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COMPOSITIONAL MODELLING OF FLUID POWER SYSTEMS USING PREDICTIVE TRADEOFF MODELS

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Abstract

System-level decisions can have a large impact on the success of any design project, including those in the fluid power domain. Regardless of efforts by designers to optimize individual fluid power components, poor decisions at the systems level can lead to poor system performance and unsatisfied design requirements. In this paper, the principles of system-level decision making are applied to the design of fluid power systems. Describe a methodology for modelling fluid power component technology using predictive modelling and data mining techniques in a way that facilitates system-level modelling and decision making is described. This approach is demonstrated on the design of a hydraulic log splitter.

Keywords: systems design, tradeoff modelling, parameterized Pareto frontiers

1 A Systems Perspective on Fluid Power Systems Design

The success of a design project involving fluid power technology depends on how well designers manage tradeoffs from a system-level perspective. For example, poor choices about circuit topology can limit efficiency and system performance regardless of how well designers optimize individual components. Even for a good topology choice, failure to relate system-level requirements to component specifications appropriately can limit system performance.

According to the principles of systems engineering, designers should approach systems design problems using a top-down hierarchical approach, with high-level decisions between alternative architectures and technologies preceding decisions about implementation details (Royce, 1970; Boehm, 1988; Forsberg and Mooz, 1992; Buede, 2000; Sage and Armstrong Jr., 2000). The systems engineering approach can be effective for designing fluid power systems because such systems are comprised of well-defined functional components, e.g., pumps, valves, and accumulators, to which designers can allocate system-level requirements (also called requirements flowdown or requirements derivation). To decide between alternative configurations (e.g., load-sensing versus constant-displacement) or technologies (e.g., vane pumps versus gear pumps), designers can compare the "sized" system alternatives in light of their decision-making preferences.

Many of the requirements allocation procedures in common practice are effective within a limited scope, but are deficient from the perspective of system-level decision making. Designers usually are willing to make sacrifices in one system attribute in order to achieve gains in another (e.g., giving up technical performance to save cost, paying extra for increased reliability). However, many requirements allocation procedures force designers to assume fixed values for certain attributes in order to compute others and to neglect attributes beyond a fairly narrow scope (for examples from the fluid power industry, see (Sauer-Sundstrand Co., 1997; Eaton Corp., 1998)). Although such procedures are useful for verifying that a system meets its minimum technical requirements, they are insufficient for system-level decision making.

One alternative is to use parametric optimization techniques to search for the best combination of component-level attributes for a given system configuration. However, this approach easily can yield component requirements that designers cannot meet (e.g., high performance at unrealistically low cost). System

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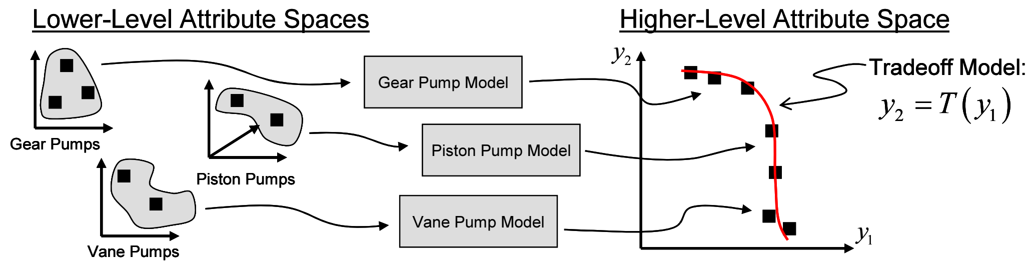

Fig. 1: *Visualization of the distinction between tradeoff models and the models typically used for evaluating designs*

designers can avoid this problem, but to do so requires accurate models of the relationships among the component-level attributes that can be difficult to create.

The focus of this article is on defining and demonstrating an approach by which the designers of fluid power systems can make sound requirements allocation decisions. The approach is based on predictive tradeoff modelling, which is a data-driven means for abstracting the capabilities of a system or technology in a way that is useful for system-level decision making (Malak and Paredis, 2007; Malak et al., 2008). One generates a tradeoff model for a type of component (e.g., pumps, cylinders, engines) based on data about existing implementations of it. This allows one to capture relationships between attributes for which a precise causal relationship may be unknown or difficult to derive analytically (e.g., ram force and cost, mass and maximum flow rate). Given a library of such models, designers can compose a model for a system-level design alternative using standard modelling and simulation practices and evaluate the alternative using optimization methods. Compared to approaches for selecting components from a database (e.g., (Papadopoulos and Davliakos, 2004; Hansen et al., 2005)), this approach permits designers to identify novel combinations of component attributes while being confident that the solution is both feasible from a technical standpoint and desirable from a decision making standpoint.

A mathematical basis for tradeoff modelling has been established previously. The focus here is on defining a methodology suitable for fluid power systems and demonstrating it on the design of a hydraulic log splitter. Section 2 is an overview of tradeoff modelling and a description of the proposed modelling methodology. Section 3 is a discussion of tradeoff model generation for common hydraulics components from a database of component attribute data. Section 4 is a demonstration of using a tradeoff models to model the hydraulics system of a log splitter. Section 5 is a comparison of the decision reached using tradeoff modelling to the results of an exhaustive search of the database of components used to generate the tradeoff models.

