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Robin Chhabra and M Reza Emami

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Abstract

This article details a holistic concurrent design framework, based on fuzzy logic, which is suitable for multidisciplinary systems. The methodology attempts to enhance communication and collaboration between different disciplines through introducing the universal notion of *satisfaction* and expressing the holistic behavior of multidisciplinary systems using the notion of *energy*. Throughout the design process, it uses fuzzy logic to formalize subjective aspects of design including the impact of the designer's attitude, resulting in the simplification of the multi-objective constrained optimization process. In the final phase, the methodology adjusts the designer's subjective attitude based on a holistic system performance by utilizing an energy-based model of multidisciplinary systems. The efficiency of the resulting design framework is illustrated by improving the design of a 5-degree-of-freedom industrial robot manipulator.

Keywords

concurrent design, multidisciplinary systems, mechatronics, robot manipulator, fuzzy logic

Introduction

Multidisciplinary engineering systems are complex systems whose interconnected subsystems belong to different physical domains. Whereas traditional design methodologies for such systems rely on subsystem partitioning, and hence, they often result in more iteration and less desirable outcomes, a concurrent approach emphasizes on the physical integration and communication among the subsystems. However, the challenge is to consider a large number of design variables and attributes simultaneously (Alvarez Cabrera et al., 2010) and to develop a unified multidisciplinary model that can evaluate the attributes concurrently.

Researchers have developed different multidisciplinary design optimization (MDO) formulations (Cramer et al., 1992, 1994) suitable for various applications (Balling and Wilkinson, 1997; Martz and Neu, 2009; Nosratollahi et al., 2010; Yokoyama et al., 2007). A multidisciplinary design process normally leads to a multi-objective (each of which is called a design attribute) constrained optimization. In many MDO methods, a single-objective function is introduced that is a mapping from the space of all design variables and attributes to real numbers; hence, the resulting multi-objective optimization problem is reduced to a single-objective constrained optimization. Some well-developed MDO formulations can be listed as multidisciplinary feasible (MDF), all-at-once (AAO), individual-discipline feasible (IDF) (Cramer et al., 1994), collaborative optimization (CO) (Braun et al., 1996), and concurrent subspace optimization (CSSO) (Bloebaum et al., 1992). Some of these MDO methods have been generalized to deal with multi-objective optimization in the design process; and since design problems often consist of competing design attributes, the outcome is a pareto-optimal solution (Huang et al., 2007).

A multidisciplinary design problem often involves subjective notions, besides the objective attributes. The subjectivity is mainly due to communication between designers (and customers) in different disciplines and

University of Toronto, Institute for Aerospace Studies, Toronto, ON, Canada

Corresponding author:
M Reza Emami, University of Toronto, Institute for Aerospace Studies, 4925 Dufferin Street, Toronto, ON M3H 5T6, Canada.
Email: emami@utias.utoronto.ca

their interpretation of design goals. Hence, any effective multidisciplinary design formulation should provide a communication means that can not only convey qualitative and subjective notions but also formalize them rigorously (Bradley, 2010; Fruchter et al., 1996; Wang et al., 1996). Although MDO methods attempt to take into account the interconnection between subsystems, a majority of them do not employ a unified multidisciplinary modeling algorithm (Basdogan, 2009). This shortcoming usually increases the complexity of the optimization in MDO formulations and reduces the efficiency of the communication between disciplines.

This article introduces the *holistic concurrent design* (HCD) methodology that addresses the above-mentioned issues based on the notions of *satisfaction* in the synthesis and *energy* in the analysis of multidisciplinary systems. The methodology utilizes tools of fuzzy logic to systematically define some subjective aspects, such as satisfaction, customer's preference, and designer's attitude, which play a vital role in a design process in addition to objective aspects in the form of design attributes. In order to adjust the subjective notions, the methodology examines the set of satisfactory design candidates against a *performance supercriterion* that is defined based on a holistic multidisciplinary model of the system. As a result, the HCD formally reduces the multi-objective constrained optimization problem to two single-objective unconstrained optimizations. Consequently, not only does the HCD facilitate the communication between different disciplines but it also results in a more practical solution for a multi-objective, multidisciplinary design problem. As a case study, the HCD methodology is then implemented to develop a generic design framework for serial-link robot manipulators as notable multidisciplinary systems. The efficacy of this framework is illustrated through improving the design of a 5-degree-of-freedom (DOF) industrial robot manipulator.

A number of systematic synthesis approaches for robotic systems have been suggested in the literature, some of which attempt to solve a multi-objective constrained optimization. For instance, evolutionary algorithms (Chocron, 2008), axiomatic design theory (Bi et al., 2004; Li et al., 2011), and genetic algorithms (Bi and Zhang, 2001; Coello et al., 1998) are employed to perform the multi-objective optimization in the design of robotic systems. Recently, Rout and Mittal (2010) utilized evolutionary optimization techniques, and Kim et al. (2009) used a deconvolution method to design serial-link robot arms. In the field of engineering design, a number of concurrent design methodologies have been introduced, among them axiomatic design theory (Suh, 1998) tries to develop a hierarchical approach to the design of engineering systems. In addition, some approaches attempt to include subjective notions in the design process using fuzzy logic tools (Dhingra et al., 1990; Dhingra and Rao, 1995; Otto and Antonsson, 1995). A notable example is the method of imprecision (MoI), which takes into account the imprecision in design (Otto and Antonsson, 1995). This approach defines a set of designer's preference for design variables and performance parameters to model the imprecision in design. It determines and maximizes the global performance under one of the two conservative or aggressive design trade-off strategies and uses fuzzy logic operators for trade-off in the design space.

Fuzzy connectives are first briefly discussed in section "Fuzzy connectives and fuzzy aggregation," and then, a step-by-step formulation of the HCD methodology is presented in section "HCD methodology." Section "Application to robot manipulators" discusses the application of the HCD methodology to robot manipulators. Some concluding remarks are made in section "Conclusion."

Fuzzy connectives and fuzzy aggregation

Unlike the classic set theory where the membership of an element to a set is binary, in fuzzy set theory, the membership of an element to a fuzzy set can be *partial*, that is, the membership degree of an element is a number in the interval [0, 1]. Accordingly, the classic logical connectives AND, OR, and NOT are also generalized as functions of the membership degrees to perform operations in fuzzy set theory. In fuzzy logic, AND and OR connectives have been interpreted through different classes of *triangular norms* (t-norm) and *triangular conorms* (t-conorm), respectively, such as *Max-Min Operators* (T_{min}, S_{max}), *Algebraic Product and Sum* (T_{prod}, S_{sum}), and *Drastic Product and Sum* (T_W, S_W). Using the basic properties of these operators, it can be shown that for any t-norm T and t-conorm S and for all $a_i \in [0, 1] (i = 1, \ldots, n)$ (Yager and Filev, 1994)

$$\begin{aligned} T_W(a_1, \ldots, a_n) \le T(a_1, \ldots, a_n) \le T_{min}(a_1, \ldots, a_n) \\ S_{max}(a_1, \ldots, a_n) \le S(a_1, \ldots, a_n) \le S_W(a_1, \ldots, a_n) \end{aligned} \quad (1)$$

To represent the range of operators in equation (1), various types of parametric formulations have been suggested in the literature. In particular, Emami et al. (1999) introduce a class of parametric operators for fuzzy reasoning whose parametric t-conorm operator is defined as

$$\begin{aligned} & S^{(p)}(b_1, \ldots, b_n) \\ & \equiv \left[b_1^p + (1 - b_1^p)[\cdots[b_{n-2}^p + \cdots + (1 - b_{n-2}^p) \right. \\ & \left. [b_{n-1}^p + (1 - b_{n-1}^p)b_n^p]] \cdots]\right]^{1/p} \end{aligned} \quad (2)$$

where $b_i \in [0, 1]$ and $p > 0$, and the corresponding parametric t-norm operator is defined based on De Morgan laws using standard complementation operator (NOT connective), that is, $C(a) = 1 - a \quad \forall a \in [0, 1]$, as

$$T^{(p)}(a_1, \ldots, a_n) = 1 - S^{(p)}((1 - a_1), \ldots, (1 - a_n)) \quad (3)$$

Note that, $(T^{(p)}, S^{(p)})$ approaches (T_{min}, S_{max}) as $p \to +\infty$, (T_{prod}, S_{sum}) as $p \to 1$, and (T_W, S_W) as $p \to 0$.

