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Decentralized Determination Of Design Variables Among Cooperative Designers For A General Aviation Aircraft Product Family

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Abstract The objective of this paper is to provide a mechanism to determine design variables among cooperative designers in a decentralized decision-making environment where decision authority and information are dispersed among autonomous designers. We demonstrated this using a General Aviation Aircraft product family design problem by applying an augmented Lagrangian-based algorithm such that the designers achieve a common goal without having a global view of the entire decision environment. The results showed that quality solutions can be obtained in decentralized environments with less information exchange and comparatively minimal designer computational effort.

Keywords Product family, Product platform design, Decentralized coordination, Non-linear multi-objective optimization, Multi-agent

1. Introduction

A product family refers to a set of products that share components and/or functions, while each product maintains its unique specifications [1]. The common parts or components shared among the products in a family is termed a product platform [2]. With a product family, companies can leverage mass customization by providing a variety of products meeting demands from different market segments. Pirmoradi et al. [1] highlights three stages that make up the product family development process: the first stage, comprises the translation of identified customer needs into functional requirements; in the second stage, functional requirements are mapped to design variables, and the third stage involves process planning and determination of process variables. The focus of platform-based product family design is ensuring that the design variables determined in the second stage are feasible for the desired functionality. Jiao et al. [3] mentions scalable approach as one method to design platform-based product family. Scalable approach involves two stages; determination of design variables that take common values (also known as platform selection) followed by the search for the optimal values of both common and distinct variables subject to performance requirements. The platform selection can be assumed to be known *a priori* [3].

If the product platform is known and the percent degree of commonality [4] —the ratio of the common-valued variables to the total number of variables is known, then the only problem is determination of the optimal values of these design variables. Finding an optimal design value is a complicated task for a number of reasons. One is the platform strategy. For instance, with a single product platform strategy (restricted commonality [5]) all the design variables are shared by the entire products in the family and so it offers a great deal of computational simplicity.However, with this platform strategy low-end products may be over-designed while high-end products may be under-designed [6]. For a multiple product platform alternative (also known as generalized commonality [5]), design variables can be shared by any subset of the products within the family and so favors a wider coverage of the solution space, but, it is computationally complex [7]. Additionally, the design problem of the product family is structural and collaborative where different views need to be solicited to make a decision [8]. Consequently, the determination of the design variables must explicitly consider the impact of all product designers involved simultaneously during decision-making and that requires a decentralized mechanism. Our focus in this work therefore, is the realization of design variables for a product platform using a decentralized coordination mechanism. Decentralized here means that no designer associated with the development of the product family has the entire necessary information to determine the design variables independently.

Related studies include: Text mining and tree matching techniques, employed by Jiao et al. [9] to cope with structural and textual data types underlying the common operations routings shared among production processes for products of the same family in process platform development. Moon et al. [10] introduced a dynamic multi-agent system for product family design using an auction-based negotiation mechanism by modeling the agent environment as an electronic market. In the work, Moon et al. [10] determined the appropriate number of common modules and further introduced a mathematical model that reflects the tradeoffs in product platform establishment. Thevenot et al. [11] studied the design for commonality and diversity method (DCDM) for designers based on two commonality indices, that is, a comprehensive metric for commonality and the commonality diversity index. Moon et al. [12] proposed a multi-objective particle swarm optimization (MOPSO) algorithm to identify platform design variables for a product family.

The problem in this paper considers a single product platform product family design environment assuming the design variables and degree of commonality is known *a priori*. The proposed decentralized mechanism allows each designer to maintain autonomy while sharing information with other designers to achieve a common goal. We also present a model of the problem where no single designer has a global view of the environment.

The remainder of the work herein proceeds as follows: we present the General Aviation Aircraft (GAA) problem section 2. The proposed model, algorithm and results are discussed in section 3 and finally conclude the work in section 4.

