A Linguistic Approach to Concurrent Design

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Abstract

This paper outlines a concurrent design methodology for multidisciplinary systems, which employs tools of fuzzy theory for the tradeoff in the design space. This methodology enhances communication between designers from various disciplines through introducing the universal notion of *satisfaction* and expressing the behaviour of multidisciplinary systems using the notion of *energy*. It employs membership functions and parametric connectives in fuzzy logic to formalize subjective aspects of design, resulting in the simplification of the multi-objective constrained optimization of a design process. The methodology attempts to find a pareto-optimal solution for the design problem. In the primary phase of the methodology, a fuzzy-logic model is utilized to identify a region in the design space that contains the pareto-optimal design state, and a proper initial state is suggested for the optimization in the secondary phase, where the pareto-optimal solution is found. Finally, the impact of the designer's subjective attitude on the design is adjusted based on a system performance by utilizing an energy-based model of multidisciplinary systems. As an application, it is shown that the design of a five-degree-of-freedom industrial robot manipulator can be enhanced by using the methodology.

Key Words:
Fuzzy connectives
Fuzzy logic
Concurrent design
Multidisciplinary systems

1. Introduction

The demand for higher precision, speed and efficiency has given rise to concurrent methodologies for designing multidisciplinary systems. The emphasis is on the physical integration and communication amongst the subsystems in different physical domains, whereas traditional approaches rely on subsystem partitioning. However, the challenge is to consider a large number of design variables and attributes simultaneously (Cabrera et al. 2010), and to develop a unified multidisciplinary model that can evaluate the attributes concurrently in a design process.

Researchers have developed different Multidisciplinary Design Optimization (MDO) formulations (Cramer et al. 1992 & 1994) suitable for various applications (Balling and Wilkinson 1997; Yokoyama et al. 2007; Martz and Neu 2009; Nosratollahi et al. 2010). 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 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). Further, 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 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. The underlying premise is to provide a common language for different engineering disciplines and also devise a means for helping them to collaborate towards a common goal (Bradley 2010). Although MDO methods attempt to take into account the interconnection between subsystems, a majority of them do not employ a unified multidisciplinary modeling algorithm. This shortcoming usually reduces the efficiency of the communication between disciplines.

This paper introduces a linguistic approach to Concurrent Design, named as *Linguistic Concurrent Design* (LCD) methodology, which 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 theory, i.e., membership functions and parametric connectives, to systematically define some subjective aspects such as designer/customer's preference and designer's *attitude* that play a significant 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. Further, the LCD formally reduces the multi-objective constrained optimization problem to three single-objective unconstrained optimizations. Consequently, not only does the LCD facilitate the communication between different disciplines, but it also results in a more practical solution for a multi-objective, multidisciplinary design problem.

In the field of engineering design, a number of concurrent design methodologies have also been introduced that attempt to take into account subjective aspects of design. For instance, Axiomatic Design theory (Suh 1998), which has been used in different applications (Bi et al. 2004; Li et al. 2011), formalizes a hierarchical approach to system design by considering subjective notions. Some other design methodologies employ fuzzy-logic tools to offer solutions to the conceptual and detailed phases of concurrent design problem (Wang 2001; Gheorghe et al. 2004; Dhingra et al. 1990; Otto and Antonsson 1995; Dhingra and Rao 1995; Jones and Hua 1998; Chen and Ngai 2008; Chen and Ko 2009). As for conceptual phase of design, a fuzzy outranking preference model was developed to model the imprecise preference relation between design solutions (Wang 2001). In addition, fuzzy outranking index was defined for different design criteria and they were aggregated with an adjustable strategy (by choosing a degree of optimism and aggressiveness) to find the best set of design solutions (Gheorghe et al. 2004).

A notable example for detailed phase of concurrent design is the Method of Imprecision (MoI) that takes into account the imprecision in design (Otto and Antonsson 1995). This approach, which has been used in various engineering applications such as product planning (Chen and Ngai 2008; Chen and Ko 2009), defines a set of designer's preferences (Wood et al. 1992) for design variables and performance parameters to model the imprecision in design. It determines and maximizes the global performance (a function from the space of design variables and performance parameters to the real numbers) under one of the two conservative or aggressive design tradeoff strategies, and uses fuzzy connectives for tradeoff in the design space (Scott and Antonsson 1998). Although this methodology offers a number of advantages that are crucial in concurrent design, it does not distinguish the constraints from the goals in the aggregation process and simply considers two extreme designer attitudes that are not justified throughout the design process. To remedy these shortcomings, the LCD methodology, presented in this paper, **a)** divides the design attributes into two inherently different classes, namely *wish* and *must* attributes; and **b)** aggregates satisfactions defined for the design variables and attributes using parametric fuzzy connectives, so that the designer's attitude, i.e. the connectives parameters, can be adjusted based on an objective supercriterion.