In fuzzy logic, the meaning of a connective can be neither pure OR (t-conorm) nor AND (t-norm), with its complete lack of compensation. Such connectives are called *mean operators*. As an example, a parametric operator of this class, namely, *generalized mean operator*, is introduced in Yager and Filev (1994)

$$G^{(\alpha)}(a_1, \ldots, a_n) \equiv \left(\frac{1}{n} \sum_{i=1}^{n} a_i^{\alpha} \right)^{1/\alpha} \quad (4)$$

where $\alpha \in R$. It appears that this type of connective monotonically varies between T_{min} operator as $\alpha \to -\infty$ and S_{max} operator as $\alpha \to +\infty$.

HCD methodology

Formulation of design process

A design problem consists of two sets: *design variables* $X \equiv \{X_1, \ldots, X_n\}$ and *design attributes* $A \equiv \{A_1, \ldots, A_N\}$ such that any design solution can be identified by vectors $\mathbf{X} \equiv [X_1, \ldots, X_n]^T \in R^n$ and $\mathbf{A} \equiv [A_1, \ldots, A_N]^T \in R^N$, respectively. In this article, vectors are denoted by bold letters. Design variables are to be assigned to satisfy the *design requirements* associated with the design attributes, subject to the *design availabilities* $D \equiv D_1 \times \cdots \times D_n$, such that $D_j \subset R(j = 1, \ldots, n)$. For each design attribute A_i, there is a mapping $F_i : \mathrm{R}^n \to \mathrm{R}$ that relates a design state $\mathbf{X}$ to the attribute, that is, $A_i = F_i(\mathbf{X})(i = 1, \ldots, N)$. These functional mappings can be of any form, such as closed-form equations, heuristic rules, or sets of experimental or simulated data. A design process can be modeled as a multi-objective optimization subject to a number of constraints on the design variables and attributes due to the design availabilities and design requirements specified by the customer

$$\begin{gathered} \min_{X \in D} [F_1(\boldsymbol{X}), \ldots, F_{N_W}(\boldsymbol{X})]^T \text{ subject to} \\ \{F_i(\boldsymbol{X}) \in G_i, G_i \subset R, i = N_W + 1, \ldots, N\} \end{gathered} \quad (5)$$

where N_W and $N_M \equiv N - N_W$ are the number of attributes that should be optimized and the number of constraints, respectively.

Given a set of design variables and a set of design attributes, the HCD methodology first assigns *satisfactions* to the values of design variables and attributes based on the designer/customer's preference reflected in the design availabilities and design requirements. Then, using parametric fuzzy connectives, introduced in section "Fuzzy connectives and fuzzy aggregation," it aggregates the satisfactions to obtain the *overall satisfaction*. This will transform the multi-objective constrained optimization in equation (5) to a single-objective unconstrained optimization problem whose optimum set of inputs is locally pareto-optimal for equation (5). The solution to the single-objective optimization depends on the choice of the aggregation parameters (corresponding to the parametric connectives) that model different *designer's attitude* in aggregating the satisfactions, that is, different trade-off strategies in design. The closer the parametric t-norm and the generalized mean operator are to T_{min}, the more conservative the design strategy is, and the farther they are from T_{min}, the more aggressive the design strategy would be (Otto and Antonsson, 1991). However, different designers may not have a consensus of opinion on the trade-off in design. Therefore, in the last phase of the HCD, the designer's attitude is adjusted through enhancing a holistic system performance, called *performance supercriterion*. Hence, the HCD methodology breaks down the multi-objective constrained design optimization into two levels of single-objective unconstrained optimization and incorporates features of both human subjectivity and physical objectivity.

Definition 1 (satisfaction).

1. A mapping $x_j : \mathrm{R} \to [0, 1]$ for the design variable X_j is called satisfaction if for any two different values $X_{j1}, X_{j2} \in \mathrm{R}$ one has $[x_j(X_{j1}) > x_j(X_{j2})] \Leftrightarrow [X_{j1} \succ X_{j2}]$ or $[x_j(X_{j1}) = x_j(X_{j2})] \Leftrightarrow [X_{j1} \approx X_{j2}]$. The symbols $\succ$ and $\approx$ denote strictly superior and as superior, respectively, which are interpreted based on the design availabilities.
2. A mapping $\mu_{A_i} : \mathrm{R} \to [0, 1]$ for the design attribute A_i is called satisfaction if for any two different states of the design variables $\boldsymbol{X}_1, \boldsymbol{X}_2 \in \mathrm{R}^n$ one has $[\mu_{A_i} \circ F_i(\boldsymbol{X}_1) > \mu_{A_i} \circ F_i(\boldsymbol{X}_2)] \Leftrightarrow [F_i(\boldsymbol{X}_1) \succ F_i(\boldsymbol{X}_2)]$ or $[\mu_{A_i} \circ F_i(\boldsymbol{X}_1) = \mu_{A_i} \circ F_i(\boldsymbol{X}_2)] \Leftrightarrow [F_i(\boldsymbol{X}_1) \approx F_i(\boldsymbol{X}_2)]$, where $\succ$ and $\approx$ are interpreted based on the design requirements. The symbol "$\circ$" is the composition operator. For brevity, in this article, the satisfaction for a design attribute is denoted by $a_i(\boldsymbol{X}) \equiv \mu_{A_i} \circ F_i(\boldsymbol{X})$. The value of 1 for a satisfaction corresponds to the ideal case, and 0 means the worst case or the least satisfactory design variable or attribute.

In the conceptual phase, design requirements are usually qualitative notions that imply the designer/customer's criteria for design. These requirements are naturally divided into *demands* and *desires*. Accordingly, in the HCD, the design attributes are divided into two subsets.

Definition 2 (wish design attribute). A design attribute is called *wish* if it refers to designer/customer's desire, that is, its associated design requirement permits room for compromise, and it should be satisfied as much as possible. These attributes form a set denoted as $W \equiv \{W_1, \ldots, W_{N_W}\}$ whose corresponding vector $[W_1, \ldots, W_{N_W}]^T \equiv [F_1(\boldsymbol{X}), \ldots, F_{N_W}(\boldsymbol{X})]^T$ should be optimized.

Definition 3 (must design attribute). A design attribute is called *must* if it refers to designer/customer's demand, that is, the achievement of its associated design requirement is mandatory with no room for compromise. These attributes form a set denoted as $M \equiv \{M_1, \ldots, M_{N_M}\}$, and they should usually satisfy inequalities, that is, $M_i \equiv F_i(\boldsymbol{X}) \in G_i \subset R (i = N_W + 1, \ldots, N)$. Note that the design availabilities have the same nature of *must* design attributes and they are treated the same in the HCD.

