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From user requirements to commonality specifications: an integrated approach to product family design

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Abstract Many companies design families of products based on product platforms that enable economies of scale and scope while satisfying a variety of market applications. Product family design is a difficult and challenging task, and a variety of methods and tools have been created to support this platform-based product development. Unfortunately, many of these methods and tools have been developed—and consequently exist—in isolation from one other. In this paper, we introduce an approach to integrate several of these disparate tools into a framework to translate user needs and requirements into commonality specifications during product family design. The novelty of the approach lies in how we integrate the market segmentation grid, Generational Variety Index (GVI), Design Structure Matrix (DSM), commonality indices, mathematical modeling and optimization, and multi-dimensional data visualization tools to identify what to make common, what to make unique, and what parameter settings are best for each component and/or subsystem in the product family. The design of a family of unmanned ground vehicles (UGVs) demonstrates the proposed approach and highlights its benefits and limitations.

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1 Introduction

Across many industries, the prevailing practice is to design families of products that exploit commonality to take advantage of economies of scale and scope while targeting a variety of market applications. A *product family* is a group of related products that are derived from a common set of components, modules, and/or subsystems to satisfy a variety of market applications where the common "elements" constitute the *product platform* (Meyer and Lehnerd 1997). The platform is used to create individual products either through addition/subtraction/substitution of one or more modules to realize a module-based product family or by scaling and/or "stretching" one or more design variables to realize a scale-based product family (Simpson 2004). Successful examples can be found in a variety of companies, including Airbus (Aboulafia 2000), Black & Decker (Meyer and Lehnerd 1997), Boeing (Sabbagh 1996), and Rolls Royce (Rothwell and Gardiner 1990).

Product family design is a difficult task—it involves all of the complexities of product design compounded by the challenges of coordinating the design of multiple products. There are many advantages to product families, however, most of which stem from increased commonality among the set of products. As Robertson and Ulrich (1998) point out, "By sharing components and production processes across a platform of products, companies can develop differentiated products efficiently, increase the flexibility and responsiveness of their manufacturing processes, and take market share away from competitors that develop only one product at a time." Platforms promote better learning across products, and the use of common components and modules can decrease lead-time and risk in the development stage since the technology has already been proven in other products (Collier 1981, 1982). Inventory and handling costs are also reduced due to the presence of fewer components in inventory. The reduction in product line complexity, the reduction in setup and retooling time, and the increase in standardization and repeatability improve processing time and productivity and hence also reduce costs (Collier 1981; Kim and Chhajed 2000). Fewer components also need to be tested and qualified, which reduces cost as well as time-to-market (Fisher et al. 1999; Rothwell and Gardiner 1990).

Successful development of a platform and deployment of a product family require input from multiple disciplines (e.g., marketing, engineering, manufacturing as discussed in Jiao et al. (2007a)); unfortunately, many of the tools and methods for product family design have been developed—and consequently exist—in isolation from one other. Therefore, in this paper, we introduce a new approach for effectively integrating several of these disparate tools to translate user requirements into commonality specifications during product family design. Section 3 introduces our approach for integrating these tools and methods into a coherent framework, and Sect. 4 demonstrates the proposed approach using an example based on a family of unmanned ground vehicles (UGVs). The benefits and limitations of the proposed approach along with future work are discussed in Sect. 5.

2 Related work: methods and tools to support product family design

A variety of tools and methods have been developed over the past two decades to support product family design and platform-based product development (Jiao et al. 2007a; Simpson et al. 2005). For instance, Meyer and Lehnerd (1997) introduced the market segmentation grid to help marketing and engineering identify potential platform leveraging strategies for the product family as it is being developed. As shown in Fig. 1, market segments (e.g., user groups) are listed on the horizontal axis, while the price/performance tiers (i.e., range of uses) are plotted on the vertical axis. Within this grid, four platform leveraging strategies can be identified: (1) no leveraging; (2) horizontal leveraging, which shares common technology across several market segments within a given price/performance tier; (3) vertical leveraging, which scales technology up/down within market segment to address different price/performance tiers; and (4) beachhead approach, which combines vertical and horizontal leveraging to attack all of the market segments within a single platform. Market segmentation grids are useful in a wide range of applications (Marion and Simpson 2005; Meyer and Lehnerd 1997), including platform-based development at start-up firms (Marion and Simpson 2009). They have also been used to identify platform leveraging strategies during product family redesign (Farrell and Simpson 2008).

Identifying ways to leverage a platform and reuse common "elements" within a product family is not trivial. Martin and Ishii (2002) modified Quality Function Deployment (QFD)—a good tool for integrating marketing and engineering (Hauser and Clausing 1988)—to compute a Generational Variety Index (GVI) that can be used to help identify subsystems/components that will need to be redesigned over the lifetime of the product line; those that are not subject to a lot of redesign are potential platformable "elements" within the family.

Figure 2 illustrates part of the seven-step process that Martin and Ishii (2002) use to compute GVI. After determining the market and desired life for the platform (Step 1), a QFD matrix is used to map customer requirements to engineering requirements (Step 2); the example in Fig. 2 is for a water cooler that has four planned variants over its lifetime—the requirements for each variant are not shown. The expected changes in customer requirements (Step 3) and engineering metric target values (Step 4) are identified, and a normalized target value matrix is calculated (Step 5) based on the mapping of engineering requirements to subsystems and components (see QFD Matrix II in Fig. 2). Using the GVI rating scale shown in the lower right of the figure, the GVI matrix is created by replacing each x in the second QFD matrix with a 1, 3, 6, or 9 (Step 6). Finally, the ratings in each column are tallied (Step 7) to compute the GVI value for each subsystem/component. As noted in the figure, subsystems and components with low GVI values will not require a lot of redesign over the life of the product line; therefore, they can be integrated into the platform. Meanwhile, the "elements" with high GVI