2 Overview of Compositional Tradeoff Modelling

2.1 Tradeoff Modelling

Tradeoff modelling is an approach to abstracting the capabilities of a system or technology in a manner that is useful for system-level decision making. A tradeoff is a compromise designers must make when a decision involves conflicting objectives (e.g., to maximize efficiency while also minimizing cost). Tradeoff models capture relationships between attributes at one level of abstraction that occur due to the structure of the system at lower levels of abstraction (e.g., a relationship between efficiency and cost due to manufacturing, materials, or other constraints). Designers identify these relationships using data about existing design implementations, which enables them to generate models without knowing the underlying causal mechanism and helps ensure that predictions correspond to feasible designs. This is in contrast with the engineering analysis models designers typically use, which relate attributes at different levels of abstraction and often are physics-based. For example, a traditional model for a hydraulic piston pump might compute pump displacement as a function of piston dimensions, whereas a tradeoff model might relate pump displacement to cost or efficiency. Figure 1 is an illustration of this distinction.

Using predictions from a tradeoff model, designers can compare alternative system concepts and establish requirements for the detailed design of their components. As a simple example, designers could predict whether a load-sensing or constant-displacement circuit is preferable for their problem and, in the process, identify requirements (in terms of target attribute values) for designing the pump, valves and other components. Predictions depend on the preferences of a particular designer, so multiple designers can use the same tradeoff model and produce predictions appropriate for their respective problems.

Prior investigation of tradeoff modelling covers both decision making for cases in which risk is negligible (Malak and Paredis, 2007; Malak et al., 2008) and decision making under uncertainty (Malak and Paredis, 2008). The focus of this paper is on decisions in which one can assume risk is negligible, which one can formulate using multi-attribute value theory (MAVT)

(Fishburn, 1965; Keeney and Raiffa, 1993). In MAVT, one formalizes preferences for different attributes (e.g., cost, mass, settling time) of a system and tradeoffs between these attributes. The formal representation of these preferences is called a value function.

Mathematically, a tradeoff model computes one or more of the attributes for a type of component as a function of its other attributes. For example, to model hydraulic cylinders one could relate cost to mass, stroke, bore and maximum pressure. Designers obtain a tradeoff prediction by searching the input space of the tradeoff model using optimization methods with a search objective of maximizing the value function. Figure 2 is an illustration of this procedure for two hypothetical decision alternatives represented by the two tradeoff models, $T_1(\cdot)$ and $T_2(\cdot)$ ($V(\cdot)$ is a value function). A conventional approach to solving this decision problem would be to formulate an optimization problem in terms of the lower-level attribute spaces of the alternatives. In contrast, tradeoff models allow designers to abstract such lower-level details. Their role in the optimization problem is to constrain the search to solutions that are both feasible and desirable i.e., ones that rational designers can and would implement without designers having to model explicitly what constitutes feasibility or rationality. This is because they are based on data about actual design implementations.

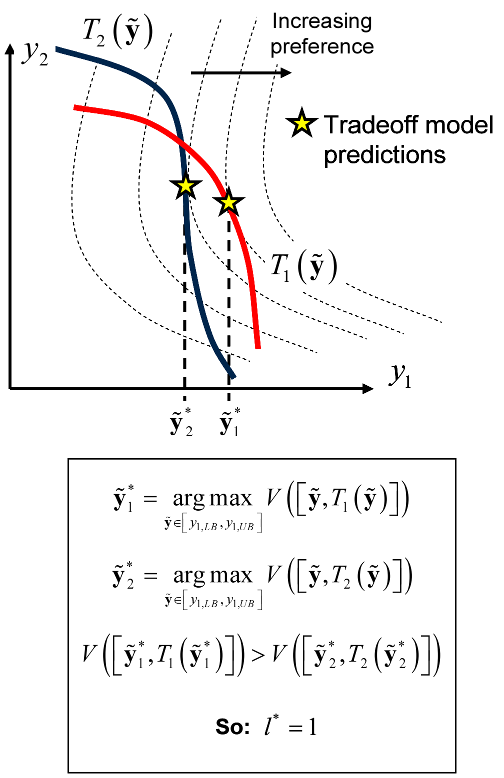

Fig. 2: *Visualization of prediction and selection procedure using tradeoff models. The dashed curves are iso-preference curves*

2.2 Tradeoff Modelling Methodology for Fluid Power Systems

The tradeoff modelling methodology consists of two phases: (1) tradeoff model generation and (2) system composition and decision making. Designers can execute these independently. For example, model generation can be an ongoing process in which one updates models as new data becomes available.

2.2.1 Tradeoff Model Generation Phase

Table 1: Summary of tradeoff model generation phase of the compositional tradeoff modelling methodology

