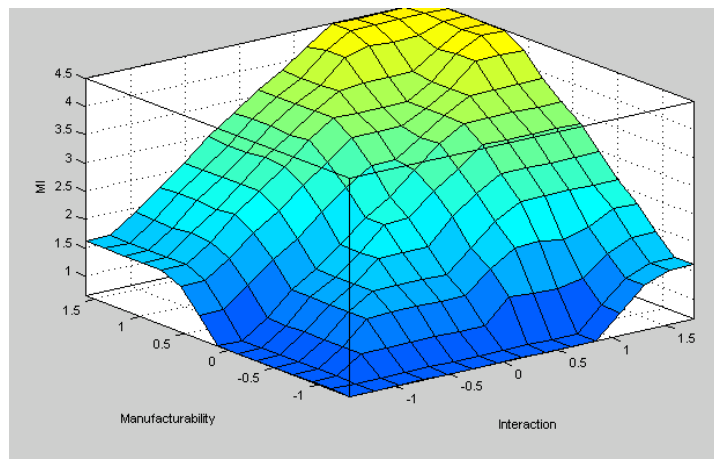


Figure 3. Mamdani fuzzy inference model surface view for two inputs and one output

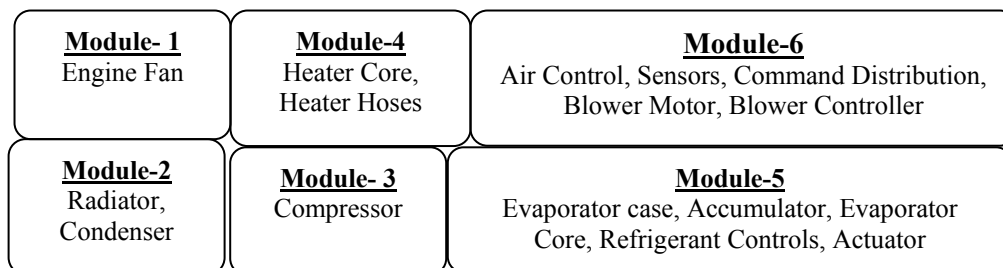


Figure 4. Optimal modules and their configurations for automotive climate control system

### 3.5 Post-Optimality Analysis of Climate Control Modular Architecture

Post-optimality analysis was performed to study the impact of variation in cost of modularization on the overall modular architecture of the climate control system in terms of manufacturability of the modules. In order to do so, the CPI goal constraint (Equation 8) was first converted into a hard constraint by removing the deviation variable ( $\delta$ ) from the constraint



equation; and then the optimization model was rerun for different values of RHS or aspiration level for cost. Table 6 shows the nine scenarios that were run for analyzing the modular architecture of the given automotive climate control case study.

Table 6. Scenario analysis of modular architecture of climate control system

Scenario No	Increase in RHS of cost constraint (%)	Optimal Number of Modules	Gain in manufacturability index
1	-15	7	-8.92%
2	-10	7	-7.32%
3	-5	7	-5.96%
4 (original solution)	<b>0</b>	<b>6</b>	<b>0.00%</b>
5	5	6	1.68%
6	10	6	3.03%
7	15	5	4.64%
8	20	5	10.60%
9	30	5	12.05%

The results show that there could be a significant increase in gain in total manufacturability index if we increased the total cost index by 20%. However, the gain in MFI diminishes beyond this point. The post optimality results were reviewed with design engineers. Based on this analysis, the modular architecture (Figure 5) resulted from scenario 8 was recommended for the given automotive climate control system.

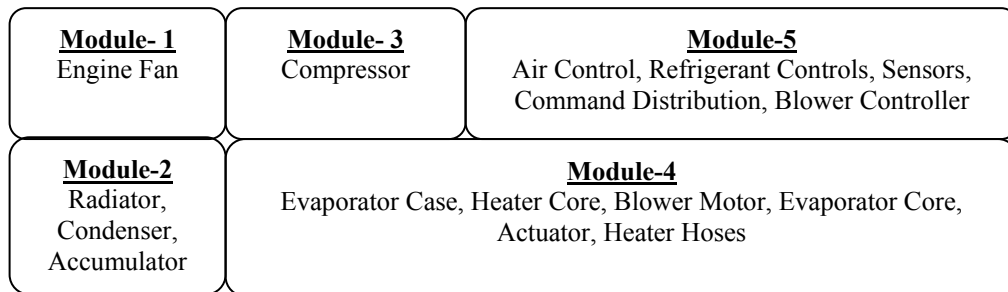


Figure 5. Recommended Five-module solution for climate control system architecture after post optimality analysis

#### 4. CONCLUSIONS AND FURTHER RESEARCH

While a substantive amount of work has been published on articulating the importance of modular architecture and commonality in product family design, a formal modularization process is still in demand. Further, although it has been widely recognized that modular design improves the assemblability, the manufacturability of modules themselves have rarely been considered during modularization. In this paper, we presented a multi-objective optimization framework to identify the optimal modules considering manufacturability and costs metrics. An automotive climate control system was used to validate the application of the proposed methodology. The results suggested a five well-defined modules solution as opposed to the existing two 'grey' modules. Our work also showed that this analysis can be an appropriate decision support tool during engineering design reviews to help reduce late design changes. Moreover, our proposed framework is generic; thus, it can be used in product and system settings beyond the automotive industry in situations where simultaneous optimization of more than two design goals is desired. Product development decision making is a complex process that typically involves multiple factors, including a supplier's capability, packaging and reliability. These decisions cannot be made based only one or two criteria. Future research, therefore, should incorporate these issues into product development modularization while defining design requirements and other variables that might affect modularization in manufacturing environments.