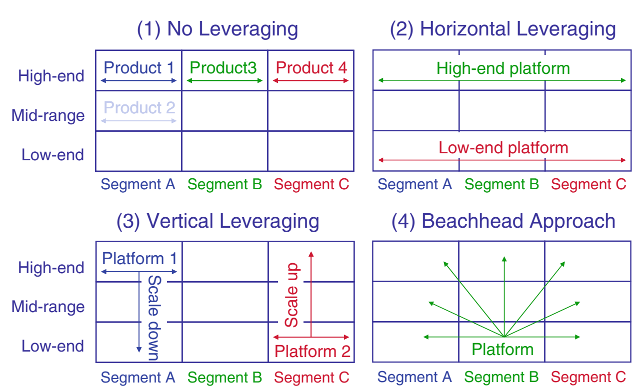

Fig. 1 Market segmentation grid and platform leveraging strategies (adapted from Meyer and Lehnerd 1997)

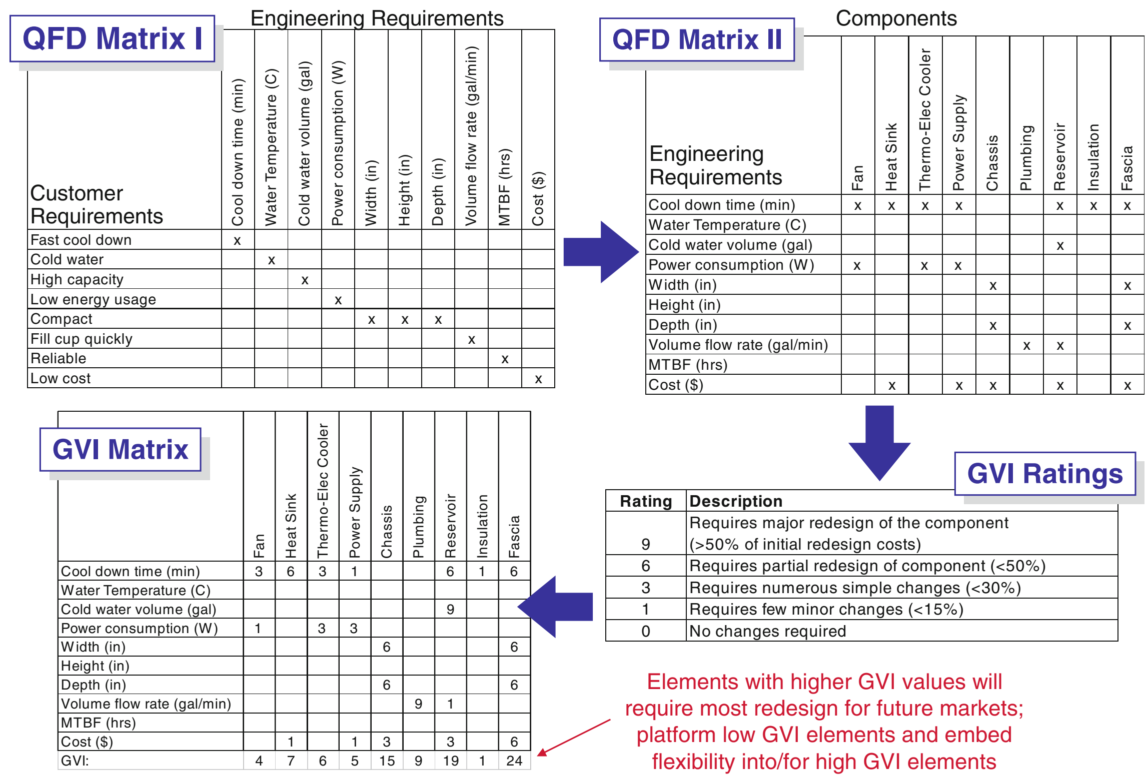

Fig. 2 Example of computing GVI for a water cooler (adapted from Martin and Ishii 2002)

values will require a lot of redesign to accommodate the anticipated variation in the customer requirements; therefore, these subsystems/components should not be part of the platform.

To complement the GVI analysis, Martin and Ishii (2002) introduce a Coupling Index derived from the product's Design Structure Matrix (DSM) (Steward 1981) to identify ways to modularize the product and standardize interfaces between high GVI "elements", thereby minimizing the impact of their redesign on the system. There are many different types of DSMs (Braha and Maimon 1998; Browning 2001); our focus here is on component-based DSMs given their ability to represent a product's architecture (Sharman and Yassine 2004; Yu et al. 2007). Component-based DSMs have been used extensively for identifying modules within a product architecture (Helmer et al. 2010; Huang and Kusiak 1998; Kusiak and Larson 1995), which influences not only how the product family will be designed (Dahmus et al. 2001; Sudjianto and Otto 2001) but also how teams should be staffed, structured, and organized for effective product development (Sosa et al. 2003). Component-based DSMs are also being used to identify platforms within a family (Kalligeros et al. 2006) as well as strategies for embedding flexibility into subsystems/components that may vary over the product lifecycle (Suh et al. 2007). These approaches draw heavily on the findings from recent research into change propagation in complex systems (Clarkson et al. 2004; Eckert et al. 2004).