2. GAA product family platform design problem

The GAA product platform design problem is about the development of differentiated aircrafts from a common platform thereby allowing mass customization. The product family involves three aircrafts to accommodate 2-, 4- and 6-seater configuration. Key issues of concern include maximization of commonality and reduction of performance losses. The objective of the problem is to determine the best values of key design variables (table 1) satisfying both performance and economic requirements. Details of the problem can be found in Moon et al. [12].

Table 1 shows the selected design variables for the GAA problem and the designers assigned to them. Min and Max in table 1 represent the minimum and maximum allowable values for each design variable. Rep means the concise representation of the design variable

TABLE 1. Selected GAA design variables.

Design variable	Name	Min.	Max	Rep.	Designer-in-charge
Cruise Speed	CSPD	0.24	0.48	y_1	Engine
Aspect Ratio	AR	7	11	y_2	Wing
Sweep Angle	SWEEP	0	6	y_3	Wing
Propeller Diameter	DPROP	5.5	5.986	y_4	Engine
Wing Loading	WINGLD	19	25	y_5	Wing
Engine Activity Factor	AF	85	110	y_6	Engine
Seat Width	SEATW	14	20	y_7	Fuselage
Tail Length/Diameter Ratio	ELODT	3	3.75	y_8	Wing
Taper Ratio	TAPER	0.46	1	y_9	Wing

in the model. Design variables are controlled only by the designer-in-charge and the platform designer. Assignment of the design variables and the responses to their respective designers is based on experts' opinion. Significant parameters (responses) that measure the performance of the aircraft are given in table 2. These responses are selected in accordance with the work of Moon et al [12]. The response-designer assignment is used in the development of the model in section 3. Similar to the design variables, only the assigned designer to the response has knowledge of the response function and does not share with other designers.

TABLE 2. Goal targets for GAA 2-, 4- and 6-seater product family.

			2-seater		4-seater		6-seater		
Response	Name	Pref.	Limit	Goal	Limit	Goal	Limit	Goal	Designer
Takeoff Noise (dB)	NOISE	min	75	-	75	-	75	-	Engine
Empty Weight (lb)	WEMP	min	2200	1900	2200	1950	2200	2000	Fuselage
Direct Operating Cost ($/h)	DOC	min	80	60	80	60	80	60	Platform
Ride Roughness	ROUGH	min	2	-	2	-	2	-	Platform
Fuel Weight (lb)	WFUEL	min	450	450	475	400	500	350	Platform
Purchase Price ($ in 1970)	PURCH	min	-	41000	-	42000	-	43000	Platform
Flight Range (nm)	RANGE	max	2000	2500	2000	2500	2000	2500	Engine
Max L/D	LDMAX	max	-	17	-	17	-	17	Wing
Max Cruise Speed (kts)	VCMAX	max	-	200	-	200	-	200	Wing

In table 2, goals represent the desired response values to be attained and the limit values indicate the minimum or maximum values that serve as upper or lower bounds respectively. Values within the range of the upper or lower bounds and the goal are considered as acceptable. Note that the responses are functions of the design variables and have been omitted for brevity. The main goal of the GAA product family design problem [13] is to determine design variables that:

(1) minimize DOC, PURCH and WEMP to their targets
(2) maximize VCMAX, RANGE and LDMAX to their targets
(3) satisfy limits for NOISE, ROUGH, DOC, WEMP, WFUEL and RANGE.

3. Model description

To achieve a decentralized setting, we separate the decision-making over the following product designers; fuselage, engine and wing. We introduce an artificial platform designer that coordinates the decision process. Let P denote the set of products, that is, 2-, 4- and 6-seaters where product 1 is the 2-seater and so on. Let vectors $\boldsymbol{l}$ and $\boldsymbol{d}$ denote the limits and goals for each product respectively. Here, l_p and d_p represent the limit and goal of a response respectively for product p. Also let ub_j and lb_j represent the upper and lower bounds of design variable j given in table 1 as the Min and Max values.