Step	Description
1. Model planning and scope definition	Decide what to model and how to model it. For fluid power systems, identify a type of component to model and the attributes designers typically associate with it in a decision-making context. Define clearly what constitutes a component of a given type.
2. Data collection	Gather data about components within tradeoff model scope. Possible data sources: published datasheets and catalogues, manufacturers and vendors, experimental test data, and mathematical models of a component.
3. Data validation and data mining analysis	Verify that data fits tradeoff model scope. Data should appear plausible upon inspection by an expert. Examine for outliers. If necessary, use clustering analysis to rescope into multiple tradeoff models. Many texts cover the required data analysis methods (e.g., (Hand et al., 2001; Kutner et al., 2005; Witten and Frank, 2005)).
4. Dominance analysis	Eliminate data points that are dominated by the parameterized Pareto dominance criterion (Malak and Paredis, 2007; Malak et al., 2008).
5. Model fitting	Fit a tradeoff model to the non-dominated data using function approximation (e.g., regression, artificial neural network) or interpolation (e.g., Kriging). Model computes one or more attributes as a function of the others. Choice of inputs and outputs is arbitrary.
6. Model validation	Validate the model fit and estimate prediction error. For regression models, standard statistical analyses are reasonable. For other function approximation methods (e.g., artificial neural networks) and interpolation methods (e.g., Kriging), the hold-out or cross-validation approaches are more appropriate.
7. Domain characterization	Identify valid domain for model inputs to prevent automated search routines from extrapolating too far beyond the data. Often more complex than upper and lower bounds. If data set is convex, convex hull algorithms (e.g., qhull (Barber et al., 1996)) are useful. Recent work involving support-vector machines is promising as a method for domain description (Malak and Paredis, 2009).

Table 1 is a summary of the tradeoff model generation phase. With the exception of the dominance analysis step, this phase is similar to common data-driven modelling procedures (e.g., see (Hand et al., 2001; Kutner et al., 2005; Witten and Frank, 2005)). The main concerns are defining what data to collect, how to validate the data prior to generalization and how best to generalize it into a valid continuous model.

Dominance analysis (Step 4) improves the accuracy of tradeoff predictions and is a key distinction between tradeoff modelling and other uses of predictive modelling in design (e.g., modelling cost (Dean, 1976; Daschbach and Apgar, 1988; Farineau et al., 2001) or environmental impact (Dewulf, 2003)). Domination is a decision-theoretic concept that is useful for eliminating alternatives a rational decision maker never would choose. The dominance criterion one uses for tradeoff modeling - called *parameterized Pareto dominance* - is an extension of the classical Pareto dominance criterion to the problem of modelling individual components in a systems design context. To apply the rule, one categorizes attributes into two groups: those for which designer preferences always have the same orientation (e.g., all other factors being equal, designers would maximize reliability, minimize cost), called *monotone attributes*, and those for which designer preferences are problem-dependent (e.g., gear ratio) or conflicting (e.g., objectives to increase cylinder speed and ram force yield conflicting preferences for cylinder bore diameter), called *parameter attributes*. Designers can test whether one component dominates another by comparing their monotone attributes provided their parameter attributes are equivalent. For a formal definition and justification of this rule, see (Malak et al., 2008).

Formal domain characterization of a tradeoff model (Step 7) is of greater importance for tradeoff modelling than for other data-driven modelling problems. This is because one uses a tradeoff model in concert with optimization methods that rely on a formal domain definition to remain in a region of valid predictions. It often is insufficient simply to identify upper and lower bounds for each attribute. Figure 3 is an illustration of this using engine data from the example study (2D projection of 6D data). Note that this is not necessarily an indication of poor data collection, as such associations can occur due to marketing concerns (there may be no demand for certain combinations of attribute values) or physical constraints (it may be impossible to produce a component with certain properties).

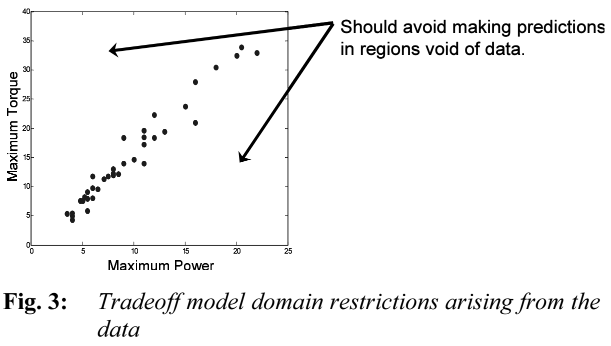

Fig. 3: *Tradeoff model domain restrictions arising from the data*

2.2.2 System Modelling and Decision Making Phase

The system modelling and decision making phase is similar to other approaches for solving decision problems using optimization methods, but with the exception that designers use tradeoff models at the lowest level of abstraction. One creates a system-level model in the same way as if no tradeoff models were involved and then uses tradeoff models to constrain the search of the system model input space. This ensures that the resulting requirements correspond to components that are physically possible to implement (i.e., not beyond the barrier of current technology) and the predictions of overall system value are accurate.

Table 2: Summary of model composition and decision making phase of compositional tradeoff modelling methodology

Step	Description
1. Formulate decision problem	Identify objectives and associated attributes for system-level decision (see (Clemen 1996) for how to identify objectives and attributes). Formalize preferences for tradeoffs between attributes using multi-attribute value theory (MAVT) (Fishburn 1965; Keeney and Raiffa 1993). The formalized preferences are called a value function.
2. Identify system-level alternatives	Creative process. Identify alternative system configurations and component technologies that might solve the design problem.
3. Model system-level alternatives	For each system-level alternative: Model the relationship between component-level and system-level attributes mathematically. This is called the system composition model, and may consist of multiple independent models.
4. Identify relevant tradeoff models	For each system-level alternative: Retrieve a tradeoff model from the library for each component in the system or create new tradeoff models as needed. Tradeoff model attributes must match attributes of component in system.
5. Search for most preferred tradeoff (requirements allocation)	For each system-level alternative: Use optimization methods to search tradeoff model input space for solution that maximizes decision preferences (value function from Step 1). Use tradeoff model domains to bound search space. Inputs at maximum are specifications for the components.
6. Final selection	Select system-level alternative that achieves largest value in Step 5 search.