A step-by-step formulation of the Linguistic Concurrent Design methodology is presented in Section 2. Section 3 discusses the application of the LCD to robot manipulators, where the efficacy of the methodology is illustrated through improving the design of a five-degree-of-freedom (d.o.f.) industrial robot manipulator, namely CRS CataLyst-5. It is shown that the system performance can be further improved by considering all design variables concurrently through the LCD methodology. Some concluding remarks are made in Section 4.

2. Linguistic Concurrent Design

2.1. Formulation of Design Process

A design problem consists of two sets: *design variables* $X \equiv \{X_1,\dots,X_n\}$ and *design attributes* $A \equiv \{A_1,\dots,A_N\}$ such that any design solution can be identified by vectors $\boldsymbol{X} \equiv [X_1,\dots,X_n]^T \in \mathbb{R}^n$ and $\boldsymbol{A} \equiv [A_1,\dots,A_N]^T \in \mathbb{R}^N$, respectively. In this paper vectors are denoted by bold letters. Design variables are to be assigned in the feasible ranges of design variables, namely *design availabilities* $D \equiv D_1 \times \dots \times D_n$ such that $D_j \subset \mathbb{R}$ (j=1,…,n) (normally D_j's are intervals of $\mathbb{R}$), to satisfy the *design requirements* associated with the design attributes. For each design attribute A_i there is a mapping $F_i : \mathbb{R}^n \to \mathbb{R}$ that relates a design state $\boldsymbol{X}$ to the attribute, i.e., $A_i = F_i(\boldsymbol{X})$ (i=1,…,N). These functional mappings can be of any form, such as closed-form equations, fuzzy rule-base, or sets of experimental or simulated data. A design process can be defined 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.

$$\min_{\boldsymbol{X} \in D}[F_1(\boldsymbol{X}),\dots,F_{N_W}(\boldsymbol{X})]^T \quad \text{subject to} \quad \left\{F_i(\boldsymbol{X}) \in G_i, G_i \subset \mathbb{R}, i = N_W + 1,\dots,N\right\}; \tag{1}$$

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. In (1), it is assumed that the constraints in a design process are in the form of inequalities, and each G_i is an interval of real numbers that represents the inequalities corresponding to the design attribute A_i.

Given a set of design variables, a set of design attributes and the design availabilities, the Linguistic Concurrent Design 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 requirements. In the *primary phase*, the LCD uses a fuzzy-logic model of the system to define a linguistic fuzzy rule-base describing the satisfaction of designer/customer in order to find a region of the design space where a pareto-optimal solution of (1) exists. This phase emulates the conceptual phase of design, and it also introduces a set of initial values for the optimization in the *secondary phase*. The secondary phase, which corresponds to the detailed phase of design, uses a proper aggregation of the satisfactions to obtain the *overall satisfaction* and transform the multi-objective constrained optimization in (1) to a single-objective unconstrained maximization of the overall satisfaction. It is shown that the optimum set of design variables for the resulting single-objective optimization is locally pareto-optimal for (1). A locally pareto-optimal solution of (1) is a vector $\boldsymbol{X}_O \in D$ such that it satisfies all of the constraints, and there does not exist any other feasible vector in a neighborhood of $\boldsymbol{X}_O$ that would decrease one component of $[F_1(\boldsymbol{X}),...,F_{N_W}(\boldsymbol{X})]^T$ without a simultaneous increase in at least one other component. 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, i.e., different tradeoff 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 tradeoff in design. Therefore, in the last phase of the LCD the designer's attitude is adjusted through enhancing a holistic system performance, called *performance supercriterion*, over the satisfactory design alternatives. Hence, the LCD methodology systematically breaks down the multi-objective constrained design optimization into three levels of single-objective unconstrained optimization, and incorporates features of both human subjectivity, i.e., designer/customer's preference and designer's attitude, and physical objectivity in the form of design attributes and performance supercriterion.

In the following, the *satisfaction* for a design variable or attribute is first defined as a unified notion that corresponds to the availability of a design variable or the achievement level of a design attribute according to the corresponding design requirements specified by the customer and/or designer. Next, *must* and *wish* design attributes are introduced as two inherently different subsets of design attributes. And finally, the overall satisfaction in design is defined as a proper aggregation of the satisfactions assigned to the design variables and attributes.