The proposed algorithm is in two phases. First phase assumes an independent design environment where product designers determine values for their respective design variables. From phase I we obtain multiple solutions. Table 3 presents the problems for each designer in phase I of the algorithm. In our model, designers do not share constraints and objective function form with other designers. Also, the constraints are same for both phase I and phase II. With the exception of the platform designer, the product designers only control a subset of the design variables. Let vector $\boldsymbol{y}^{designer}$ denote the set of variables controlled by a designer. We also introduce a Lagrangian multiplier vector $\boldsymbol{\pi}$ which is used to ensure a compromise among the designers. Likewise $\boldsymbol{\pi}^{designer}$ is the sub vector of multipliers associated with the variables the designer is in charge of. Also $\boldsymbol{ub}^{designer}$ and $\boldsymbol{lb}^{designer}$ follows similar pattern. For example, $\boldsymbol{y}^{wing} = \{y_2, y_3, y_5, y_8, y_9\}$. Let vector $\boldsymbol{z}$ be the copy of the design vector $\boldsymbol{y}$ controlled by the platform designer. Then it suffices to say that an agreed solution means $\boldsymbol{y} = \boldsymbol{z}$. During a product designer-platform designer interaction we denote the subset of platform designer variables sent to a product designer for negotiation by $\boldsymbol{z}^{designer}$. In addition, let $\boldsymbol{z}_{out}^{designer} = \{\boldsymbol{z} - \boldsymbol{z}^{designer}\}$. To illustrate, if $\boldsymbol{z}^{wing} = \{z_2, z_3, z_5, z_8, z_9\}$ then $\boldsymbol{z}_{out}^{wing} = \{z_1, z_4, z_6, z_7\}$.

Table 3. Designer problems

Designer	Phase I problem	Phase II problem
Fuselage	Min $\sum_{p=1}^{\|P\|} \|WEMP_p - d_p\| + \boldsymbol{y}^{fuselage}\boldsymbol{\pi}^{fuselage} + \frac{\rho}{2}\|\boldsymbol{y}^{fuselage} - \boldsymbol{z}^{fuselage}\|^2$ st. $WEMP_p \le l_p, \forall p \in P$ $\boldsymbol{lb}^{fuselage} \le \boldsymbol{y}^{fuselage} \le \boldsymbol{ub}^{fuselage}$	Min $\sum_{p=1}^{\|P\|} \|WEMP_p - d_p\| + \boldsymbol{y}^{fuselage}\boldsymbol{\pi}^{fuselage} + \frac{\rho}{2}\|\boldsymbol{y}^{fuselage} - \boldsymbol{x}^{fuselage}\|^2 + \frac{\rho}{2}\|\boldsymbol{y}^{fuselage} - \boldsymbol{y}^{fuselage*}\|^2$
Wing	Min $\sum_{p=1}^{\|P\|} \|VCMAX_p - d_p\| + \boldsymbol{y}^{wing}\boldsymbol{\pi}^{wing} + \frac{\rho}{2}\|\boldsymbol{y}^{wing} - \boldsymbol{z}^{wing}\|^2$ st. $LDMAX_p \le d_p, \forall p \in P$ $\boldsymbol{lb}^{wing} \le \boldsymbol{y}^{wing} \le \boldsymbol{ub}^{wing}$	Min $\sum_{p=1}^{\|P\|} \|VCMAX_p - d_p\| + \boldsymbol{y}^{wing}\boldsymbol{\pi}^{wing} + \frac{\rho}{2}\|\boldsymbol{y}^{wing} - \boldsymbol{x}^{wing}\|^2 + \frac{\rho}{2}\|\boldsymbol{y}^{wing} - \boldsymbol{y}^{wing*}\|^2$
Engine	Min $\sum_{p=1}^{\|P\|} \|RANGE_p - d_p\| + \boldsymbol{y}^{engine}\boldsymbol{\pi}^{engine} + \frac{\rho}{2}\|\boldsymbol{y}^{engine} - \boldsymbol{z}^{engine}\|^2$ st. $NOISE_p \le l_p, \forall p \in P$ $RANGE_p \ge l_p, \forall p \in P$ $\boldsymbol{lb}^{engine} \le \boldsymbol{y}^{engine} \le \boldsymbol{ub}^{engine}$	Min $\sum_{p=1}^{\|P\|} \|RANGE_p - d_p\| + \boldsymbol{y}^{engine}\boldsymbol{\pi}^{engine} + \frac{\rho}{2}\|\boldsymbol{y}^{engine} - \boldsymbol{x}^{engine}\|^2 + \frac{\rho}{2}\|\boldsymbol{y}^{engine} - \boldsymbol{y}^{engine*}\|^2$
Platform designer	Min $\sum_{p=1}^{\|P\|} (\|PURCH_p - ld_p\|) + \sum_{j=1}^{9} -\pi_j z_j + \frac{\rho}{2}\sum_{j=1}^{9} \|y_j - z_j\|^2$ st. $d_p \le DOC_p \le l_p, \forall p \in P$ $ROUGH_p \le l_p, \forall p \in P$ $l_p \le WFUEL_p \le d_p, \forall p \in P$ $lb_j \le y_j \le ub_j, \forall j \in \{1, 2, ..., 9\}$	Min $\sum_{j=1}^{9} \|y_j - z_j\|^2 + \sum_{j=1}^{9} \|z_j - x_j\|^2$