Concurrently, metrics for product family design have focused primarily on assessing (1) modularity and (2) commonality. Metrics for modularity abound in the literature and are reviewed elsewhere (Gershenson et al. 2003; Hölttä-Otto and de Weck 2007); instead, we focus on commonality indices for product family design and their use as surrogates for estimating the manufacturing and production cost savings of platform-based product development (Fixson 2007). Numerous commonality indices have been developed to assess the "goodness" of a product family from one or more perspectives, e.g., design, fabrication, assembly (Thevenot and Simpson 2006). While most of these indices rely on discrete component and part counts [e.g., count the number of component instances that have the same size/shape, material/manufacturing, and assembly/fastening scheme within a family (Kota et al. 2000)], a few indices have been developed to assess parametric variety, i.e., variations in the settings of design parameters across products in a family (Khajavirad and Michalek 2007). One such index is the Product Family Penalty Function (PFPF) introduced by Messac et al. (2002), which can be used during product family optimization. As defined in Eq. (1), PFPF is used to measure the dissimilarity among the different parameter settings for each design variable used to define the product family.

$$\mathrm{PFPF} = \sum_{j=1}^{n} \frac{\mathrm{deviation}_j}{\bar{x}_j} \quad \text{where } \bar{x}_j = \sum_{i=1}^{p} \frac{x_{ij}}{p}$$
$$\mathrm{deviation}_j = \sqrt{\sum_{i=1}^{p} \frac{(x_{ij} - \bar{x}_j)^2}{(p-1)}} \tag{1}$$

In Eq. (1), x_{ij} is the individual value of the ith design variable for the jth product, n is the number of design variables being considered, and p is the number of products in the family. The deviation is expressed as a percentage of the mean for each design variable, so that while the parameter values change during optimization, the percent deviation is normalized against the mean value of each variable—variables that approach or have a mean of zero should be scaled accordingly. Minimizing PFPF during product family optimization reduces the parametric variation in the family, which is equivalent to maximizing commonality in the family. PFPF has been applied to electric motor family design (Messac et al. 2002) as well as the design of a family of General Aviation Aircraft (Simpson and D'Souza 2004).

Finally, to support product family optimization, more than 40 different optimization-based methods have been developed as reviewed in (Simpson 2005). These range from engineering-centric (Bhandare and Allada 2009; Dai and Scott 2007) to those that include manufacturing considerations (Fujita 2002; Rai and Allada 2003) and market analysis (Li and Azarm 2002; Michalek et al. 2006). A wide range of algorithms have been used to support product family optimization, including linear and non-linear programming (e.g., sequential linear/quadratic programming, generalized reduced gradient) as well as derivative-free methods such as pattern search, simulated annealing, and genetic algorithms (Simpson 2005). Newer optimization algorithms such as ant colony optimization are also finding use in product family design (Kumar and Allada 2007); however, genetic algorithms (GAs) are becoming the predominant approach for product family optimization given the flexibility in their problem formulation, capability to handle multiple objectives, and their ability to run in parallel computing environments (Jiao et al. 2007b; Khajavirad et al. 2009). Multi-objective optimization approaches for product family design are also being used to combine other methods and tools, such as the market segmentation grid to identify effective platform leveraging strategies (Kumar et al. 2009), and integrate engineering design, customer value, and production cost models to identify profitable portfolios of products and platforms (de Weck 2005). Given the potential synergies among these methods and tools, an integrated approach to product family design would provide an effective means to translate user requirements into commonality specifications. Our proposed approach is introduced next.

3 Proposed approach: an integrated framework for product family design

The starting point for our integrated approach is the product platform planning framework introduced and popularized by Robertson and Ulrich (1998). Their framework consists of three phases as shown in Fig. 3: (1) product plan, (2) differentiation plan, and (3) commonality plan. In the product plan, the goal is to identify which products to offer when. Identifying how products will be positioned within each market segment is part of the differentiation plan. Finally, the commonality plan outlines which "chunks" (i.e., subsystems/components) will be shared between each of these products. Taken together, the three phases define the product platform plan for a product family.

While the framework is a useful guide to structure product platform planning, it can be difficult to implement as it has not been linked to specific methods and tools to support each phase (Simpson et al. 2006). Therefore, we propose the integrated approach in Fig. 4 to link the methods and tools discussed in the previous section into the product family planning framework of Robertson and Ulrich (1998). In particular, we integrate the market segmentation grid, DSMs, GVI, commonality indices, and optimization to translate user requirements (i.e., customer needs) into commonality specifications for a product family (i.e., what to make common, what to make unique, and what parameter settings are best for each component and/or subsystem). The proposed approach is flexible enough, however, that additional tools and methods can be added and/or substituted based on the product family designer's specific needs.

As shown in Fig. 4, the market segmentation grid (along with reverse engineering and benchmarking of existing systems) is used to identify a promising product plan and platform leveraging strategy, which initiates the differentiation plan and the commonality plan. GVI and DSM are then used to identify "elements" that differentiate each product and corresponding modules within the family. GVI is also used to define platform "elements" that can be common within the family. These results are then verified using commonality indices and multi-objective optimization for detailed trade studies. Multi-dimensional data visualization tools (Stump et al. 2009) can be used to display results, allowing designers to change and modify their preferences, targets, etc. "on the fly" to bring the commonality and differentiation plans into alignment. In essence, our integrated approach enables a holistic "Design

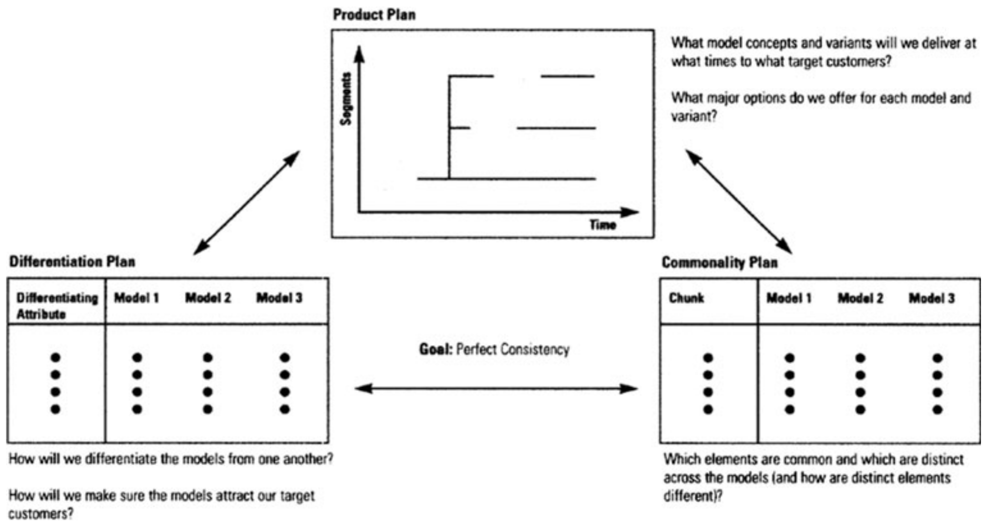

Fig. 3 Product platform planning framework of Robertson and Ulrich (1998)