To distinguish between *must* and *wish* satisfactions, the satisfaction specified for W_i is denoted by $w_i(\boldsymbol{X})(i = 1, \ldots, N_W)$, and the satisfaction corresponding to M_i is $m_i(\boldsymbol{X})(i = 1, \ldots, N_M)$.

Based on Definition 1, satisfactions can be considered as fuzzy membership functions, and suitable fuzzy connectives can be used to aggregate them.

Definition 4 (overall satisfaction). For a design state X, the overall satisfaction, as a global measure of design achievement, is the aggregation of *wish* and *must* satisfactions and the satisfactions for the design variables with the proper fuzzy connectives, which is detailed in the following subsection.

Calculation of overall satisfaction

In this subsection, separate aggregation strategies are suggested for combining *must* and *wish* satisfactions to introduce the *overall must* and *overall wish satisfactions*. Subsequently, the overall *must* and *wish* satisfactions are aggregated to determine the overall satisfaction in design.

Aggregation of must design attributes. The design requirements associated with *must* attributes have to be fulfilled simultaneously with no room for compromise. Therefore, for aggregating *must* satisfactions, an AND logical connective is suitable, which is interpreted through a family of t-norm operators in fuzzy logic.

Axiom 1. Given *must* design attributes and their satisfactions, $\{(M_i, m_i) : \forall i = 1, \ldots, N_M\}$, and considering the satisfactions of design variables, $\{(X_j, x_j) : \forall j = 1, \ldots, n\}$, the overall *must* satisfaction is the aggregation of satisfactions corresponding to the *must* attributes and design variables using the *p*-parameterized class of t-norm operators defined by equations (2) and (3). Therefore, the overall *must* satisfaction $\mu_M^{(p)}(\boldsymbol{X})$ is quantified by

$$\mu_M^{(p)}(\boldsymbol{X}) = T^{(p)}(m_1(\boldsymbol{X}), \ldots, m_{N_M}(\boldsymbol{X}), x_1(X_1), \ldots, x_n(X_n)) \quad p > 0 \tag{6}$$

The parameter p can be adjusted to control the nature of aggregation. Larger values of p would imply a more conservative attitude toward aggregating the *must* attributes, and values of p closer to 0 represent a more aggressive attitude.

Aggregation of wish design attributes.

Definition 5 (cooperative wish attributes). For a design state X, a subset of *wish* design attributes is called *cooperative* if the corresponding satisfactions vary in the same direction for equal infinitesimal positive perturbations of the design variables. *Wish* attributes can be divided into two cooperative subsets:

1. *Positive-differential wish attributes*. For a design state $\boldsymbol{X}$, positive-differential subset of *wish* attributes contains those with nonnegative perturbed satisfactions as the result of equal infinitesimal positive perturbations of the design variables. Therefore

$$W_X^+ \equiv \left\{ W_i \in W : \sum_{j=1}^{n} \frac{\partial w_i}{\partial X_j}(\boldsymbol{X}) \geq 0 \right\} \tag{7}$$

   This subset consists of all *wish* design attributes that tend to reach higher satisfaction values.

2. *Negative-differential wish attributes*. For a design state $\boldsymbol{X}$, negative-differential subset of *wish* attributes contains those with negative perturbed satisfactions as the result of equal infinitesimal positive perturbations of the design variables. Therefore

$$W_X^- \equiv \left\{ W_i \in W : \sum_{j=1}^{n} \frac{\partial w_i}{\partial X_j}(\boldsymbol{X}) < 0 \right\} \tag{8}$$

This subset includes all *wish* attributes that tend to reach lower satisfaction values.

Note that positive- and negative-differential subsets of *wish* attributes depend on the design state $\boldsymbol{X}$, and they change in the design process. Since *wish* attributes are cooperative in each subset, their corresponding design requirements can be fulfilled simultaneously.

According to Axiom 1, a q-parameterized class of t-norm operators is suitable for aggregating satisfactions in either subset of *wish* attributes. Therefore, the *overall positive*- and *negative-differential wish satisfactions* are defined by

$$\mu_{W^{\pm}}^{(q)}(\boldsymbol{X}) \equiv T^{(q)}\left(w_1(\boldsymbol{X}), \ldots, w_{N_{W^{\pm}}}(\boldsymbol{X})\right), \quad q > 0 \tag{9}$$

where $N_{W^{\pm}}$ is the number of positive- or negative-differential *wish* attributes for a design state $\boldsymbol{X}$. Note that $N_{W^{\pm}}$ changes with $\boldsymbol{X}$.

The two subsets of *wish* attributes cannot be improved simultaneously as their design requirements compete with each other. Therefore, some compromise is necessary for aggregating their satisfactions, and a class of mean operators reflects the averaging and compensatory nature of their aggregation.

Axiom 2. Given the overall positive- and negative-differential *wish* satisfactions $\mu_{W^+}^{(q)}(\boldsymbol{X})$ and $\mu_{W^-}^{(q)}(\boldsymbol{X})$, respectively, the overall *wish* satisfaction $\mu_W^{(q,\alpha)}(\boldsymbol{X})$ can be calculated using the α-parameterized generalized mean operator defined by equation (4)

$$\mu_W^{(q,\alpha)}(\boldsymbol{X}) = \left[\frac{1}{2}\left(\left(\mu_{W^+}^{(q)}(\boldsymbol{X})\right)^{\alpha} + \left(\mu_{W^-}^{(q)}(\boldsymbol{X})\right)^{\alpha}\right)\right]^{1/\alpha}, \quad \alpha \in R \tag{10}$$

which is monotonically increasing with respect to α between T_{min} and S_{max} operators. Therefore, it offers a variety of aggregation strategies from conservative to aggressive, respectively. The overall *wish* satisfaction is governed by two parameters q and α, which offer a range of trade-off strategies. Larger values of α or smaller values of q represent a more optimistic attitude of designer and vice versa.

Aggregation of overall wish and must satisfactions. The aggregation of all *wish* satisfactions can be considered as one *must* attribute, that is, it has to be fulfilled with other *must* attributes with no compromise. Otherwise, in the design process, a scenario may occur that the overall satisfaction is non-zero while the overall *wish* satisfaction is zero, which is unacceptable. Therefore, based on Axiom 1, the overall satisfaction $\mu^{(p,q,\alpha)}(\boldsymbol{X})$ is quantified by aggregating the overall *must* and *wish* satisfactions with the p-parameterized class of t-norm operators

$$\mu^{(p,q,\alpha)}(\boldsymbol{X}) = T^{(p)}\left(\mu_M^{(p)}(\boldsymbol{X}), \mu_W^{(q,\alpha)}(\boldsymbol{X})\right) \tag{11}$$

In equation (11), three parameters, p, q, and α, called *attitude parameters*, govern the overall satisfaction.

Optimization of the overall satisfaction

In the first phase of the HCD methodology, the design formulation in equation (5) is formally reduced to a single-objective unconstrained maximization of the overall satisfaction. One can employ any standard optimization method to perform this optimization. The locally unique solution $\boldsymbol{X}_s$ of

$$\mu^{(p,q,\alpha)}(\boldsymbol{X}_s) = \max_{X \in R^n} T^{(p)}\left(\mu_M^{(p)}(\boldsymbol{X}), \mu_W^{(q,\alpha)}(\boldsymbol{X})\right) \tag{12}$$

is called a *satisfactory design alternative*. In equation (12), various attitude parameters result in different optimum values of design variables. Hence, $\boldsymbol{X}_s$ is implicitly a function of the attitude parameters. For example, the parameter p assigns the way that a designer regards the constraints of a design problem. By varying p from a small value (close to zero) to a large amount, the solution of equation (12) will change from an aggressive nature to a conservative one. Similarly, the two parameters q and α, involving the design objectives, offer a range of trade-off strategies. That is, larger values of α or smaller values of q represent a more optimistic attitude of designer in a design solution and vice versa. A set of satisfactory design alternatives that is generated by changing the attitude parameters is denoted by $C_s \equiv \{\boldsymbol{X}_s(p,q,\alpha) : p, q > 0, \alpha \in R\}$.