Table 2 is a summary of the procedure for this phase of the methodology. One repeats steps 3 through 5 for each system-level alternative or skips step 6 if there is only one system-level alternative. Informational dependencies mean these steps should proceed more-or-less in sequence, but some iteration may be required. For example, a designer could change his or her decision objectives or preferences, or could identify a new alternative.

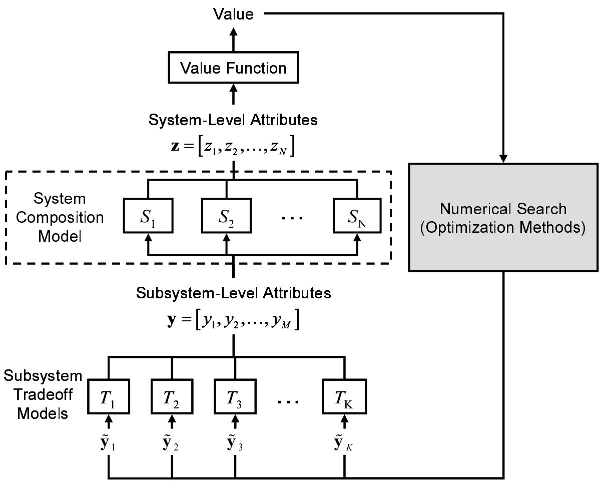

Fig. 4: *Compositional modelling framework. Component attributes are mapped to system-level attributes via the system composition model*

Figure 4 is a diagram of how the system composition model, tradeoff models, value function and optimization method relate to one another. The value function is the objective function for the optimization routine (value is to be maximized). The value function computes a scalar as a function of the system-level attributes. These attributes are a function of the component-level attributes. The system composition model consists of several individual models, $S_i(\cdot)$, that effect this mapping. Any $S_i(\cdot)$ may use only a subset of the component-level attributes, but every component-level attribute is an input to some $S_i(\cdot)$. The optimization routine controls the tradeoff model inputs and the tradeoff models compute the remaining component-level attributes.

3 Generating Tradeoff Models for Hydraulics Components

To demonstrate the model generation phase of the tradeoff modelling methodology, a library of tradeoff models for hydraulics components is generated from a database of hydraulic components. The database consists of information about the attributes of gear pumps, directional control valves, cylinders and engines. This data is acquired primarily from publicly-available data sheets and catalogues, with the remainder obtained from corporate partner companies or their vendors. The pricing data reflects the cost of purchasing the components from a supplier and all data points are for similar purchase quantities. Whenever necessary, data has been "anonymized" to protect proprietary interests.

Table 3: Summary of hydraulic component database

Compo-	Description	Attribute	Symbol	Min	Max	Units
Pump	Single-stage gear pump with relief valve	Cost	c_{pump}	213	859	$
		Weight	w_{pump}	4.98 (2.26)	45.2 (20.5)	kg (lb)
		Displacement	V_g	1.18 (0.072)	48 (2.93)	cm^3/rev (in^3/rev)
		Max. op. pressure	$\Delta p_{\text{max, pump}}$	120 (1740)	250 (3625)	bar (psi)
		Max. op. speed	$n_{\text{max, pump}}$	3000	4000	rpm
		Efficiency (total)	η	0.44	0.92	-
Cylinder	Dual-acting medium- or heavy-duty.	Cost	c_{cyl}	57	404	$
		Weight	w_{cyl}	25.3 (11.47)	390 (177)	kg (lb)
		Stroke length	L_{cyl}	0.2 (8)	1.52 (60)	m (in)
		Bore diameter	b_{cyl}	0.038 (1.5)	0.127 (5)	m (in)
		Max. op. pressure	$\Delta p_{\text{max, cyl}}$	172 (2500)	207 (3000)	bar (psi)
Directional Control Valve (DCV)	Manual, spool-type, three-way closed centre or four-way closed centre (w/ open position) w/ load-side relief valve or detent	Cost	c_{dcv}	70	168	$
		Weight	w_{dcv}	15.4 (7)	35.3 (16)	kg (lb)
		Max. op. flow rate	Q	60.6 (16)	113.6 (30)	l/min (gal/min)
		Max. op. pressure	$\Delta p_{\text{max, dcv}}$	138 (2000)	310 (4500)	bar (psi)
Engine	Internal combustion engine (gasoline-powered)	Cost	c_{eng}	180	1907	$
		Weight	w_{eng}	3.4 (7.5)	58.5 (129)	kg (lb)
		Max. power output	$P_{\text{max, eng}}$	0.75 (1.0)	18.6 (25.0)	kW (hp)
		Speed at max. power output	$n_{\text{eng, maxP}}$	3600	7500	rpm
		Max. torque output	$t_{\text{max, eng}}$	1.08 (0.8)	55 (40.6)	Nm (lb-ft)
		Speed at max. torque output	$n_{\text{eng, maxT}}$	2200	5500	rpm