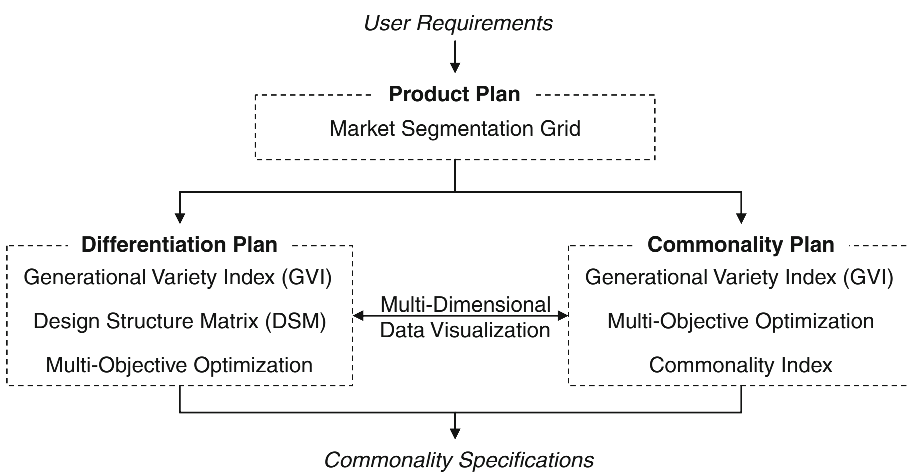

Fig. 4 Integrated approach to product family design

by Shopping" paradigm (Balling 1999) for product family design.

4 Example: design of a family of unmanned ground vehicles

To demonstrate the proposed approach, consider the design of a family of unmanned ground vehicles (UGVs) for explosive ordnance disposal. Examples of existing systems include the Foster-Miller Talon and iRobot Packbot. While effective, there is no sharing or part commonality across existing systems as there is little to no incentive for manufacturers to collaborate with one another. As a result, users must maintain multiple sets of spare parts, manuals, and tools; keep multiple specialized technicians on staff for logistical support and maintenance; and conduct different sets of training and certification procedures for each robot since the operating systems and user controls are different for each. Furthermore, there is no plug-and-play capability across systems from different manufacturers, e.g., a manipulator arm from one manufacturer will not work on the other manufacturer's UGV and vice versa. By applying our approach to this problem, we hope to identify promising opportunities for commonality within future UGV systems.

4.1 Market segmentation and product plan for UGV family

To develop the product plan for the UGV family, we defined requirements for the UGV capabilities (e.g., weight, speed, range, lift capacity) for different potential missions, and threshold and objective values were identified for each capability for each mission. Threshold values represent the minimum values that must be met in order to complete a mission, while the objective values provide targets that users would like to achieve. Over 50 different potential missions were identified based on type of ordnance, UGV functionality (e.g., dig, detonate, diffuse), location of operation, etc. Initially, formal clustering techniques (e.g., fuzzy clustering Moon et al. 2006; Zhang et al. 2007) were used to group similar missions into representative "market segments", but it made better sense to group the UGVs into three classes consistent with current systems. In the end, three "performance tiers" were identified corresponding to small, medium, and large UGVs based on weight; threshold and objective values were defined for each of these three weight classes.

In parallel to this effort, we also dissected and analyzed several existing systems, including the Talon, Packbot, Bombot, and RONS (see Fig. 5). The capabilities of each UGV were measured (e.g., weight, speed, battery life, lift capacity) to establish a baseline for comparison as well as provide data for validating the mathematical models developed for optimization and product family trade studies. These systems were also used to construct a "generic" UGV architecture, which is shown in the DSM in Fig. 6. This DSM shows not only the connections between subsystems and components but also the extent to which a change in one component is likely impact another component (L = low, M = medium, H = high) by taking into consideration the potential for change propagation within the system (Clarkson et al. 2004), which helps when assigning redesign ratings during GVI analysis.

4.2 Commonality and differentiation plans

With this as our "generic" reference architecture for the UGV family, we proceeded to compute GVI for each subsystem based on the requirements for the different "performance tiers", i.e., small, medium, and large UGVs. The GVI results are summarized in Fig. 7. Subsystems with low GVI values will not vary much across the family, while subsystems with high GVI values will vary considerably in order to achieve the performance requirements for the different sized UGVs. For instance, the arm and gripper had high GVI values based on the different capabilities and desired functionality for each size robot; therefore, the recommendation is to modularize these subsystems and standardize their interfaces in order to allow different manipulators and grippers to be easily swapped out (and upgraded) for different missions. Batteries, on the other hand, have a low GVI value, and it appears that common batteries may be used across different UGVs; however, the number of batteries needs to be scalable given the different power requirements for small, medium, and large UGVs. Meanwhile, the chassis falls in the middle—many requirements drive chassis sizing (e.g., long vs. short and wide vs. narrow for maneuverability and stability, as well as reach capability). Note that while GVI helps identify which subsystems/components can be common between products in the family, it does not indicate what the best parameters settings are for those shared "elements"; this is the primary role for optimization in our integrated approach.