Proposition. The locally unique solution to equation (12) is locally pareto-optimal for equation (5).

Proof. The local pareto-optimality of the solution is a direct consequence of the way that the satisfactions are defined and aggregated throughout subsections "Formulation of design process" and "Calculation of overall satisfaction." Assume that $\boldsymbol{X}_s$ is not locally pareto-optimal. Then, there exist $\boldsymbol{X}_1 \in R^n$ and an i_0 such that $F_{i_0}(\boldsymbol{X}_1) \succ F_{i_0}(\boldsymbol{X}_s)$. Therefore, according to Definition 1, $a_{i_0}(\boldsymbol{X}_1) \geq a_{i_0}(\boldsymbol{X}_s)$. If F_{i_0} corresponds to a *must* attribute, due to the monotonicity of the t-norm operator in equation (7), $\mu_M^{(p)}(\boldsymbol{X}_1) \geq \mu_M^{(p)}(\boldsymbol{X}_s)$. Similarly, if F_{i_0} corresponds to a *wish* attribute, due to the monotonicity of both the t-norm and the generalized mean operators in equation (11), $\mu_W^{(q,\alpha)}(\boldsymbol{X}_1) \geq \mu_W^{(q,\alpha)}(\boldsymbol{X}_s)$. Finally, the monotonicity of the t-norm in equation (12) leads to $\mu^{(p,q,\alpha)}(\boldsymbol{X}_1) \geq \mu^{(p,q,\alpha)}(\boldsymbol{X}_s)$ inequality that contradicts with the fact that $\mu^{(p,q,\alpha)}(\boldsymbol{X}_s)$ is the maximum.

Performance supercriteria

In the second phase of the HCD methodology, the best design needs to be selected from the set of satisfactory design alternatives C_s through the optimization of a proper criterion. In the previous design stages, decision making was biased by the designer/customer's preference (satisfaction membership functions) and designer's attitude (aggregation parameters). Hence, in this phase of design, the outcome must be checked against a supercriterion that is defined based on a holistic system performance. Indeed, such a supercriterion adjusts the designer's attitude based on the physical performance of the system. As the synergy in the concurrent design of multidisciplinary systems necessitates, a suitable supercriterion should take into account interconnections between the subsystems and consider the system as a whole.

Although multidisciplinary systems consist of various subsystems in different physical domains, the universal concept of energy and energy exchange is common to all of their subsystems. Therefore, an energy-based model can deem all subsystems together with their interconnections and introduce generic design criteria suitable for concurrent design. A successful attempt in this direction was introducing the concept of *bond graphs* in the early 1960s (Paynter, 1961). Bond graphs are domain-independent graphical descriptions of dynamic behavior of physical systems. In this modeling strategy, all components are recognized by the energy they supply or absorb (*source* or *sink* elements: S_e, S_f), store or dissipate (*storage* elements: I and C or *dissipative* elements: R), and reversibly or irreversibly transform (*transformer* elements: *TF; gyrator* elements: *GY*; and *distributing* elements: *0* (*zero*), *1* (*one*) *junctions* or *irreversible transducer* elements: *RS*). In Borutzky (2009) and Breedveld (2004), bond graphs are utilized to model multidisciplinary systems, and in Chhabra and Emami (2011), bond graphs are used to define three holistic design criteria for such systems, which are reviewed in sequel.

Energy. A multidisciplinary system is designed to perform a certain amount of work on its environment while input energy is supplied to it. Based on the first law of thermodynamics, the *supplied energy* $SE(\boldsymbol{X})$ does not completely convert into the *effective work* $EW(\boldsymbol{X})$. A portion of $SE(\boldsymbol{X})$ is stored or dissipated in the system elements and transacted with the environment through physical constraints or external fields. This *cost energy* $CE(\boldsymbol{X})$ in any system is the overhead energy for performing the effective work. Therefore, $CE(\boldsymbol{X})$ is considered as a supercriterion, called *energy supercriterion*, which should be minimized. Based on the principle of conservation of energy, for a predefined effective work (i.e. EW is independent of $\boldsymbol{X}$)

$$SE(\boldsymbol{X}) = EW + CE(\boldsymbol{X}) \tag{13}$$

which shows that minimizing SE is equivalent to minimizing the energy supercriterion. Therefore, by minimizing the supplied energy with respect to the attitude parameters, the best design can be achieved

$$SE(\boldsymbol{X}^*) = \min_{(p,q,\alpha)} SE(\boldsymbol{X}_s(p,q,\alpha)) \tag{14}$$

In the bond graph representation, the supplied energy is the energy that is added to the system at the source elements that are distinguishable by S_e and S_f with the bonds coming out of them. For a time interval, $SE(\boldsymbol{X}_s(p,q,\alpha))$ can be calculated by integrating the supplied power at all source elements (Chhabra and Emami, 2011).

Entropy. Based on the second law of thermodynamics, after a slight perturbation of the supplied energy, an energy system reaches its equilibrium state once the entropy generation of the system approaches its maximum. While the system moves toward the equilibrium, its capability of performing effective work on the environment reduces continuously. The less the work loss of a system, the higher its aptitude is to do effective work. In the bond graph modeling, this work loss is equal to the irreversible heat exchange $Q_{irr}(t_{eq}(\boldsymbol{X}),\boldsymbol{X})$ at the dissipative elements, where t_{eq} is defined as follows (Chhabra and Emami, 2011): given a unit step change of the supplied energy, the equilibrium time $t_{eq}(\boldsymbol{X})$ is the time instant after which the rate of change of dissipative heat remains below a small threshold ε, that is

$$t_{eq}(\boldsymbol{X}) = Inf\left\{t_0 : \forall t > t_0 \frac{\partial Q_{irr}}{\partial t}(t;\boldsymbol{X}) < \varepsilon\right\} \tag{15}$$

The $Q_{irr}(t_{eq}(\boldsymbol{X}),\boldsymbol{X})$ can also be considered as a holistic performance criterion that is called *entropy supercriterion*. Using this supercriterion, the best design can be attained by

$$Q_{irr}\left(t_{eq}(\boldsymbol{X}^*),\boldsymbol{X}^*\right) = \min_{(p,q,\alpha)} Q_{irr}\left(t_{eq}(\boldsymbol{X}_s(p,q,\alpha)),\boldsymbol{X}_s(p,q,\alpha)\right) \tag{16}$$

This criterion is usually used in the design of thermal systems (Bejan et al., 1996).