Table 4: Summary of data eliminations and tradeoff model generation

Component	Engine (A)	Engine (B)	Pump	Cylinder	DCV
Total # in DB	59		61	188	36
# after outlier analysis	49		43	158	32
# after dom. analysis	14	5	24	137	8
Validation results: $\sqrt{MSE}$ (% of mean)	45.8 (15%)	33.2 (2%)	3.63 (1%)	14 (9%)	14.2 (13%)
Notes:	Kriging interpolation used for all tradeoff models All tradeoff models predict cost as a function of the other attributes Engine split into two models after clustering analysis				

Table 3 is a summary of the scope of the components in the database and Table 4 is a summary of the results from data analysis and model fitting. A number of points were removed prior to fitting based on our data analysis results. A vast majority of the data had nearly the same maximum operating pressure, which rendered that attribute uninformative from a prediction standpoint. Accordingly, any components with a maximum pressure below this level - about 172 bar (2500 psi) - were eliminated and that attribute was removed from the tradeoff models. A similar observation applies to the engine speed data: the speed at maximum power was the same for most engines in our database (3600 rpm), and the same was true for speed at maximum torque (2500 rpm). Consequently, any engine data deviating from these marks by more than 100 rpm was eliminated and these attributes were not used in the tradeoff models. A small percentage of components were eliminated on the basis of being obvious outliers or appearing suspect in some way (e.g., unusually high or low price for the stated performance attributes). After making these changes, the parameterized Pareto domination test was applied and resulted in a large number of data eliminations (see Table 4).

The tradeoff model for each component is formulated to predict cost as a function of its other attributes. Kriging methods and the DACE Matlab Kriging Toolbox (Lophaven et al., 2002) are used to fit the tradeoff models and validation is performed using leave-one-out cross validation (Witten and Frank, 2005).

Initially, the engine model fit was poor. The data was re-examined using the *k*-means clustering algorithm (Hand et al., 2001), which identified two distinct clusters and independent tradeoff models were fit to each. The partitioning groups the engines into ones with higher maximum torque (those above 30 N-m (22 ft-lb)) and ones with lower torques. This improves prediction accuracy significantly, but at the expense of requiring two independent optimization searches (one using each engine tradeoff model).

4 System Composition and Requirements Allocation for a Hydraulic Log Splitter

This section is a demonstration of the system composition and decision making phase of the methodology (Fig. 4). It relies on the modelling expertise of a designer to formalize the relationships between component-level attributes and system-level attributes for each system alternative. Designers use these models together with their value function (i.e., formalized preferences for system-level attributes), tradeoff models and optimization methods to allocate requirements to each component and compare system alternatives.

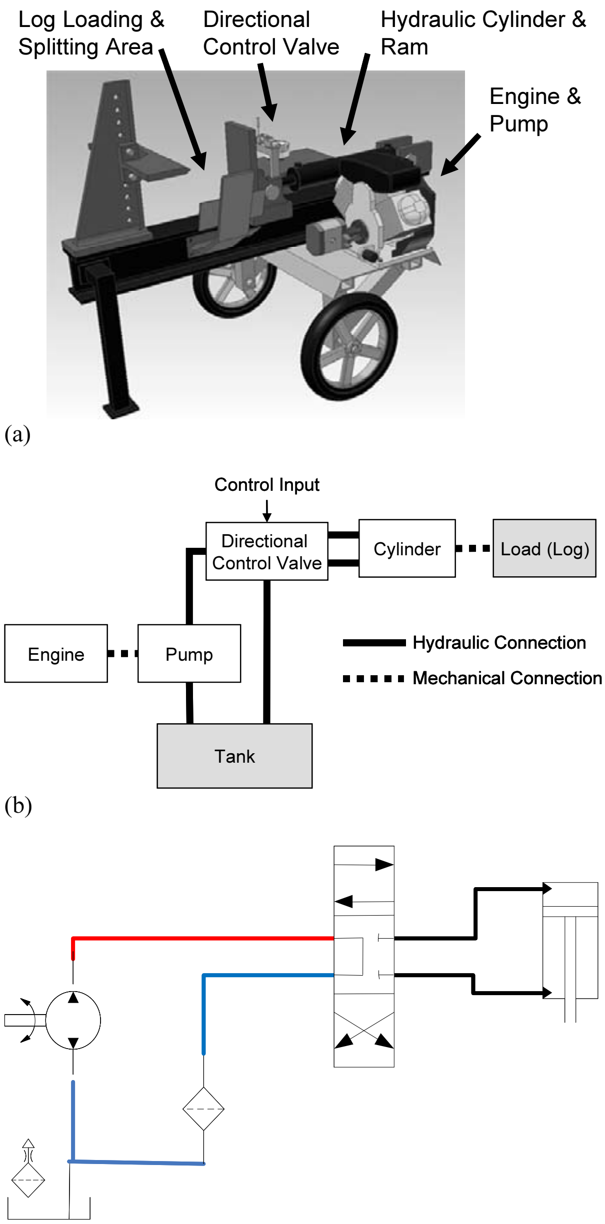

Fig. 5: *Hydraulic log splitter: (a) physical layout, (b) functional configuration, where white boxes correspond to tradeoff models, and (c) circuit diagram*

A hydraulic log splitter is used as an example in this paper due to its simplicity. A log splitter is a system that divides a roughly cylindrical log into two or more pieces, typically in association with the harvesting of firewood. Several physical configurations are possible, but the example is limited to a horizontal-acting type (Fig. 5(a)). An operator loads a log into the system and then operates a control to drive a wedge into the log. The wedge action is aligned with the grain of the wood, so minimal effort is required after initiating the split. The primary function of the hydraulic subsystem is to apply the driving force for this wedge. Critical system requirements include portability (typically light weight, has wheels for transport, etc.), cost and splitting capabilities (maximum size of log it can handle, maximum force it can apply at wedge, etc.).