	Chassis	Battery	Flipper	Main Track	Comm Box	Elec Box	Manipulator	Mast	Head	Gripper	Cameras	Payload Bay	Antenna	OCU
Chassis		M	M	M			M	L			L	H	L	
Battery	M					M								
Flipper	M			M										
Main Track	M		M											
Communications Box						M					L		M	
Electronics Box		M			M		L			L				
Manipulator	M					L		L	M	H	L			
Mast	L						L				L			
Head							M				L			
Gripper						L	H							
Cameras	L				L		L	L	L					
Payload Bay	H													
Antenna	L				M									M
OCU													M	

Fig. 6 DSM of "generic" UGV architecture (Donaldson 2010)

(a) Bombot http://www.defensetech.org **(b)** Talon http://www.foster-miller.com **(c)** Packbot http://www.irobot.com **(d)** RONS http://www.globalsecurity.org

Fig. 5 Existing UGVs dissected and analyzed

	Subsystem										
Requirement	Chassis	Battery	Tracks	Communication box	Electronics box	Manipulator	Gripper	Cameras	Payload bay	Antennae	OCU
Range (feet)				6						6	
Slope Climb (deg)	3		3			1					
Maneuver width (in)	3		3								3
On board vol (in^3)	6				3				6		
On board wt (lb)	6				3				6		
Drag/Roll/Push (lb)	6	3	6			6	6				
Horiz reach (in)	6	3				9	1				
Vert high reach (in)	1					9	1				
Sensing type									3		
Video vert high reach (in)	1					9	1				
Large Obj Pickup (length)						3	6				
Large Obj Pickup (width)						3	6				
Large Obj Pickup (height)						3	6				
Lift capac (lb)	6					9	3				
Tool precision				1			6	1			1
Tool size (in^3)						3	6				
Tool wt (lb)						3	6				
Comm range (ft)		3		6						6	
GVI Values	**38**	**9**	**12**	**13**	**6**	**58**	**48**	**1**	**15**	**12**	**4**

Fig. 7 GVI analysis for "generic" UGV architecture (Donaldson 2010)

A subsequent analysis of each pair of UGVs (e.g., small and medium, medium and large, small and large) was used to translate these GVI recommendations to the parameter level (Donaldson 2010); in families with many variants, using Martin and Ishii's Coupling Index will be a more efficient approach (Martin and Ishii 2002). Based on this analysis, for instance, we sought to identify potential opportunities for scaling the chassis in one or more dimensions based on the threshold and objective values for each UGV pair, even though the chassis will vary across each weight class. This analysis helped us understand each subsystem at the parameter level before creating mathematical models to estimate the performance of new UGV designs. The final GVI recommendations are listed in Table 1 where an "x" indicates common settings across two or more UGVs, e.g., chassis height can be common to all three UGVS, but only the small and medium UGVs have common chassis length and width based on the threshold and objective requirements. Based on these GVI recommendations, we develop a mathematical model and use multi-objective optimization, commonality indices, and multi-dimensional data visualization to perform trade studies and determine the best parameter settings for the subsystems/components in the UGV family.

4.3 Mathematical modeling and multi-objective optimization

In order to finalize our commonality specifications for the UGV family, we developed a mathematical model to simulate system performance (Bobuk 2010; Logan 2010). The model was developed to estimate UGV capabilities for the specific threshold and objective requirements that defined each "market segment", e.g., the analysis for the chassis needed to compute its weight as well as estimate its stair climbing capability and ground clearance for obstacle avoidance. The DSM was also used to help identify subsystem interactions of interest to include in the model, e.g., the interactions between the chassis and manipulator that dictate lift capacity and center of gravity, which impacts tipping, self-righting, etc.

The model was developed in Simulink® and employed a combination of physics-based models, allometric design principles, curve fits, and look-up tables to estimate the capabilities of the different subsystems in a new UGV design alternative. The overall structure of the model is shown in Fig. 8, which is divided into 14 analysis blocks. The first 11 blocks size the specified subsystem, while the last 3 blocks compare the predicted performance against the capabilities defined for each weight class to compute an effectiveness measure for each UGV based on how well the threshold and objective values are met. The blocks are sequenced to minimize feedback loops in the model as each block relies on a combination of user-specified inputs (e.g., battery type) and inputs from other subsystems (e.g., chassis mass) in order to perform its analysis. Key parameters that serve as both inputs and outputs for analysis (e.g., chassis mass, vehicle mass, vehicle velocity) require iteration in the model as indicated by the feedback loops in Fig. 8. Even with these iterations, the model executes a complete analysis in 4 s on a moderately equipped desktop PC. Note that the model depicted in Fig. 8 generates potential designs and evaluates the design effectiveness, but it does not attempt to solve for an "optimal" design; the selection of the optimal design is performed by the designer using the trade space visualization software.

After model convergence was verified, we confirmed trends in the model, e.g., as battery size increased, vehicle range increased for a given vehicle mass and velocity. We validated the individual subsystems and overall model using data from the four existing UGVs that we dissected and analyzed (see Fig. 5). The model is linked directly to our trade space visualization software (ATSV) (Stump et al. 2009), which is used to generate new design alternatives to study the tradeoff between commonality and effectiveness in the UGV family. Details on model

Table 1 GVI recommendations for commonality in key subsystems of UGV family

Subsystem	Design parameters	Small	Medium	Large
Chassis	Length	x	x	
	Width	x	x	
	Height	x	x	x
Mobility	Wheels/tracks	x	x	x
	Wheel diameter			
	Track width			
	Wheelbase			
Batteries	Length	x	x	x
	Width	x	x	x
	Mass	x	x	x
Manipulators	Outer arm radius	x	x	
	Arm segment length	x	x	
	Number of links	x	x	