Definition 1 (Satisfaction):

a) A mapping $\mu_{X_j}:\mathbb{R}\to[0,1]$ for the design variable X_j is called satisfaction if for any two different values $X_{j1}, X_{j2}\in\mathbb{R}$ one has $[\mu_{X_j}(X_{j1})>\mu_{X_j}(X_{j2})]$ $\Leftrightarrow[X_{j1}\succ X_{j2}]$ or $[\mu_{X_j}(X_{j1})=\mu_{X_j}(X_{j2})]$ $\Leftrightarrow[X_{j1}\approx X_{j2}]$. The symbols $\succ$ and $\approx$ denote strictly superior and as superior, respectively, which are interpreted based on the design availabilities.

b) A mapping $\mu_{A_i}:\mathbb{R}\to[0,1]$ for the design attribute A_i is called satisfaction if for any two different states of the design variables $\boldsymbol{X}_1,\boldsymbol{X}_2\in\mathbb{R}^n$ 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 paper the satisfaction for a design variable is denoted by $x_j(X_j)\equiv\mu_{X_j}(X_j)$, and the satisfaction for a design attribute is denoted by $a_i(\boldsymbol{X})\equiv\mu_{A_i}\circ F_i(\boldsymbol{X})$. A value of one for a satisfaction corresponds to the ideal case or the most satisfactory situation. On the other hand, the value zero 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*. A designer would use engineering specifications to relate design requirements to a proper set of design attributes by defining F_i's. Accordingly, in the LCD the design attributes are divided into two subsets, defined as:

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

Definition 3 (*Must* design attribute): A design attribute is called *must* if it refers to designer/customer's demand, i.e., the achievement of its associated design requirement is mandatory with no room for compromise. These attributes form a set denoted as $M \equiv \{M_1,...,M_{N_M}\}$, and they should usually satisfy inequalities, i.e., $M_i \equiv F_{i+N_W}(\boldsymbol{X}) \in G_i \subset \mathbb{R}$ $(i = 1,..., N_M)$. ■

Therefore, the set of all design attributes *A* is the disjoint union of *M* and *W*, i.e.,

$$M \cup W = A \quad \text{and} \quad M \cap W = \phi, \tag{2}$$

and the vector $\boldsymbol{A}$ can be rearranged as $[W_1,...,W_{N_W}, M_1,...,M_{N_M}]^T$. To distinguish between *must* and *wish* satisfactions, the satisfaction specified for a *wish* attribute W_i is denoted by $w_i(\boldsymbol{X})$ (i=1,…,N_W), and the satisfaction corresponding to a *must* attribute M_i is $m_i(\boldsymbol{X})$ (i=1,…,N_M).

The satisfactions are fuzzy membership functions over the universes of discourse of design variables and design attributes, and hence suitable fuzzy connectives can be utilized to aggregate the satisfactions.

Definition 4 (Overall satisfaction): For a design state $\boldsymbol{X}$, 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. A method of aggregating the satisfactions is proposed in the next sub-section. ■

2.2. A Method of Calculating the Overall Satisfaction

In this sub-section, separate aggregation strategies are suggested for combining satisfactions corresponding to *must* and *wish* design attributes in order to introduce the *overall must* and *wish satisfactions*, and subsequently determine the overall satisfaction for a design state.

2.2.1. Aggregation of Must Design Attributes

Must attributes correspond to those design requirements that are to be satisfied with no room for negotiation. That is, all design requirements associated with *must* attributes have to be fulfilled simultaneously. In addition, the designers' attitude toward combining the *must* attributes is different.

Considering *must* satisfactions as fuzzy membership degrees, a β-parameterized fuzzy connective Θ^{β} that is suitable for aggregating *must* satisfactions should satisfy the following properties, where $a_i \in [0,1]$ and $\beta \in \mathbb{R}$. Indeed, the parameter β controls the fashion of aggregation of the *must* satisfactions to model the designer's attitude.

MP1) Monotonicity, i.e.,

$\Theta^{\beta}(a_1,...,a_k,...,a_n) \geq \Theta^{\beta}(a_1,...,a'_k,...,a_n)$ when $a_k \geq a'_k$, $\forall k, \beta$, and

$\Theta^{\beta}(a_1,...,a_n) \geq \Theta^{\beta'}(a_1,...,a_n)$ when $\beta \geq \beta'$.

MP2) Commutativity, i.e.,

$\Theta^{\beta}(a_1,...,a_j,...,a_k,...,a_n) = \Theta^{\beta}(a_1,...,a_k,...,a_j,...,a_n)$, $\forall j, k, \gamma$.