Agility. For multidisciplinary systems whose response time is a crucial factor, the rate of energy transmission through the system, or *agility*, can be a holistic measure of design. Thus, the supercriterion is defined as the time that the system takes to reach a steady state after a unit step change of some or all input parameters. In the language of bond graphs, a system is in the steady state when the rate of change of *introversive dynamic energy* $K(t;\boldsymbol{X})$ is 0. The introversive dynamic energy is defined as the energy stored in the I elements of the system. This energy is equivalent to the kinetic energy of masses in mechanical systems or the energy stored in inductors in electrical systems (Chhabra and Emami, 2011). Given a unit step change of input variables, the response time, denoted by $T(\boldsymbol{X})$, is the time instant after which the rate of change of introversive dynamic energy remains below a small threshold δ, that is

$$T(\boldsymbol{X}) = Inf\left\{t_0 : \forall t > t_0 \frac{\partial K}{\partial t}(t; \boldsymbol{X}) < \delta\right\} \quad (17)$$

As a design supercriterion, when the response time reaches its minimum value with respect to attitude parameters, the best design is attained in C_s, that is

$$T(\boldsymbol{X}^*) = \min_{(p,q,\alpha)} T(\boldsymbol{X}_s(p,q,\alpha)) \quad (18)$$

The complete flowchart of the HCD methodology is presented in Figure 1.

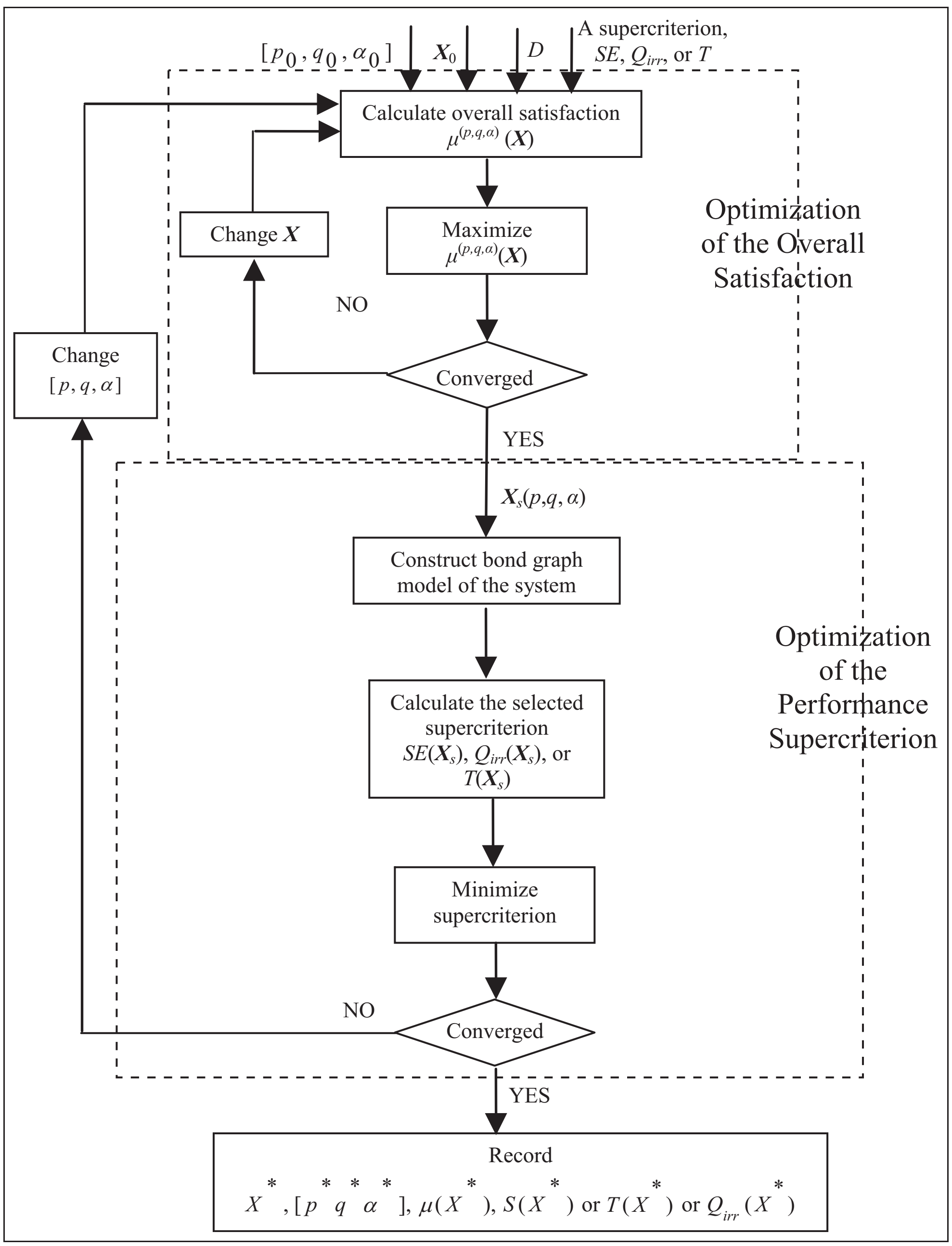

Figure 1. The holistic concurrent design flowchart.

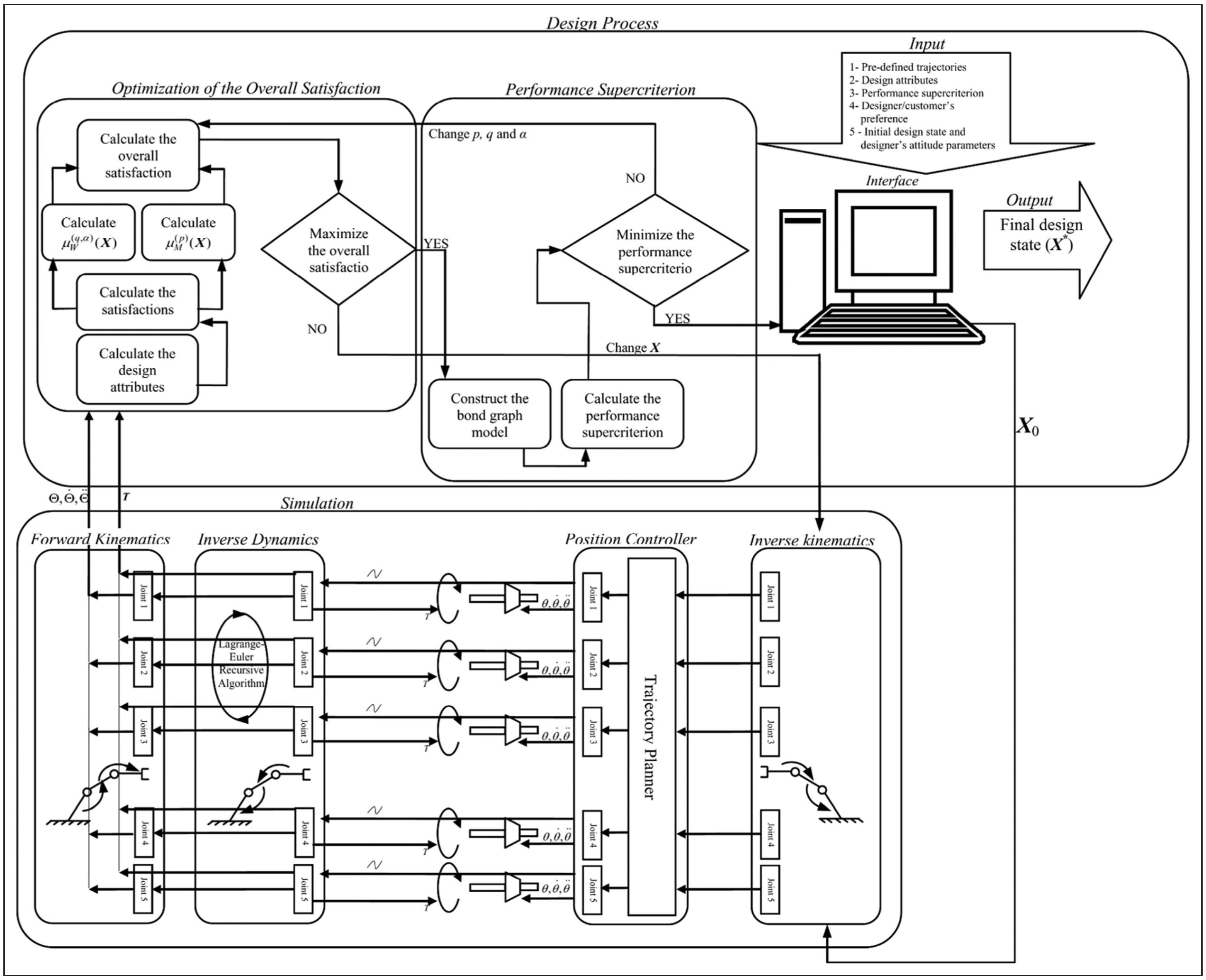

Figure 2. The HCD architecture for serial-link robot manipulators.
HCD: holistic concurrent design.