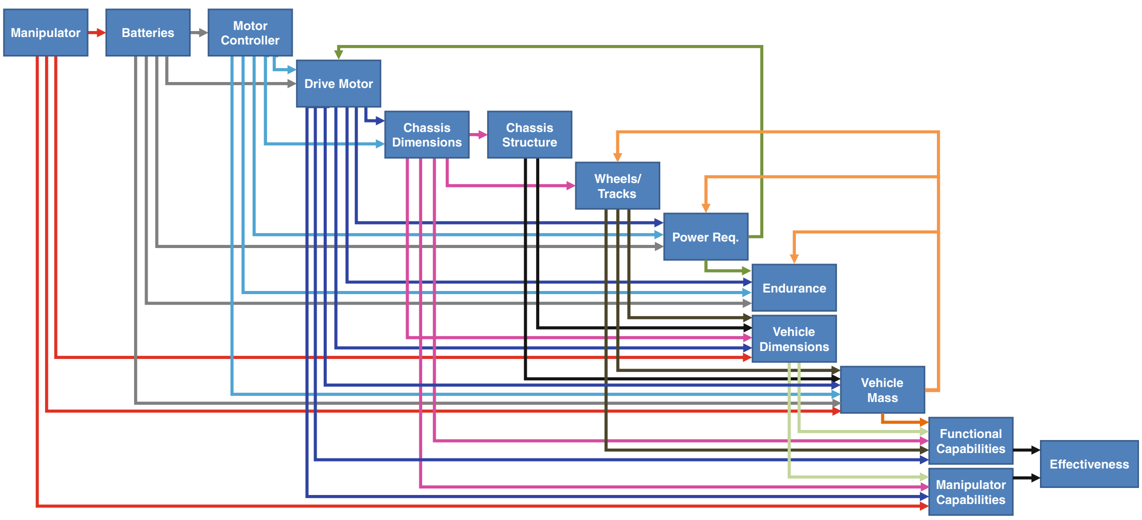

Fig. 8 System decomposition for UGV mathematical model

convergence, validation, and linking to ATSV can be found elsewhere (Bobuk 2010; Logan 2010).

Once the model is linked to ATSV, random sampling and visual steering are used to generate about 15,000 design alternatives that span the small, medium, and large weight classes. Figure 9 plots the predicted effectiveness of each UGV versus its size; the best 90 UGV designs in each weight class are highlighted in black, while the remaining designs are shown in gray. While the majority of the designs fall into the medium weight class, there are many small and large alternatives; unfortunately, while the small and medium designs appear to be relatively effective, many of the large designs in this study are not. Regardless, these design alternatives provide a basis for a product family trade study, which considers families composed of different combinations of these small, medium, and large UGVs.

4.4 Product family trade study and commonality specifications

For this product family trade study, we consider the best 90 designs from each weight class (see highlighted designs in Fig. 9) to create families based on the GVI recommendations, e.g., select a set of small, medium, and large UGVs that have common batteries, scaled chassis, and different manipulators as recommended by GVI. For each family, we compute the effectiveness of the family by averaging the individual effectiveness of each UGV as well as the dissimilarity in the family using PFPF from Eq. 1.

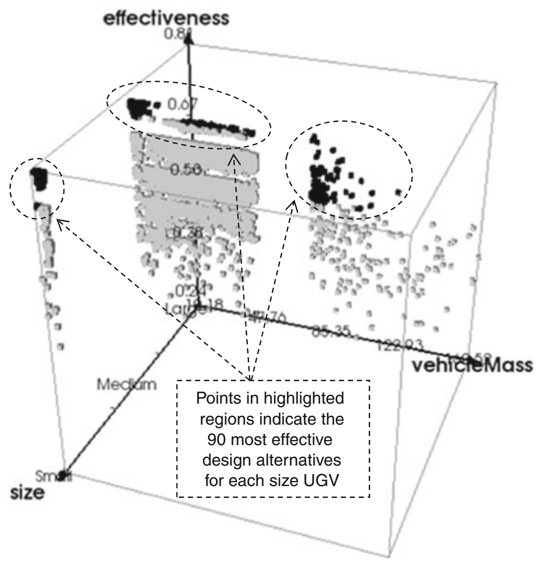

Fig. 9 Effectiveness versus size and vehicle mass

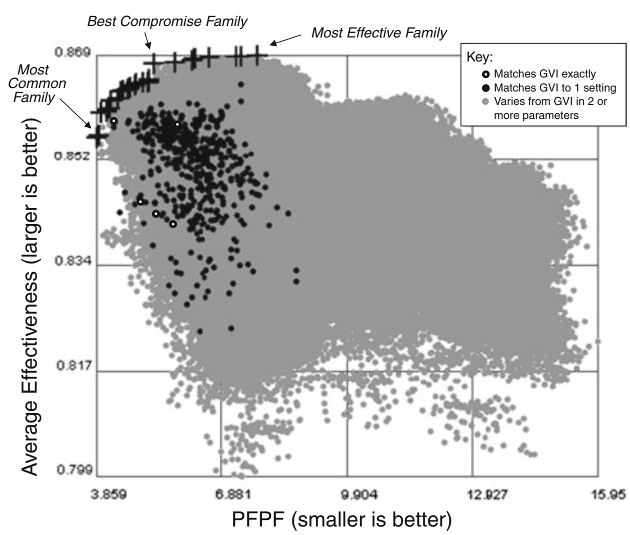

Fig. 10 UGV families based on GVI recommendations (*white/black*) and enumerated options (*gray*)

Figure 10 shows the results of this analysis with white points being an exact match with the GVI recommendations; black points match the GVI recommendations within one parameter, i.e., all but one subsystem parameter are shared as recommended by GVI. Based on this analysis, we identify five families that are an exact match and about 250 families that are within a few parameters of the GVI recommendations. Table 2 lists some of the key subsystem parameters for the five families that match the GVI recommendations. Additional parameters that are common within these families are also highlighted, indicating that we may have been too conservative and missed opportunities for commonality given the level of analysis we used.