MP3) Continuity, i.e.,

$\lim\limits_{a'_k \to a_k} \Theta^{\beta}(a_1,...,a'_k,...,a_n) = \Theta^{\beta}(a_1,...,a_k,...,a_n)$, $\forall k, \beta$, and

$\lim\limits_{\beta' \to \beta} \Theta^{\beta'}(a_1,...,a_n) = \Theta^{\beta}(a_1,...,a_n)$.

MP4) Idempotency, i.e.,

$\Theta^{\beta}(a_1,...,a_n) = \Theta^{\beta}(a_1,...,a_n)$ when $a_1 = ... = a_n$, and

MP5) Annihilation, i.e.,

$\Theta^{\beta}(a_1,...,0,...,a_n) = 0 \quad \forall \beta \in \mathbb{R}$.

Although any β-parameterized fuzzy connective Θ^{β} that satisfies **MP1-5** properties can be used to aggregate *must* satisfactions, the authors choose the parameterized t-norm operator $T^{(p)}$ defined by the following equations (Emami et al. 1999), which satisfies **MP1-5** properties, for the sake of performing computations.

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

$$S^{(p)}(b_1,...,b_n) \equiv [b_1^p + (1-b_1^p)[...[b_{n-2}^p + .. + (1-b_{n-2}^p)[b_{n-1}^p + (1-b_{n-1}^p)b_n^p]]...]]^{1/p}, \tag{4}$$

where $a_i, b_i \in [0,1]$ and p>0. In the extreme cases, the pair of t-norm and t-conorm operators ($T^{(p)}$,$S^{(p)}$) approaches *Max-Min Operators* (T_{min},S_{max}) as $p \to +\infty$, *Algebraic Product and Sum* (T_{prod},S_{sum}) as $p \to 1$, and *Drastic Product and Sum* (T_W,S_W) as $p \to 0$. The investigation on the effect of using different parameterized connectives in the LCD methodology is out of the scope of this paper.

LCD-Axiom 1: Given *must* design attributes and their satisfactions, $\{(M_i, m_i): \forall i = 1,..., N_M\}$, and considering the satisfactions for design variables, $\{(X_j, x_j): \forall j = 1,..., n\}$, 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 (3) and (4). Note that, availability of design variables is considered as a part of *must* attributes. The overall *must* satisfaction $\mu_M^{(p)}(\boldsymbol{X})$ is quantified by

$$\mu_M^{(p)}(\boldsymbol{X}) = T^{(p)}(m_1(\boldsymbol{X}),..., m_{N_M}(\boldsymbol{X}), x_1(X_1),..., x_n(X_n)) \quad p > 0\ . \tag{5}$$

Changing the value of *p* makes it possible to obtain different tradeoff strategies. Larger values of *p* would imply a more conservative attitude toward aggregating the *must* attributes. On the other hand, values of *p* closer to zero represent a more aggressive attitude. ■

2.2.2. 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. Thus, *wish* attributes can be divided into two cooperative subsets:

a) *Positive-differential wish attributes*: For a design state ***X***, positive-differential subset of *wish* attributes contains those with non-negative perturbed satisfactions, i.e., $\delta w_i(\boldsymbol{X}) \geq 0$, as a result of equal infinitesimal positive perturbations of the design variables, i.e., $\delta X_1 = ... = \delta X_n = \varepsilon > 0$ for $\varepsilon \to 0$. Therefore,

$$W_{\boldsymbol{X}}^{+} \equiv \{W_i \in W : \sum_{j=1}^{n} \frac{\partial w_i}{\partial X_j}(\boldsymbol{X}) \geq 0\}\,. \tag{6}$$

This subset consists of all *wish* design attributes that tend to reach a higher satisfaction when all design variables have equal infinitesimal increments.

b) *Negative-differential wish attributes*: For a design state $\boldsymbol{X}$, negative-differential subset of *wish* attributes contains those with negative perturbed satisfactions, i.e., $\delta w_i(\boldsymbol{X}) < 0$, as a result of equal infinitesimal positive perturbations of the design variables, i.e., $\delta X_1 = \ldots = \delta X_n = \varepsilon > 0$ for $\varepsilon \to 0$. Therefore,

$$W_{\boldsymbol{X}}^{-} \equiv \{W_i \in W : \sum_{j=1}^{n} \frac{\partial w_i}{\partial X_j}(\boldsymbol{X}) < 0\}\,. \tag{7}$$

This subset includes all *wish* attributes that tend to reach a lower satisfaction when all design variables have equal infinitesimal increments. ■