Application to robot manipulators

In this section, the HCD methodology is implemented to develop an efficient design architecture for generic serial-link robot manipulators, as an example of multidisciplinary systems. In order to evaluate the design attributes in the phase of overall satisfaction optimization, a simulation package is integrated with the HCD methodology, consisting of forward and inverse kinematics, and a recursive Lagrange–Euler inverse dynamics. A generic bond graph model of a serial-link manipulator is also utilized to calculate the performance supercriterion in the phase of supercriterion optimization. A detailed description of the bond graph model is presented in Chhabra and Emami (2011). The resulting design architecture (shown in Figure 2) is employed to concurrently design a 5-DOF robot manipulator to follow a number of predefined trajectories, including step, ramp, pick-and-place, and periodic, subject to 1 kg payload.

Design variables and attributes

The kinematic, dynamic, and control parameters of a 5-DOF manipulator with rotary joints are considered as the design variables. Kinematic parameters of the robot, that is, its geometry, are defined based on standard Denavit–Hartenberg convention (Denavit and Hartenberg, 1955). Length l_i, offset d_i, and twist α_i (Figure 3) are deemed as the kinematic design variables of the ith link. To take into account dynamic parameters, each link is modeled as an L-shaped circular cylinder along the link length and offset. The radius of the corresponding cylinder r_i, as a design variable, specifies dynamic parameters of the ith link, that is, mass,

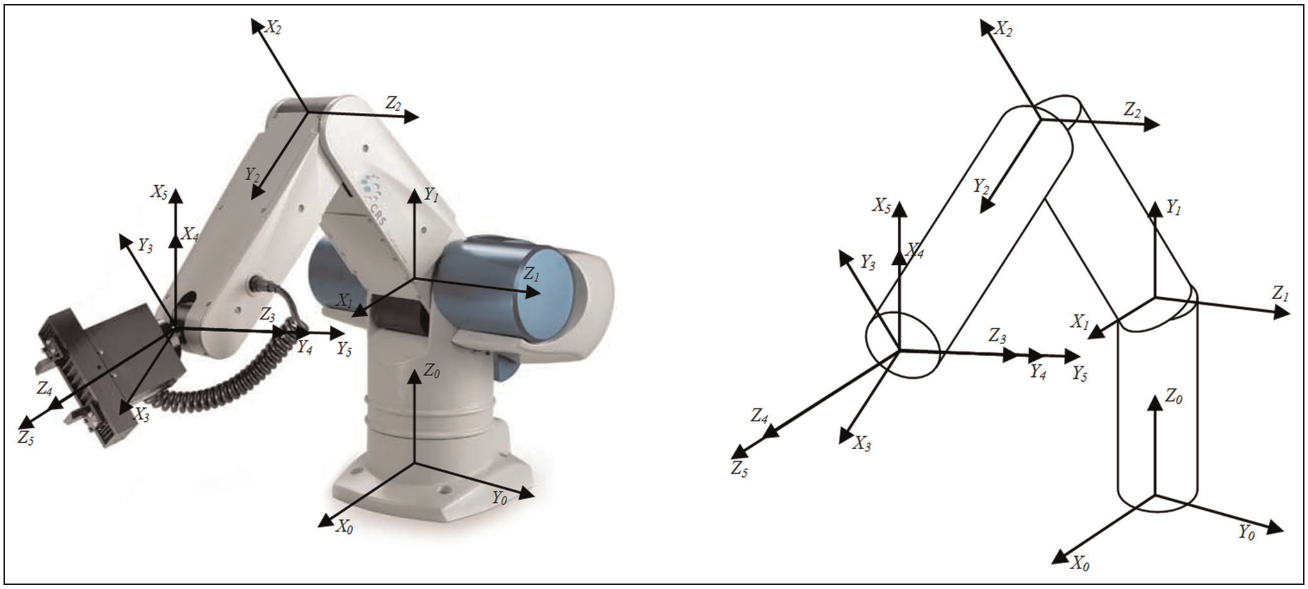

Figure 3. The CRS CataLyst-5 manipulator, its schematic and link coordinate frames, and D-H parameters.
D-H: Denavit–Hartenberg.
l_i is the length of common normal between Z_{i-1} and Z_i along X_i; d_i is the distance from X_{i-1} to X_i measured along Z_{i-1}; α_i is the angle between Z_{i-1} and Z_i measured about X_i; θ_i is the angle between X_{i-1} and X_i measured about Z_{i-1}.

moment of inertia, and the position of the center of mass. From the control point of view, a *PI* position controller with velocity feedback and feedforward is considered for each joint. Hence, the control design parameters for the ith joint consist of proportional P_i, integral Int_i, velocity feedback $Kv_{fb,I}$, and velocity feedforward $Kv_{ff,i}$ gains. Consequently, this design problem deals with 40 design variables, in total.

In the HCD methodology, design attributes are divided into *must* and *wish* attributes, which are listed below, for this case study.

M1: design availabilities, that is, a set of inequalities for the design variables X_j's

$$X_j^{min} \leq X_j \leq X_j^{max} (j = 1, \ldots, 40) \tag{19}$$

M2: joint restrictions, that is, a set of inequalities for the ith joint variable at instant t, $\theta_i(t; \boldsymbol{X})$

$$\theta_i^{min} \leq \theta_i(t; \boldsymbol{X}) \leq \theta_i^{max} (i = 1, \ldots, 5) \tag{20}$$

M3: torque restrictions, that is, a set of inequalities for the torque of joint i at instant t, $\tau_i(t; \boldsymbol{X})$

$$|\tau_i(t; \boldsymbol{X})| \leq \tau_i^{max} (i = 1, \ldots, 5) \tag{21}$$

M4: the restriction on the farthest point of the end-effector reachable workspace, that is, $Ri(\boldsymbol{X}) \leq Ri^{max}$.