Concurrent to identifying the GVI-based families, we enumerated all 729,000 possible UGV families (=90 small designs × 90 medium designs × 90 large designs) and computed the average effectiveness and PFPF for each family. These UGV families are shown in gray in Fig. 10. Unfortunately, when compared with all of these possible options, none of the GVI-based families fall on the Pareto frontier—the families indicated by +'s in the figure that offer the best combination of commonality (i.e., minimum PFPF) and effectiveness. Of the families located on the Pareto frontier, three are of particular interest as highlighted in the figure: (1) the Most Effective Family, (2) the Most Common Family, and (3) the Best Compromise Family. The Most Effective Family does the best job of satisfying the effectiveness requirements for the small, medium, and large UGVs (average effectiveness = 86.8%), but it has less commonality than the other families, although by no means the worst. The Most Common Family provides the opposite—it offers the most commonality among the three UGVs in the family, but this comes at a small sacrifice in performance (average effectiveness = 86.0%). Finally, the Best Compromise Family falls between the two—it has more commonality than the Most Effective Family but with less sacrifice in performance compared to the Most Common Family. In fact, the average effectiveness is 86.7%, indicating a remarkably good compromise in this family given the high degree of commonality that is achieved.

The corresponding parameter settings for these three UGV families are listed in Table 3. Parameter values that are common are highlighted in italic; similar values (i.e., values that are within 5% across two or more UGVs within a given family) are shown in bold italic. Note that even though some of the parameter values are the same across families (i.e., they all use tracks, and nearly all of them have the same battery specifications), the coding for common and similar parameter values is within a single family, not across the three families.

Comparing Tables 2 and 3, we see that UGV families that lie on the Pareto frontier have less commonality than the GVI-based families as one might expect. While key battery and manipulator parameters are made common across both sets of families along with the use of tracked designs, the families on the Pareto frontier have very few chassis parameters in common. At best, the chassis height or length is shared between the medium and large UGVs, and the small UGV has a completely different chassis in all cases. It is interesting that the results differ so much and yet the average effectiveness of the family is within 1–2% of each other given how we used the best 90 designs.

Finally, to gain more insight into the differences between the UGV families based on the GVI recommendations and the enumerated families, we code all of the

Table 2 UGV families that most closely resemble GVI recommendations

Robot	Chassis			Mobility			Batteries			Manipulator		
	Vehicle length (m)	Chassis width (m)	Chassis height (m)	Wheels (=1)/ tracks (=2)	Wheel diameter (m)	Wheel or track width (m)	Battery length (m)	Battery width (m)	Battery mass (kg)	Outer arm radius (m)	Arm segment length (m)	Number of arm links
Family 1												
Small	*0.557*	*0.227*	*0.318*	***2***	***0.261***	0.028	*0.112*	*0.062*	*1.4*	*0.021*	*0.565*	*3*
Medium	*0.592*	*0.221*	*0.334*	***2***	***0.291***	0.032	*0.112*	*0.062*	*1.4*	*0.021*	*0.524*	*3*
Large	0.665	0.301	***0.344***	***2***	0.181	0.130	*0.112*	*0.062*	*1.4*	***0.021***	0.306	***3***
Family 2												
Small	*0.544*	*0.203*	*0.079*	***2***	***0.269***	0.034	*0.112*	*0.062*	*1.4*	*0.021*	*0.134*	*3*
Medium	*0.575*	*0.191*	*0.086*	***2***	***0.279***	0.043	*0.112*	*0.062*	*1.4*	*0.021*	*0.133*	*3*
Large	0.911	0.500	***0.079***	***2***	0.121	0.061	*0.112*	*0.062*	*1.4*	***0.021***	0.112	***3***
Family 3												
Small	*0.578*	*0.208*	*0.080*	***2***	***0.277***	0.030	*0.112*	*0.062*	*1.4*	*0.021*	*0.569*	*3*
Medium	*0.603*	*0.205*	*0.080*	***2***	***0.297***	0.035	*0.112*	*0.062*	*1.4*	*0.021*	*0.568*	*3*
Large	0.911	0.500	***0.079***	***2***	0.121	0.061	*0.112*	*0.062*	*1.4*	***0.021***	0.112	***3***
Family 4												
Small	*0.646*	*0.223*	*0.350*	***2***	***0.307***	0.025	*0.112*	*0.062*	*1.4*	*0.021*	*0.104*	*3*
Medium	*0.608*	*0.224*	*0.320*	***2***	***0.301***	0.035	*0.112*	*0.062*	*1.4*	*0.021*	*0.110*	*3*
Large	***0.665***	0.301	***0.344***	***2***	0.181	0.130	*0.112*	*0.062*	*1.4*	***0.021***	0.306	***3***
Family 5												
Small	*0.643*	*0.234*	*0.349*	***2***	0.307	0.021	*0.112*	*0.062*	*1.4*	*0.021*	*0.104*	*3*
Medium	*0.608*	*0.224*	*0.320*	***2***	0.301	0.035	*0.112*	*0.062*	*1.4*	*0.021*	*0.110*	*3*
Large	***0.665***	0.301	***0.344***	***2***	0.181	0.130	*0.112*	*0.062*	*1.4*	***0.021***	0.306	***3***

Italic values both GVI and PFPF suggest commonality, *bold italic values* PFPF suggests additional commonality, *unformatted values* neither GVI nor PFPF suggest commonality

families in Fig. 10 based on how closely they "match" the GVI recommendations and plot the results in Fig. 11. The scale in Fig. 11 shows that the families range from a complete or very close match (dark gray) to little to no match (light gray). As expected, the closer the match to GVI, the lower the PFPF values (i.e., the more commonality), and the tradeoff is remarkably favorable: families with high PFPF values (i.e., less commonality) actually do not perform well either. Based on the results in Fig. 9, we conclude that this drop-off in effectiveness is driven largely by the poorly performing large UGVs in this study. Apparently, these poorly performing designs are also very dissimilar to the small and medium designs, while the most effective large designs also have a lot in common with the small and medium designs. In many situations, this may not be the case; however, this is a promising and useful finding from this product family trade study.