As a result, for a design state $\boldsymbol{X}$, W is the disjoint union of positive- and negative-differential subsets of *wish* attributes, i.e.,

$$W_{\boldsymbol{X}}^{+} \cup W_{\boldsymbol{X}}^{-} = W \quad \text{and} \quad W_{\boldsymbol{X}}^{+} \cap W_{\boldsymbol{X}}^{-} = \phi. \tag{8}$$

Since *wish* attributes are cooperative in each positive- or negative-differential subset, their corresponding design requirements can be fulfilled simultaneously. According to LCD-Axiom 1, a q-parameterized class of t-norm operators can be used for aggregating satisfactions in either subset of *wish* attributes. Therefore, for a design state $\boldsymbol{X}$, the *overall positive*- and *negative-differential wish satisfactions* are defined by

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

where $N_{W^{\pm}}$ is the number of positive- or negative-differential *wish* attributes for a design state $\boldsymbol{X}$. Note that, these numbers may vary by $\boldsymbol{X}$.

The two subsets of *wish* attributes cannot be improved simultaneously as their design requirements compete with each other. Meanwhile, based on Definition 3, *wish* attributes need to improve as much as possible during the design process. Therefore, some compromise is necessary for aggregating their satisfactions, and a class of mean operators reflects the averaging and compensatory nature of their aggregation.

Considering *wish* satisfactions as fuzzy membership degrees, a γ-parameterized fuzzy connective Ω^{γ} that is suitable for aggregating overall positive- and negative-differential *wish* satisfactions should satisfy the following properties, where $a_1, a_2 \in [0,1]$ and $\gamma \in \mathbb{R}$. Indeed, the parameter γ controls the fashion of aggregation to model the designer's attitude.

WP1) Monotonicity, i.e.,

$\Omega^{\gamma}(a_1, a_2) \geq \Omega^{\gamma}(a_1', a_2)$ when $a_1 \geq a_1'$, $\forall \gamma \in \mathbb{R}$, and

$\Omega^{\gamma}(a_1, a_2) \geq \Omega^{\gamma'}(a_1, a_2)$ when $\gamma \geq \gamma'$.

WP2) Commutativity, i.e.,

$\Omega^{\gamma}(a_1, a_2) = \Omega^{\gamma}(a_1, a_2)$, $\forall \gamma \in \mathbb{R}$.

WP3) Continuity, i.e.,

$\lim_{a_k' \to a_k} \Omega^{\gamma}(a_1', a_2) = \Omega^{\gamma}(a_1, a_2)$, $\forall \gamma \in \mathbb{R}$, and

$\lim_{\gamma' \to \gamma} \Omega^{\gamma'}(a_1, a_2) = \Omega^{\gamma}(a_1, a_2)$.

WP4) Idempotency, i.e.,

$\Omega^{\gamma}(a_1, a_2) = \Omega^{\gamma}(a_1, a_2)$ when $a_1 = a_2$, and

WP5) Compensation, i.e.,

$a_1 \leq \Theta^{\beta}(a_1, a_2) \leq a_2$ when $a_1 < a_2$, $\forall \beta \in \mathbb{R}$.

Although any γ-parameterized fuzzy connective Ω^{γ} that satisfies **WP1-5** properties can be used to aggregate the overall positive- and negative-differential *wish* satisfactions, the authors choose the generalized mean operator $G^{(\alpha)}$ defined by the following equation (Yager and Filev 1994), which satisfies **WP1-5** properties, for the sake of performing computations.

$$G^{(\alpha)}(a_1,a_2) \equiv \left(\frac{1}{2}(a_1^{\alpha} + a_2^{\alpha})\right)^{1/\alpha} ; \tag{10}$$

where $a_1, a_2 \in [0,1]$ and $\alpha \in \mathbb{R}$. The investigation on the effect of using different parameterized connectives in the LCD is out of the scope of this paper.