W1: the end-effector overall position error $E_{tot}(\boldsymbol{X})$. The average of the end-effector position error over the set of N_t predefined end-effector trajectories at instant t is

$$E_{av}(t; \boldsymbol{X}) = \frac{1}{N_t} \sum_{m=1}^{N_t} \sqrt{(x_m(t; \boldsymbol{X}) - x_{d,m}(t))^2 + (y_m(t; \boldsymbol{X}) - y_{d,m}(t))^2 + (z_m(t; \boldsymbol{X}) - z_{d,m}(t))^2} \tag{22}$$

where $(x_{d,m}(t), y_{d,m}(t), z_{d,m}(t))$ are the desired coordinates of the end-effector in the mth predefined trajectory at instant t and $(x_m(t; \boldsymbol{X}), y_m(t; \boldsymbol{X}), z_m(t; \boldsymbol{X}))$ are the actual coordinates of the end-effector following the mth predefined trajectory at instant t. The time average of $E_{av}(t; \boldsymbol{X})$ for the interval $[0, t_f]$, where t_f is the final simulation time, is considered as the end-effector overall position error, that is

$$E_{tot}(\boldsymbol{X}) = \frac{1}{t_f} \int_0^{t_f} E_{av}(t; \boldsymbol{X}) dt \tag{23}$$

W2: the robot manipulability $Man(\boldsymbol{X})$

$$Man(\boldsymbol{X}) = \frac{1}{t_f} \int_0^{t_f} \left(\frac{1}{N_t} \sum_{m=1}^{N_t} cond(\boldsymbol{J}_0^m(t; \boldsymbol{X})) \right) dt \tag{24}$$

where $cond(\boldsymbol{J}_0^m(t; \boldsymbol{X}))$ is the condition number of the Jacobian matrix with respect to the base coordinate

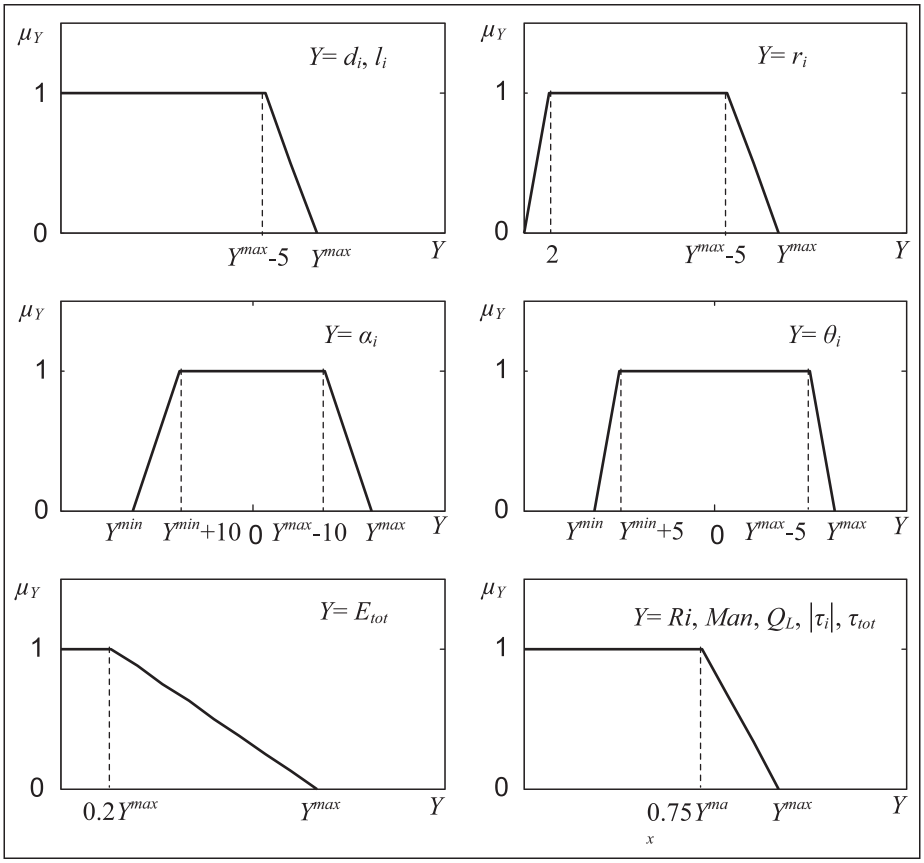

Figure 4. Satisfactions defined on design variables and attributes.

frame at time t for the mth predefined trajectory (Bi and Zhang, 2001).

W3: the structural length index of the manipulator $Q_L(\boldsymbol{X})$

$$Q_L(\boldsymbol{X}) = \sum_{i=1}^{5} \frac{(d_i + l_i)}{\sqrt[3]{Vol(\boldsymbol{X})}} \tag{25}$$

where $Vol(\boldsymbol{X})$ is the workspace volume, which is computed based on an algorithm presented in Ceccarelli et al. (2005).

W4: the average of the overall required torque at time t on the predefined trajectories $\tau_{tot}(t;\boldsymbol{X})$

$$\tau_{tot}(t;\boldsymbol{X}) = \frac{1}{N_t} \sum_{m=1}^{N_t} \sum_{i=1}^{5} \left|\tau_i^m(t;\boldsymbol{X})\right| \tag{26}$$

where $\tau_i^m(t;\boldsymbol{X})$ is the required torque for the joint i at time t in the mth predefined end-effector trajectory.

Satisfaction assignment

Satisfactions are defined as fuzzy membership functions over the universes of discourse of design variables and attributes. The *must* attributes should often satisfy inequalities while *wish* attributes are optimized. A form of fuzzy membership functions that is utilized in this case study is trapezoidal membership function (see Figure 4). This function is identified by its four corners that are specified based on the design availabilities and requirements and the designer's interpretation of inequality and optimization. The first and last corners of the trapezoid corresponding to a *must* satisfaction are the lower and upper bounds of the inequality, respectively. The middle points are chosen such that the definition of the inequality is neither too fuzzy nor too crisp. For a *wish* satisfaction that needs to be minimized, the last corner is the maximum allowable value of the attribute, and as the attribute decreases, the satisfaction approaches to 1. The middle point is selected based on the designer's interpretation of minimum. All acceptable ranges of values corresponding to the design variables and attributes are listed in Table 1.

Table 1. Initial and final design solutions.

	r_i (mm)					l_i (mm)				
	i = 1	i = 2	i = 3	i = 4	i = 5	i = 1	i = 2	i = 3	i = 4	i = 5
Initial	65.6	27.9	24.2	10.0	10.0	0.0	255.2	254.0	0.0	0.0
Final	65.9	28.0	23.0	10.1	10.2	0.0	257.9	255.1	0.0	0.0
	d_i (mm)					α_i (°)				
	i = 1	i = 2	i = 3	i = 4	i = 5	i = 1	i = 2	i = 3	i = 4	i = 5
Initial	254.0	0.0	0.0	0.0	0.0	−90.4	0.0	0.0	−89.3	0.0
Final	255.1	0.0	0.0	0.0	0.0	−90.6	0.0	0.0	−89.5	0.0
	P_i					Int_i				
	i = 1	i = 2	i = 3	i = 4	i = 5	i = 1	i = 2	i = 3	i = 4	i = 5
Initial	20.48	22.26	13.00	12.00	10.05	0.100	0.100	0.150	0.200	0.101
Final	20.73	22.35	13.07	12.04	10.08	0.100	0.101	0.152	0.201	0.101
	$Kv_{fb,i}$					$Kv_{ff,i}$				
	i = 1	i = 2	i = 3	i = 4	i = 5	i = 1	i = 2	i = 3	i = 4	i = 5
Initial	41.11	39.67	24.08	23.65	22.40	44.38	48.25	33.29	25.00	23.00
Final	40.55	39.68	24.12	23.71	22.52	45.04	48.39	33.37	25.07	23.08
	$[p, q, \alpha]$					SE (J)				
Initial	[10.00, 1.50, 0.50]					8.2850				
Final	[9.56, 1.69, 0.50]					7.8049				
	Wish design attributes									
	E_{tot}	Man	Q_L	$\tau_{tot}(t_k)$ (N·m)						
				k = 1	k = 2	k = 3	k = 4	k = 5	k = 6	k = 7
Initial	2.1948	19.5192	1.3049	14.0631	12.1214	13.0851	12.1373	12.1434	13.1062	12.1474
Final	0.6757	18.7397	1.2982	13.3135	11.3882	12.3080	11.4063	11.4128	12.3297	11.4165
	Wish satisfactions									
	μ_{Etot}	μ_{Man}	μ_{Q_L}	$\mu_{\tau_{tot}(t_k)}$						
				k = 1	k = 2	k = 3	k = 4	k = 5	k = 6	k = 7
Initial	0.000	0.738	0.747	0.591	1.000	0.828	1.000	1.000	0.823	1.000
Final	0.417	0.754	0.877	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Overall *must* satisfaction ($\mu_M^{(p)}$)					Overall satisfaction ($\mu^{(p,q,\alpha)}$)				
Initial	0.418					0.278				
Final	0.592					0.572				