Figure 6 contains the objectives hierarchy used to formulate the decision problem. Each leaf of the tree associates with an attribute the system model must compute:

- Cost: Sum of the purchase prices of the hydraulic components and the engine. Assembly and other cost factors are not considered in this example.
- Weight: Sum of the weights of the hydraulic components and the engine. The weight of the structure is not considered in this example.
- Ram Force: Maximum force the system can apply to the log.
- Log Length: The maximum length of log that will fit into the system.
- Cycle Time: An index for how long it takes to split a log. Defined as the time for the wedge to extend 0.15 meters (6 inches) at maximum engine torque (i.e., maximum ram force) plus the time to retract it with the engine running at maximum power (a conservative approximation of maximum ram speed).

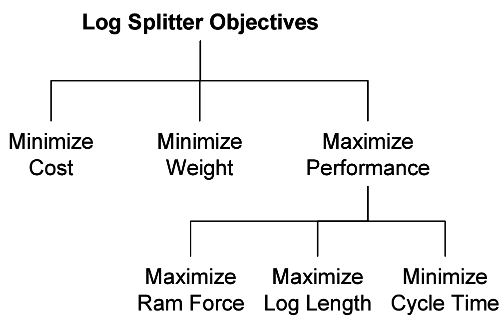

Fig. 6: *Objectives hierarchy for the log splitter problem*

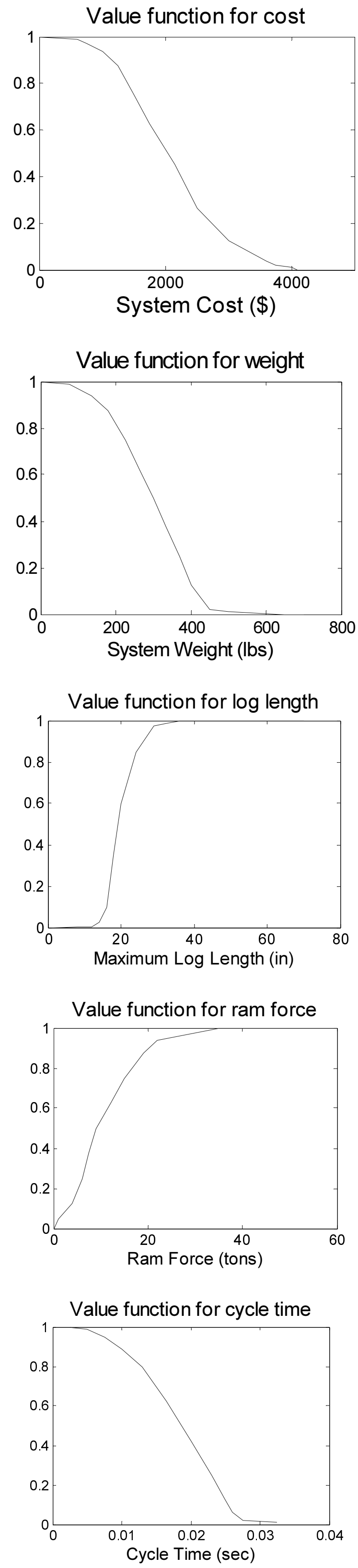

Fig. 7: *Graphs of the individual value functions for the five system-level attributes of the log splitter problem*

Figure 7 contains graphs of the individual value functions corresponding to the system attributes Preferences for tradeoffs are elicited in a hierarchical fashion, beginning with a value function for the three performance attributes followed by one that combines this result with weight and cost (for a discussion on eliciting preferences, see (Keeney and Raiffa 1993)). The performance attribute is a tradeoff among its constituent objectives:

$$\begin{aligned} v_{\mathrm{P}} = V_{\mathrm{P}}(\mathbf{z}) &= 0.0936 v_{\mathrm{T}} + 0.0936 v_{\mathrm{F}} - 0.1925 v_{\mathrm{L}} \\ &+0.163 v_{\mathrm{T}} v_{\mathrm{F}} + 0.2946 v_{\mathrm{T}} v_{\mathrm{L}} + 0.2946 v_{\mathrm{F}} v_{\mathrm{L}} \\ &+0.2530 v_{\mathrm{T}} v_{\mathrm{F}} v_{\mathrm{L}} \end{aligned} \quad (1)$$

where $v_{\mathrm{T}} = V_{\mathrm{T}}(z_{\mathrm{T}})$ is the value function result for the cycle time attribute at z_{T}, $v_{\mathrm{F}} = V_{\mathrm{F}}(z_{\mathrm{F}})$ is for the ram force attribute and $v_{\mathrm{L}} = V_{\mathrm{L}}(z_{\mathrm{L}})$ is for the log length attribute. The top-level value function is