LCD-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 (10),

$$\mu_{W}^{(q,\alpha)}(\boldsymbol{X}) = \left[\frac{1}{2}\left(\left(\mu_{W^+}^{(q)}(\boldsymbol{X})\right)^{\alpha} + \left(\mu_{W^-}^{(q)}(\boldsymbol{X})\right)^{\alpha}\right)\right]^{1/\alpha} \quad \alpha \in \mathbb{R}. \tag{11}$$

This class of generalized mean operators is monotonically increasing with respect to *α* between T_{min} and S_{max} operators, and therefore offers a variety of aggregation strategies from conservative to aggressive, respectively. The overall *wish* satisfaction is governed by two parameters *q* and *α*, which represent subjective tradeoff strategies. They can be adjusted to control the nature of aggregation. Larger values of *α* or smaller values of *q* represent a more optimistic (aggressive) attitude in the design process, and vice versa. ■

2.2.3. Aggregation of Overall Wish and Must Satisfactions

The aggregation of all *wish* satisfactions can be considered as one *must* attribute, i.e., 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. In this situation, there exists at least one *wish* attribute that is not satisfied based on the design requirements, which is unacceptable from the customer's point of view. Therefore, based on LCD-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 defined by (3) and (4), i.e.,

$$\mu^{(p,q,\alpha)}(\boldsymbol{X}) = T^{(p)}(\mu_M^{(p)}(\boldsymbol{X}), \mu_W^{(q,\alpha)}(\boldsymbol{X})) . \tag{12}$$

In (12), three parameters, p, q and α, called *attitude parameters*, govern the overall satisfaction, and they represent various tradeoff strategies in aggregating *must* and *wish* attributes.

2.3. Primary Phase

This sub-section details the primary phase of the LCD methodology as a systematic approach to the conceptual design of multidisciplinary systems, which provides an imprecise sketch of the final product and illustrates the decision-making environment. In order to capture the imprecision and *fuzziness* of the conceptual phase of design, a linguistic Multi-Input-Multi-Output (MIMO) fuzzy-logic model of the multidisciplinary system being designed is utilized in this phase, whose inputs and outputs are the feasible design variables and attributes, respectively. Such a model can be constructed from the expert knowledge, physical laws, empirical data or previous designs, which is discussed in many references (see (Yager and Filev 1994; Sugeno and Yasukawa 1993; Emami et al. 1998), for example) and it is not the scope of this paper. The system fuzzy model can be represented as:

IF X_1 is B_{11} **AND**…**AND** X_n is B_{1n} **THEN** A_1 is D_{11} **AND**…**AND** A_N is D_{1N}

ALSO

… (13)

ALSO

IF X_1 is B_{r1} **AND**…**AND** X_n is B_{rn} **THEN** A_1 is D_{r1} **AND**…**AND** A_N is D_{rN},

where B_{lj} and D_{li} (i=1,…,N, j=1,…,n and l=1,…,r) are fuzzy sets on the universes of discourse of X_j and A_i (W_i or M_i), respectively, which can be labeled linguistically. Note that this model may contain only a subset of design variables whose impact on the design attributes is more significant or even well-understood by the designer. The fuzzy-logic model also includes an inference mechanism for combining the rules and calculating the outputs for any set of input variables. For instance, Takagi-Sugeno-Kang (TSK) method (Sugeno and Yasukawa 1993) can be used that has shown high computational efficiency for engineering systems. In the following, (13) is used to define a Multi-Input-Single-Output (MISO) fuzzy rule-base represented by (14) with overall satisfaction as the consequent and to introduce a set of *suitable* ranges of the design variables accordingly.

IF X_1 is B_{11} **AND**…**AND** X_n is B_{1n} **THEN** μ is F_1

ALSO

… (14)

ALSO

IF X_1 is B_{r1} **AND**…**AND** X_n is B_{rn} **THEN** μ is F_r,

where μ is the overall satisfaction and F_l (l=1,…,r) are the fuzzy sets on μ, which can be labeled linguistically. This model represents a qualitative relationship between fuzzy (linguistic) values of the design variables and the overall satisfaction achieved in the design. Based on the definition of the overall satisfaction, the ultimate goal of design can be redefined as maximizing the overall satisfaction. Therefore, from this model the designer can choose the rule(s) with maximum consequent (overall satisfaction) as the most satisfactory rule(s), and define the antecedents of the corresponding rule(s) as the suitable ranges for the design variables. The design availabilities in the secondary phase are then properly modified by the suitable ranges. Moreover, a set of initial values for the secondary phase optimization can

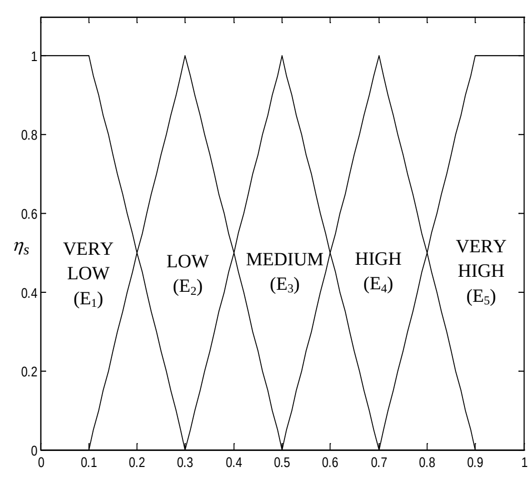


Fig. 1. Membership functions for a generic satisfaction *s*

be identified by defuzzifying the antecedents of the most satisfactory rule(s).