An important take-away from this analysis is that GVI may suggest too much commonality because it was performed at the subsystem/component level (e.g., make the chassis common) and not at the parametric level (e.g., the chassis should have common height and width but the length should be scaled). Furthermore, GVI analysis is performed for the entire family and may miss opportunities for commonality between subsets of products within the family (e.g., the small and medium chassis can be common but the large chassis should be unique). In both cases, using GVI in concert with quantitative analysis—a mathematical model of the system and optimization—will provide additional insight into the commonality-performance tradeoffs within the family. Furthermore, quantifying the benefits of parametric commonality on manufacturing and assembly cost savings may help with future product family trade studies (De Lit and Delchambre 2003; Jiao et al. 2005). In this UGV product family trade study, we are fortunate that the effective small, medium, and large designs tended to have a lot of commonality; however, that may not happen in practice. This is why multi-dimensional data visualization is important to product family trade studies: the ability to "see" trends in the data is critical to making effective design decisions particularly when identifying the platform elements within a family. Plots like Fig. 10 and 11 clearly illustrate the tradeoff between commonality and performance within the product family as it is being designed.

Table 3 Common, similar, and unique parameter settings in the UGV Pareto Frontier

Robot	Chassis			Mobility			Batteries			Motors		Manipulator		
	Vehicle length (m)	Chassis width (m)	Chassis height (m)	Wheels (=1)/tracks (=2)	Wheel diameter (m)	Wheel or track width (m)	Battery length (m)	Battery width (m)	Battery mass (kg)	Drive motor diameter (m)	Drive motor length (m)	Outer arm radius (m)	Arm segment length (m)	Number of arm links
Best compromise family														
Small	0.542	0.206	0.198	2	0.264	0.033	*0.112*	*0.062*	1.4	*0.064*	*0.096*	*0.021*	0.418	3
Medium	0.788	0.416	***0.249***	2	0.078	0.039	*0.112*	*0.062*	2.8	*0.064*	*0.096*	*0.021*	***0.243***	3
Large	1.007	0.498	***0.257***	2	0.175	0.058	*0.112*	*0.062*	2.8	*0.064*	*0.096*	*0.021*	***0.229***	3
Most common family														
Small	0.543	0.224	0.135	2	0.251	0.025	*0.112*	*0.062*	*1.4*	0.079	0.112	*0.021*	0.105	3
Medium	0.732	0.409	***0.163***	2	0.051	***0.047***	*0.112*	*0.062*	*1.4*	0.063	0.096	*0.021*	0.283	3
Large	1.007	0.475	***0.170***	2	0.178	***0.049***	*0.112*	*0.062*	*1.4*	0.052	0.083	*0.021*	0.218	3
Most effective family														
Small	0.543	0.224	0.135	2	0.251	0.025	*0.112*	*0.062*	*1.4*	0.079	0.112	*0.021*	0.105	3
Medium	***0.792***	0.418	0.236	2	0.057	0.033	*0.112*	*0.062*	*1.4*	0.051	0.082	*0.021*	0.292	3
Large	***0.763***	0.371	0.117	2	0.115	0.108	*0.112*	*0.062*	2.8	0.064	0.096	***0.022***	0.408	3

Italic values common values, ***bold italic values*** similar (<5%) values, *unformatted values* no commonality

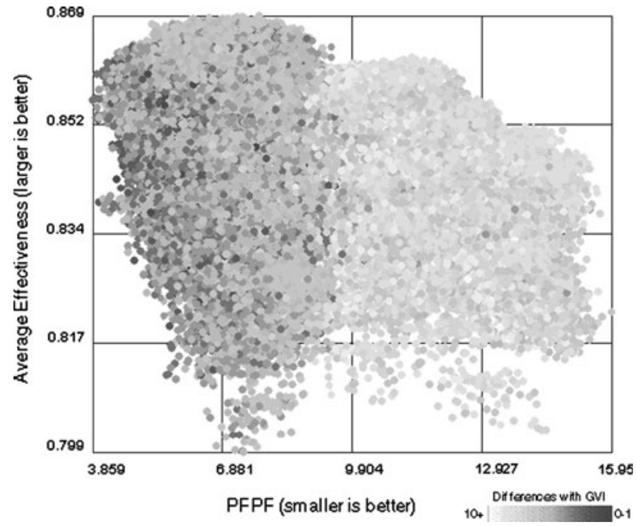

Fig. 11 Comparison of GVI-based families with enumerated families

5 Closing remarks and future work

This paper introduces an integrated approach to product family design that links several existing methods and tools within a three-step framework to help translate user requirements into commonality specifications for the family. The integrated approach includes both qualitative (e.g., market segmentation grid, GVI) and quantitative (e.g., multi-objective optimization, commonality indices) measures with multi-dimensional data visualization to realize an effective approach for product family design. The proposed approach is applied to the design of a family of unmanned ground vehicles (UGVs) to demonstrate its effectiveness and shed light on its shortcomings. Families of UGVs are successfully created based on the recommendations from GVI as well as through enumeration of all possible combinations of small, medium, and large designs. While the GVI-based families do not fall directly on the Pareto frontier, they provide reasonably good solutions that are very close to the best families that can be obtained. As such, using GVI to guide product family formation from sets of existing designs provides a basis for future work in product family commonality selection.

The impetus for this work was integrating several disparate methods and tools that existed in the literature into a coherent framework that can help translate user requirements into commonality specifications. In many cases, designers may not have the mathematical models necessary for multi-objective optimization and product family trade studies; in which case, using qualitative tools the market segmentation grid, GVI, and DSM can still assist designers in determining preliminary commonality specifications for the family, and the proposed framework is flexible enough to accommodate addition tools and methods based on the product family designer's specific needs. The next step is to integrate the tools into a single software package—the entire process would be expedited, and errors would be minimized, if the output from one tool fed directly into the input of another, which was not the case in this example. Finally, depending on the computational expense of the models involved, some multi-objective optimization approaches may become intractable and limit the ability to "steer and interact" with the data while it is being generated.

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