$$\begin{aligned} V(\mathbf{z}) &= 1.03 v_{\mathrm{C}} + 1.05 v_{\mathrm{P}} + 0.95 v_{\mathrm{W}} \\ &-1.29 v_{\mathrm{C}} v_{\mathrm{P}} - 1.18 v_{\mathrm{C}} v_{\mathrm{W}} - 1.18 v_{\mathrm{P}} v_{\mathrm{W}} \\ &+1.62 v_{\mathrm{C}} v_{\mathrm{P}} v_{\mathrm{W}} \end{aligned} \quad (2)$$

where the $v_{\mathrm{c}} = V_{\mathrm{c}}(z_{\mathrm{c}})$ is the value function for the cost evaluated at z_{c}, $v_{\mathrm{w}} = V_{\mathrm{w}}(z_{\mathrm{w}})$ is for the weight attribute, v_{p} is the performance attribute defined above and z is the system-level attribute vector. Thus, the system-level decision problem is to maximize Eq. 2, and the requirements allocation objective is to find the component-level attributes at this maximum. Let **S** represent the vector-valued system composition model (comprised of the $S_{\mathrm{i}}(\cdot)$ from Fig. 8), $\tilde{\mathbf{y}}$ denote the vector of component-level attributes controlled by the optimization routine, and $\mathbf{T}(\tilde{\mathbf{y}})$ denote the vector of all the component-level tradeoff model predictions. Thus, one can state the requirements allocation problem formally as

$$\tilde{\mathbf{y}}^{*} = \underset{\tilde{\mathbf{y}} \in \Upsilon}{\arg\max}\, V\left(\mathbf{z} = \mathbf{S}\left(\left[\tilde{\mathbf{y}}, \mathbf{T}(\tilde{\mathbf{y}})\right]\right)\right), \quad (3)$$

where Υ is the domain in which the tradeoff model predictions are valid and $\left[\tilde{\mathbf{y}}^{*}, \mathbf{T}(\tilde{\mathbf{y}}^{*})\right]$ are the most preferred component requirements for the system.

Cost	$z_{\mathrm{C}} = S_{\mathrm{C}}(\mathbf{y}) = c_{\mathrm{pump}} + c_{\mathrm{cyl}} + c_{\mathrm{dcv}} + c_{\mathrm{eng}}$
Weight	$z_{\mathrm{W}} = S_{\mathrm{W}}(\mathbf{y}) = w_{\mathrm{pump}} + w_{\mathrm{cyl}} + w_{\mathrm{dcv}} + w_{\mathrm{eng}}$
Ram Force	$z_{\mathrm{F}} = S_{\mathrm{F}}(\mathbf{y}) = \left(\Delta p_{\mathrm{max,sys}}\right)\left(b_{\mathrm{cyl}}^{2} \frac{\pi}{4}\right)$ where $\Delta p_{\mathrm{max\ sys}}$ is the maximum operating pressure of the system as dictated by the rating limitations of components or the pressure that can be generated by the engine-pump combination.
Log Length	$z_{\mathrm{L}} = S_{\mathrm{L}}(\mathbf{y}) = L_{\mathrm{cyl}}$
Cycle Time	$z_{\mathrm{T}} = S_{\mathrm{T}}(\mathbf{y}) = 1.56\left(b_{\mathrm{cyl}}^{2} \frac{\pi}{4}\right)\left(\frac{1}{Q_{\tau}} + \frac{1}{Q_{\mathrm{PWR}}}\right)$ where Q_{τ} is the maximum flow rate the system can achieve at $\tau_{\mathrm{max\ eng}}$ and Q_{PWR} is the maximum flow rate (in l/min) at $P_{\mathrm{max\ eng}}$. Both are non-decreasing functions of pump displacement, the engine speeds at the respective operating points and component rating limitations.

Fig. 8: *Summary of system composition model for log splitter design problem*

To solve the decision problem, one must relate the component-level attributes to those used in Eq. 2. Figure 8 is a summary of the system model used to achieve this for the log splitter example. It is important that one use every attribute of a tradeoff model in the system model or assign them constant value; passing unused variables to the optimization method can reduce solver efficiency significantly.

It is possible for one to develop more sophisticated system models for this problem - e.g., simulating the actual cycle time, accounting for tubing/hoses. Although these considerations are important in general, the focus here is on the application of the tradeoff modelling methodology. For an example involving other components and more complex simulation models, see the hydraulic hybrid vehicle example in (Malak, 2008).

The models are integrated according to the diagram in Table 2. Only one system configuration is under consideration, but there are two engine tradeoff models. Thus, one must solve two optimization problems, one for each engine tradeoff model, and choose the better result from the two runs.

5 Comparison to Exhaustive Search of Components Database

To demonstrate that the tradeoff modelling approach yields a reasonable requirements allocation solution for the log splitter, the results of the optimization search defined in Section 4 are compared to an exhaustive search of the components database. One typically would not do an exhaustive search in practice due to the large number of combinations that can exist. Even after removing outliers, our modestly-sized database yields nearly 13 million possible combinations for the log splitter system. One should not expect the two approaches to yield equivalent solutions, since the tradeoff models are able to generalize beyond the database contents. However, the exhaustive solution does provide a meaningful baseline for comparison. One can expect the tradeoff modelling approach to do no worse than the exhaustive search on the basis that the tradeoff models are representations of the database contents.