The construction of the MISO fuzzy-logic model is dependent on the satisfactions μ_{A_i} 's defined in the previous sub-section, and a reference set of q membership functions defined on the universe of discourse of each satisfaction, called *reference qualitative satisfaction*. As an example, the membership functions shown in Fig. 1 can be used for different values of the satisfaction μ_{A_i} . A step-by-step procedure of conducting the primary phase of the LCD methodology is presented as follows:

Step 1) Given a reference qualitative satisfaction $\{E_1,\ldots,E_q\}$ and the satisfaction μ_{A_i} for each design attribute A_i (i=1,…,N),

a) Compose μ_{A_i} with $\{E_1,\ldots,E_q\}$ to define a new reference qualitative satisfaction $\{E'_1,\ldots,E'_q\}$ in the universe of discourse of A_i.

$$E'_b(A_i) = E_b \circ \mu_{A_i}(A_i) \qquad b = 1,\ldots,q\,. \tag{15}$$

b) Find the membership function in $\{E'_1,\ldots,E'_q\}$ whose intersection with D_{li} is maximal. Denote the corresponding index to this membership function as $k_{li} \in \{1,..,q\}$ (l=1,…,r; i=1,…,N). (D_{li} is the membership function of the attribute A_i in rule l of the system's fuzzy model (13)). For the sake of computation, (amongst all well-known t-norm operators) the authors choose T_{min} as the intersection operator to find the index k_{li} . Other t-norm operators may be used to evaluate (16); however, the investigation on the effect of using different t-norm operators is not the concern of this paper.

$$S(k_{li}) = \max_{b\in\{1,\ldots,q\}} \int T_{\min}(E'_b, D_{li})\,dA_i\,. \tag{16}$$

Fig. 2 illustrates *Step 1* where k_{li} =3. Consequently, one can form the following linguistic MIMO fuzzy-logic model relating the design attributes to their satisfactions.

A_1 is D_{11} **AND**…**AND** A_N is D_{1N} **THEN** μ_{A_1} is $E_{(k_{11})}$ **AND**…**AND** μ_{A_N} is $E_{(k_{1N})}$

ALSO

… (17)