From phase I, each designer in collaboration with the platform designer obtains a solution denoted by $\boldsymbol{y}^{designer*}$. Here $\boldsymbol{y}^{designer*} = \{\boldsymbol{y}^{designer} \cup \boldsymbol{z}_{out}^{designer}\}$. A solution is obtained when $\boldsymbol{y}^{designer} = \boldsymbol{z}^{designer}$. These solutions are stored privately by each designer. At the start of phase II of the algorithm, the platform designer selects at random one of the designers' solution which we denote by $\boldsymbol{x}$. Then the product designers and the platform designer now enter an iterative negotiation to find a common set of design varaibles accetable to all designers. Using the same nomenclature pattern as explained earlier we modify the objective functions for the designers in phase II (given in table 3).

The proposed algorithm is as follows:

Phase I

(1) Initialize $r = 0, H = \{\emptyset\}$, $\beta^r = \{\emptyset\}$, δ
Let r be the overall iteration number and t be the iteration number for phase I.
Let $\boldsymbol{y}^{designer*}$ be the solution for a product designer in phase I.
$\boldsymbol{x}$ is the target solution and let H be a set containing $\boldsymbol{y}^{designer*}$
Let $\boldsymbol{\beta}^r$ be a vector of solution deviation from target solution at iteration r.
Let δ be an infinitesimal value (convergence criterion)

(2) **For** all *product designers*:
Given $t = 0$ and set arbitrarily $(\boldsymbol{\pi}^{designer})^t > 0, (\boldsymbol{z}^{designer})^t > 0$
While $|(\boldsymbol{y}^{designer})^t - (\boldsymbol{z}^{designer})^t| > \delta$
Solve phase I product designer problem for $(\boldsymbol{y}^{designer})^{t+1}$
Solve platform designer problem for $(\boldsymbol{z}^{designer})^{t+1}$
If $|(\boldsymbol{y}^{designer})^{t+1} - (\boldsymbol{z}^{designer})^{t+1}| \leq \delta$,
Stop and let $\boldsymbol{y}^{designer*} = \{(\boldsymbol{y}^{designer})^{t+1} \cup (\boldsymbol{z}_{out}^{designer})^{t+1}\}$
Store $\boldsymbol{y}^{designer*}$in H,
Else
$(\boldsymbol{\pi}^{designer})^{t+1} = (\boldsymbol{\pi}^{designer})^t + \rho[(\boldsymbol{y}^{designer})^{t+1} - (\boldsymbol{z}^{designer})^{t+1}]$
$t = t + 1$
Goto step 2 of phase I.
End while
End for