Table 5 contains results from the exhaustive search and the two tradeoff modelling optimization runs (one with each engine tradeoff model). The Engine A tradeoff model corresponds to the tradeoff model for lower-torque engines. According to the tradeoff modelling approach, a system that includes an engine from the Engine A domain is preferred to a system with an engine from the Engine B domain (preference value of 0.958 compared to 0.933). The exhaustive search corroborates this result, with its engine being virtually identical to the engine predicted using the Engine A tradeoff model.

Table 5: Comparison of requirements allocation results for log splitter design problem

Component	Attribute	Composed Tradeoff Models (Engine A)	Composed Tradeoff Models (Engine B)	Exhaustive Search of DB
Pump	Cost	\$ 223	\$ 221	\$ 223
	Weight	11.7 kg (5.3 lb)	7.9 kg (3.6 lb)	11.7 kg (5.3 lb)
	Displacement	6.1 cc/rev (0.37 in^3/rev)	5.7 cc/rev (0.35 in^3/rev)	6.1 cc/rev (0.37 in^3/rev)
	Max. op. speed	4000 rpm	4000 rpm	40000 rpm
	Efficiency	0.88	0.63	0.88
Cylinder	Cost	\$ 233	\$ 213	\$ 260
	Weight	181 kg (82.3 lb)	155 kg (70 lb)	253.75 kg (115.1 lb)
	Stroke length	0.68 m (27 in)	0.88 m (34.5 in)	0.71 m (28 in)
	Bore diameter	0.114 m (4.5 in)	0.102 m (4 in)	0.127 m (5 in)
Directional Control Valve	Cost	\$ 83	\$ 75	\$ 90
	Weight	18.7 kg (8.5 lb)	25.9 kg (11.8 lb)	15.4 kg (7 lb)
	Max. op. flow rate	68.1 l/min (17 gal/min)	73.8 l/min (19.5 gal/min)	68 l/min (18 gal/min)
Engine	Cost	\$ 330	\$ 800	\$ 300
	Weight	105 kg (47 lb)	192 kg (87 lb)	121 kg (55 lb)
	Maximum Power	6.7 kW (8.9 hp)	11.2 kW (15 hp)	6.7 kW (9 hp)
	Maximum Torque	18.8 N-m (13.8 ft-lb)	32.3 N-m (23.8 ft-lb)	19 N-m (14 ft-lb)
Value Components	Ram Force (v_F)	0.897	0.775	0.958
	Log Length (v_L)	0.944	0.996	0.963
	Cycle Time (v_T)	0.987	0.993	0.967
	Performance (v_P)	0.874	0.812	0.918
	Weight (v_w)	0.928	0.887	0.87
	Cost (v_c)	0.955	0.850	0.955
System Value (v)		**0.958**	**0.933**	**0.956**

Overall, the tradeoff modelling approach yields results similar to the exhaustive search solution. The tradeoff modelling approach identifies targets for the pump and engine that are virtually identical to those of the exhaustive search solution. However, the tradeoff modelling approach does generalize beyond the database contents for the cylinder and DCV requirements. Upon examining the system attribute valuations, one can see that the tradeoff modelling solution sacrifices small amounts in terms of the performance attributes in order to improve in the weight attribute. That this particular solution is not in the database, underscores a strength of the tradeoff modelling approach over discrete searches.

6 Conclusions

This paper contains a description and demonstration of a methodology for modelling fluid power systems for system-level decision making. The approach is rooted in systems engineering principles and represents an improvement beyond common practice within the fluid power industry. A major advantage of the tradeoff modelling approach is that it provides designers with a means to capture and reason about associations among attributes that otherwise would be difficult to relate. Another advantage is that by virtue of being fit to data about existing design implementations, tradeoff models provide predictions that correspond to feasible design solutions. This is important for minimizing redesign and iteration in a systems design project. Also noteworthy is that designers can reuse tradeoff models on different design problems. A company could maintain a library of tradeoff models for common types of components that its designers could reuse frequently, thereby maximizing return on modelling investment. One limitation of tradeoff modelling is that the models are only as good as the data upon which they are based. This can be problematic if data about a particular attribute is hard to come by (e.g., for many types of components, reliability data can be hard to find) or if only few examples of a particular type of component exist (e.g., the component database contained ample data about cylinders, but significantly less for the DCV). However, in such cases it is possible for designers to account explicitly for the risk introduced by inaccurate models by formulating decisions under uncertainty. A preliminary investigation into tradeoff modelling for decision under uncertainty has been made (Malak and Paredis, 2008), but further research is required.

Nomenclature

$V(\cdot)$	System value function	
$V_c(\cdot)$	Value function for system cost	
$V_w(\cdot)$	Value function for value for system mass	
$V_F(\cdot)$	Value function for ram force	
$V_L(\cdot)$	Value function for log length	
$V_T(\cdot)$	Value function for cycle time	
$V_P(\cdot)$	Value function for performance attributes	
$T(\cdot)$	Tradeoff model	
z	Vector of system-level decision attributes	
z_c	System cost decision attribute	[US$]
z_w	System mass decision attribute	[kg]
z_F	Ram force decision attribute	[N]
z_L	Log length decision attribute	[m]
z_T	Cycle time decision attribute	[s]
$S_i(\cdot)$	Model for the i^{th} system-level attribute	
y_i	Decision attribute for a component	
Δp_{max}	Max operating pressure	[bar]
Q_τ	Max flow rate at max engine torque	[l/min]
Q_{PWR}	Max flow rate at max engine power	[l/min]

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