Calculating the design attributes and optimizing the overall satisfaction

In the phase of overall satisfaction optimization, the function *fminsearch* in the MATLAB® optimization toolbox is employed for performing the single-objective optimization. This function uses a derivative-free search algorithm based on simplex method that is suitable for handling discontinuity, sharp corners, and noise in the objective function. At each optimization step, for the design state $\boldsymbol{X}$, the robot simulation is first run for different end-effector trajectories. And, the *must* and *wish* attributes, defined in *M1–M4* and *W1–W4*, are then computed and satisfactions are assigned based on Figure 4. Assuming small changes in the design variables in the successive optimization steps, the positive- and negative-differential *wish* attributes are specified. Then, the satisfactions are aggregated, as explained in section "Calculation of overall satisfaction," to compute the overall satisfaction. In the case study, the existing design of an industrial manipulator, that is, CRS CataLyst-5, is used as the initial state. Although this system has already been optimized using the conventional design methodologies, it is shown in this section that one can further enhance its performance using the HCD methodology.

Performance supercriterion

In the phase of supercriterion optimization, the energy supercriterion, defined in subsection "Energy," is minimized against the attitude parameters. In the design loop, this supercriterion is determined for each satisfactory design alternative using a bond graph model of a 5-DOF serial-link manipulator including its joint modules and controllers, which is programmed in MATLAB Simulink. Since the bond graph model used in this case study is identical to the one used in Chhabra and Emami (2011), the details of constructing and evaluating the model are omitted here.

In this case study, energy flows to the system through the constant voltage electric sources of the joint motors. Hence, the total energy consumption of the system as the supercriterion is calculated by

$$SE(\boldsymbol{X}_s(p,q,\alpha)) = \frac{1}{N_t}\sum_{m=1}^{N_t}\sum_{i=1}^{5}\left(V\int_i^{t_f}\left|I_i^m(t;\boldsymbol{X}_s,p,q,\alpha)\right|dt\right) \quad (27)$$

where V_i is the constant voltage and $I_i^m(t;\boldsymbol{X}_s,p,q,\alpha)$ is the current at the *i*th electric source while the manipulator is following the *m*th predefined trajectory that is evaluated by the bond graph simulation. Using a gradient-based, constrained nonlinear optimization algorithm, called *fmincon*, the energy supercriterion is minimized over the attitude parameters.

Discussion of results

The initial and final design solutions of the 5-DOF serial-link industrial manipulator, CRS CataLyst-5, are presented in Table 1. Since the initial state was that of the existing system, whose design has already been refined conventionally, some of the design variables did not change from their initial values notably. However, for the dynamic parameters, the radius of the third link has changed most notably by almost 5%. As for the kinematic parameters, the lengths of the second and third links have changed by nearly 1% and −0.5%, respectively. Considering these modifications, the masses of the first three links have been adjusted by −1.3%, −1.8%, and +9%, respectively. All control gains have been slightly modified by 0.3%−1.5% to enhance the system performance.

An improvement in all *wish* attributes is noticeable in Table 1, which indicates that the initial design state was not a pareto-optimal solution for the design attributes described in *M1–M4* and *W1–W4*. Hence, the HCD methodology was able to enhance the system performance in terms of the designer/customer's preference by effectively considering all design variables concurrently and employing a holistic synthesis and analysis strategy. The most important *wish* design attribute is the end-effector overall position error E_{tot} defined by equation (23). From Table 1, the final value of E_{tot} is almost 3.25 times smaller than its initial value. Table 1 shows 4% improvement for the manipulability attribute. The structural length index of the manipulator as a *wish* design attribute has been slightly improved as well, which shows that the final manipulator can cover a bigger workspace with less overall amount of material. The average of the overall required torque for predefined trajectories is shown in Table 1 at seven different times, each of which is considered as a *wish* attribute. All of them have decreased by almost 6%−7%. Furthermore, the overall *must* satisfaction has also increased indicating that the final design is more fault-tolerant.

All satisfactory design alternatives were checked against a purely objective supercriterion, as part of the HCD methodology, to adjust the designer's attitude in the aggregation process. The energy supercriterion, introduced in subsection "Energy," was used to finalize the design process. According to Table 1, the energy consumption has decreased by nearly 6%, which is consistent with the change in the total input torque in the manipulator. Comparing the final attitude parameters with the initial ones shows a 5% decrease in the *must* aggregation parameter p, which indicates that the designer was initially slightly conservative. Hence, instead of focusing on the least satisfactory *must* attribute, the designer should give more weight to the other *must* satisfactions as well. In terms of *wish* satisfaction aggregation, the value of α did not change significantly, that is, the designer was able to appropriately compromise between the two competitive *wish* attribute subsets. On the other hand, parameter q has been adjusted by 13% increase, which means that the initial designer's attitude was too aggressive. Thus, the designer should not try to enhance all cooperative *wish* attributes at once and should instead focus more on improving the minimum attribute.

Conclusion

HCD as a concurrent design methodology for multidisciplinary systems was formalized. In addition to the objective criteria, the HCD methodology considers subjective notions of design in the form of *satisfaction* and *attitude parameters*, in the hope of enhancing the communication between different disciplines. Furthermore, it formally converts a multi-objective constrained optimization to a single-objective unconstrained problem, which makes it feasible to iterate on numerous design variables with different natures concurrently. In the HCD methodology, the ultimate goal of design is redefined based on the qualitative notions of *wish* and *must* satisfactions. The methodology also studies the effect of designer's subjective attitude in the design process, which can be adjusted based on the reality of system performance expressed in terms of performance supercriterion and determined by bond graphs. The application of the HCD to robot manipulators was illustrated through a case study involving the redesign of a 5-DOF industrial manipulator. It was shown that an existing design based on traditional methodologies can be further improved by considering the holistic notions of *satisfaction* in the synthesis and *energy* in the analysis and accordingly taking into account all design variables concurrently.

Declaration of conflicting interests

The authors declare that there is no conflict of interest.

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Author biographies

Robin Chhabra received the MASc degree in aerospace engineering from the University of Toronto Institute for Aerospace Studies (UTIAS), Canada, in 2008. He is currently a PhD candidate at the Space Mechatronics Laboratory in UTIAS. His research area includes mathematical modeling, control, and design of multidisciplinary systems, especially robotic systems.

M Reza Emami has a PhD degree in robotics and mechatronics from University of Toronto and has worked in the industry as a project manager in 1997–2001. He is a professional engineer and has been a faculty member at University of Toronto Institute for Aerospace Studies since 2001. He is the Director of Space Mechatronics Group and Coordinator of the Aero-Design Undergraduate Laboratories at University of Toronto. His research centers on concurrent engineering of mechatronic systems and intelligent robot teams and their aerospace applications.