Phase II

(1) Select at random product designer a and let $\boldsymbol{x}^r = \boldsymbol{y}^{a*} in H$
(2) ***For*** all *product designers*:
Solve phase II product designer problem $(\boldsymbol{y}^{designer})^{r+1}$
Compute $\beta^r_{designer} = \|[\boldsymbol{y}^{designer})^{r+1} \cup (\boldsymbol{z}_{out}^{designer})^r - \boldsymbol{x}^r\|^2$
Solve phase II platform designer problem for $(\boldsymbol{z}^{designer})^{r+1}$
End for
Select product designer b with $\tau^r =$ arg max (β^r)
If $\tau^r \leq \delta$
Stop
Else $\boldsymbol{x}^{r+1} = (\boldsymbol{y}^b \cup \boldsymbol{z}^b_{out})^{r+1}$

(3) $(\boldsymbol{\pi}^{designer})^{r+1} = (\boldsymbol{\pi}^{designer})^r + \rho[(\boldsymbol{y}^{designer} \cup \boldsymbol{z}_{out}^{designer})^{r+1} - \boldsymbol{x}^{r+1}]$
$r = r + 1$,
Goto step 2 of phase II.

4. Results and discussion

The proposed algorithm was implemented in MATLAB R2016b and the experiment conducted on a 2.85GHz Intel i5 CPU with 8GB RAM. Since the response variables are nonlinear functions of the design variables, it implies that the product designers' and platform

designer's problems are non-linear. The non-linear problems were solved using a Sequential Quadratic Programming (SQP) algorithm implemented in MATLAB R2016b. We consider two cases —no commonality and all commonality. No commonality means the 2-, 4- and 6- seater aircrafts (or products 1, 2 and 3) are considered separately during optimization and all commonality means simultaneously optimizing the design variables for the 3 different products. Table 4 shows the results from the proposed algorithm for the two cases considered. In the no commonality, the design variable for each of the aircrafts is different as the variables are not under equality restrictions across the three products. Only one design variable (TAPER) is the same across the three products while all others are different. For the all commonality case, all the design variables have the same values across the three products.

Table 4. Decentralized algorithm solution.

	No commonality case			All commonality case		
Name	2-seater	4-seater	6-seater	2-seater	4-seater	6-seater
CSPD	0.240	0.290	0.327	0.240	0.240	0.240
AR	7.000	7.477	7.543	7.000	7.000	7.000
SWEEP	2.895	6.000	6.000	0.000	0.000	0.000
DPROP	5.5010	5.500	5.500	5.500	5.500	5.500
WINGLD	21.210	24.853	25.000	21.214	21.214	21.214
AF	85.000	110.000	103.573	85.000	85.000	85.000
SEATW	18.455	15.825	16.844	18.736	18.736	18.736
ELODT	3.000	3.000	3.750	3.000	3.000	3.000
TAPER	0.460	0.460	0.460	0.512	0.512	0.512

Table 5. Comparison with centralized algorithm for no commonality case.

		Decentralized			Centralized		
Response	Pref.	2-seater	4-seater	6-seater	2-seater	4-seater	6-seater
NOISE	min	**73.261**	**73.278**	**73.283**	73.473	73.543	73.527
WEMP	min	1881.046	1860.378	1906.390	**1883.218**	**1911.743**	**1939.535**
DOC	min	**63.667**	**72.795**	79.339	73.870	73.728	**74.217**
ROUGH	min	2.000	**1.924**	**1.848**	**1.993**	1.967	1.945
WFUEL	min	**450.000**	474.866	427.729	449.996	**420.877**	**392.109**
PURCH	min	**41812.960**	**42003.018**	**42913.894**	42372.702	42853.739	43349.341
RANGE	max	**2540.550**	2010.949	1999.999	2113.788	**2015.341**	**2011.880**
LDMAX	max	15.172	15.437	**15.571**	**15.886**	**15.554**	15.440
VCMAX	max	191.992	**200.396**	**200.104**	**198.546**	197.412	195.963

Bold face indicates the better value.