#### 5. REFERENCES

1. Anderson, D. M. (2001). Design for Manufacturability: Optimizing cost, quality and time-to-market, CIM Press, Cambria, California, USA, ISBN: 10-987-6543.

2. Baldwin, C.Y. and Clark, K.B. (1997). Managing in an Age of Modularity, *Harvard Business Review*, (September-October): 84-93.
3. Bellman, R.E. and Zadeh, L.A. (1995). Decisions making in fuzzy environment, *Management Science*, 17(4):144-64.
4. Boothroyd, G., Dewhurst, P. and Knight, W. (2002). *Product Design for Manufacture and Assembly*, Second Edition, Marcel Dekker, Inc., New York, USA, ISBN: 0-8247-9176-2.
5. Dahmus, B. J., Gonzalez-Zugasti, J.P. and Otto, K.N. (2001). Modular product architecture, *Design Studies*, 22: 409-424.
6. Ericsson, A. and Erixon, G. (1999). Controlling Design Variants: Modular product platforms, ASME Press, USA, ISBN: 0-87263-514-7.
7. Fujita, K. (2002). Product variety optimization under modular architecture, *Computer Aided Design*, 34: 953-965.
8. Gershenson, J.K., Prasad, G.J. and Zhang, Y. (2004) 'Product Modularity: Measures and Methods', *Journal of Engineering Design*, Vol. 15 (1), pp. 33-51.
9. Gu, P. and Sosale, S. (1999). Product modularization for life cycle engineering, *Robotics and Computer Integrated Manufacturing*, 15: 387-401.
10. Huang, C.C and Kusiak, A. (1999) 'Synthesis of modular mechatronic products: a testability perspective', *IEEE/ASME Transactions on Mechatronic*, Vol. 4(2), pp.119-132.
11. Ignizio, J.P. and Cavalier, T.M. (1994). *Linear Programming*, Prentice Hall International Series in Industrial and Systems Engineering, Englewood Cliffs, New Jersey, USA, ISBN: 0-13-183757-5.
12. Ishibuchi, H. and Nakashima, T. (2001). Effects of rule weights in Fuzzy rule-based classification systems, *IEEE Transactions on Fuzzy Systems*, 9(4): 506-515.
13. Jang, J.S.R., Sun, C.T. and Mizutani, E. (1997). *Neuro-Fuzzy and soft computing: a computational approach to learning and machine intelligence*, Prentice Hall Publication, Upper Saddle River, New Jersey, USA.
14. Kim, K. and Chhajed, D. (2000). Commonality in product design: cost saving, valuation change and cannibalization, *European Journal of Operational Research*, 125: 602-621.
15. Krishnan, V. and Ulrich, K.T. (2001). Product development decisions: a review of the literature, *Management Science*, 47(1): 1-21.
16. Muffato, M. (1999). Introducing a platform strategy in product development, *International Journal of Production Economics*, 60-61: 145-153.
17. Nepal, B.P. (2005). An integrated framework for multi-objective optimization of modular product architecture, Ph. D. Dissertation, Wayne State University, Detroit, MI, USA.
18. Nepal, B. P., Monplaisir, L. and Singh, N. (2005). Integrated fuzzy logic based model for product modularization during concept development phase, *International Journal of Production Economics*, 96: 175-174.
19. Nepal, B. P., Monplaisir, L. and Singh, N. (2006) 'A methodology for integrating design for quality in modular product design', *Journal of Engineering Design*, Vol. 17 (5): 387-409.
20. Pahl, G. and Beitz, W. (1984). *Engineering Design: A systematic approach*, Springer-Verlag, second edition, London, UK, ISBN: 3-540-19917-9.
21. Pimpler, T. and Eppinger, S.D., (1994). Integration analysis of product decompositions, *Proceedings of ASME Design Engineering Theory and Methodology Conference*, 68.
22. Salhieh, S.M. and Kamrani, A.K. (1999). Macro level product development using design for modularity, *Robotics and Computer Integrated Manufacturing*, 15: 319-329.
23. Sanderson, S. and Uzumeri, M. (1995). Managing product families: the case of the Sony Walkman, *Research Policy*, 24: 761-782.
24. Schwarz, N. and Hippler, H-J. in Biemer, 1990. Chapter 3. Response alternatives: The impact of their choice and presentation order, *Measurement errors in survey* (Editors: Biemer, Groves, Lyberg, Mathiowetz, and Sudman), John Wiley & Sons, New York: 41-56.
25. Simpson, T. W. and D'Souza, B. (2004) Assessing Variable Levels of Platform Commonality within a Product Family Using a Multiobjective Genetic Algorithm, *Concurrent Engineering: Research and Applications*, 12 (1):119-130.
26. Simpson, T. W., Maier, J. R. A. and Mistree, F. (2001). Product Platform Design: Method and Application, *Research in Engineering Design*, 13 (1): 2-22.
27. Stone, R.B., Wood, K.L. and Crawford, R. H. 2000. A heuristic method for identifying modules for product architectures, *Design Studies*, 21: 5-31.
28. Tsai, Y.T., and Wang, K.S. (1999). The development of modular-based design in considering technology complexity, *European Journal of Operational Research*, 119: 692-703.
29. Ulrich, K. (1995). The role of product architecture in the manufacturing firm, *Research Policy*, 24: 419-440.
30. Ulrich, K.T. and Eppinger, S.D. (2003). *Product Design and Development*, Third Edition, McGraw-Hill Inc., USA,

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