We now compare our results to the centralized algorithm proposed by Moon et al. [12] in Table 5. The 9 responses are categorized as goal-responses and limit-responses. In the case of the limit-responses, we regard that the response values from either of the algorithms are satisfactory as long as they fall within the limits (i.e. NOISE and ROUGH) and say one outperforms the other in terms of the response preference, i.e., lower value for min preference and larger value for max preference. For the goal-responses (i.e. WEMP, DOC, WFUEL, PURCH, RANGE, LDMAX and VCMAX), the performance is measured by the deviation of the response values from the goal. If two responses have the same deviations from the goal, then similar to the limit responses, the smaller (larger) value is considered to outperform the other in the case of min (max) response preference. For the 2-seater aircraft, the proposed algorithm achieved the more preferred value for 5 out of the 9 responses; 5 out of 9 responses for both 4-seater and 6-seater aircrafts. Both the proposed decentralized algorithm and the

Table 6. Comparison with centralized algorithm for all commonality case.

		Decentralized			Centralized		
Response	Pref.	2-seater	4-seater	6-seater	2-seater	4-seater	6-seater
NOISE	min	**73.262**	**73.262**	**73.261**	73.610	73.611	73.611
WEMP	min	**1889.946**	1924.417	1949.856	1917.698	**1954.067**	**1983.545**
DOC	min	**63.650**	**64.567**	**64.850**	78.730	79.090	79.479
ROUGH	min	1.994	1.983	1.957	**1.959**	**1.944**	**1.919**
WFUEL	min	**440.927**	**406.318**	380.351	414.697	376.954	**346.294**
PURCH	min	**41964.950**	**42521.994**	**43029.668**	42926.636	43499.990	44034.615
RANGE	max	**2477.240**	**2393.213**	**2370.948**	2141.048	2076.830	2044.719
LDMAX	max	15.104	14.872	14.832	**15.713**	**15.391**	**15.239**
VCMAX	max	191.505	189.413	189.065	**196.024**	**193.593**	**192.199**

Bold face indicates the better value.

centralized algorithm satisfied the limit for the limit-responses. In the all commonality case, the proposed algorithm achieved the more preferred value for 6 out of the 9 responses; 5 out of 9 responses for the 4-seater and 4 out of 9 responses for the 6-seater aircrafts. Our results indicate a more unique family of aircrafts in the no commonality case than the centralized approach. Since both approaches do not violate any of the constraints and are arguably similar in terms of average deviation from goals, the choice for a particular alternative must be based on other factors such as cost. Take for instance the two response variables, DOC (direct operating cost) and PURCH (purchase price) in the no commonality case. Purchase price on average (for the 3 aircrafts) for the decentralized approach is approximately \$42243 and \$42858 for the centralized approach. This represents about \$615(1.4%) in monetary savings for the decentralized approach. Also, we have on average about \$74/h DOC for the centralized approach compared to \$72/h for the decentralized approach accounting for about 2.7% savings in direct operation costs again favoring the decentralized approach. Using the same analysis, there is on average about 2.3% and 18.6% savings in purchase price and direct operating costs respectively in favor of the decentralized approach for the all commonality case.

5. Conclusion

In this paper, we have discussed a decentralized decision-making mechanism that can generate a solution for a product family design problem when the degree of commonality in the family is given. We have also proposed a mathematical model that supports agent-based collaborative decision-making in design environments under information restrictions. Our objective for comparison with the centralized algorithm is not to show that the proposed algorithm generates better solutions but to show that an acceptable solution can be obtained. Since the method generates a single solution it is applicable in optimization domains where decision-makers have no prior preferences, that is, use the solution obtained as a starting point to obtain comparatively better solutions. Future research could focus on simultaneous determination of the product platform and optimal values of the design variables.

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