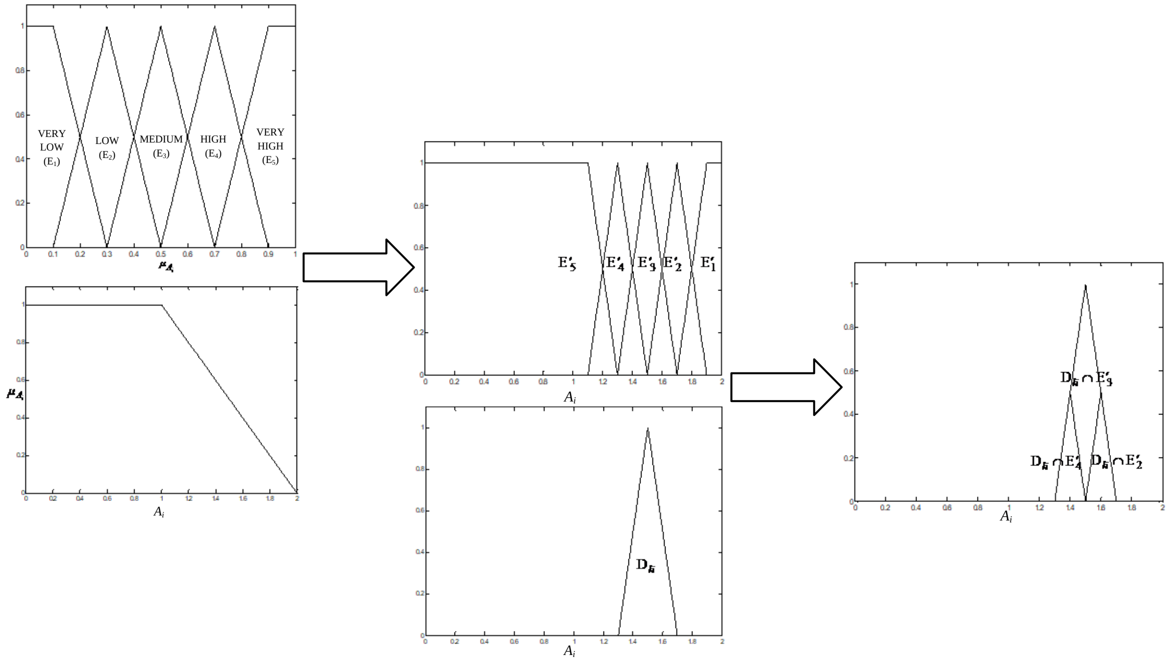


Fig. 2. An illustration of *Step 1*

ALSO

A_1 is D_{r1} **AND**…**AND** A_N is D_{rN} **THEN** μ_{A_1} is $E_{(k_{r1})}$ **AND**…**AND** μ_{A_N} is $E_{(k_{rN})}$.

Step 2) Given the fuzzy rule-base in (17), in each rule defuzzify the consequent membership functions (using the Centre of Area (CoA) method (Yager and Filev 1994), for example) and then aggregate them using T_{min} operator to obtain the overall satisfaction. The resulting rule-base relates the design attributes to the overall satisfaction. The reason for using T_{min} operator is that in the conceptual phase of design the designer is often conservative to include as many design solutions as possible, and both parametric operators employed in the previous sub-section for aggregating satisfactions, i.e., $T^{(p)}$ and $G^{(\alpha)}$, approach T_{min} for a conservative strategy. As a result, for the l^{th} rule in (17) one can find the membership function $E_{(k_{li})}$ whose centre of area is minimum for i=1,…,N. Denote the corresponding index to this membership function as $k_l^* \in \{1,..,q\}$.

$$\mathrm{CoA}(\mathrm{E}_b) = \frac{\int s\mathrm{E}_b(s)ds}{\int \mathrm{E}_b(s)ds}. \tag{18}$$

$$\mathrm{CoA}(\mathrm{E}_{(k_l^*)}) = T_{\min}(\mathrm{CoA}(\mathrm{E}_{(k_{l1})}),...,\mathrm{CoA}(\mathrm{E}_{(k_{lN})})) . \qquad (19)$$

Therefore, the resulting MISO fuzzy rule-base becomes:

IF X_1 is B_{11} **AND**…**AND** X_n is B_{1n} **THEN** μ is $\mathrm{E}_{(k_1^*)}$

ALSO

… (20)

ALSO

IF X_1 is B_{r1} **AND**…**AND** X_n is B_{rn} **THEN** μ is $\mathrm{E}_{(k_r^*)}$.

Note that any aggregation strategy suggested in Sub-section 2.2 can be used instead of the conservative strategy to calculate the overall satisfaction at this step.

Step 3) Defuzzify the consequents of (20) (by the CoA method, for example) to assign a crisp value to each rule representing the overall satisfaction. Find the $l^{*\text{th}}$ rule with maximum overall satisfaction. The antecedents of this rule define suitable ranges C_j for the design variables X_j. Finally, choose the initial value $\boldsymbol{X}_0$ for the secondary phase of design by defuzzifying the l^{*th} rule antecedent membership functions (using the CoA method).

$$\mathrm{CoA}(\mathrm{E}_{(k_{l^*}^*)}) = \max_{l=\{1,...,r\}} T_{\min}(\mathrm{CoA}(\mathrm{E}_{(k_{l1})}),...,\mathrm{CoA}(\mathrm{E}_{(k_{lN})})) . \qquad (21)$$

$$\boldsymbol{X}_0 = [\mathrm{CoA}(\mathrm{B}_{l^*1}),...,\mathrm{CoA}(\mathrm{B}_{l^*n})]^T . \qquad (22)$$

Note that, depending on how much the membership functions of the reference qualitative satisfaction are distinguished from each other, there may be more than one rule having a maximum overall satisfaction, and the designer can then further refine these membership functions to come up with a single most satisfactory rule.

The MISO fuzzy rule-base in (14) can be constructed using various methods of fuzzy-logic modeling. For instance, in the case study presented in the next section, where knowledge of the system is available from simulation and/or experimentation data, a systematic fuzzy-logic modeling approach presented in

(Emami et al. 1998) is adopted.

2.4. Secondary Phase

This sub-section details the secondary phase of the LCD methodology as an approach to the detailed design of multidisciplinary systems. By defining and aggregating the satisfactions for design variables and attributes in Sub-section 2.1&2, the design formulation in (1) is formally reduced to a single-objective unconstrained maximization of the overall satisfaction. To find a region of the design space which contains the maximum of the overall satisfaction, suitable ranges of design variables were obtained in the primary phase. The satisfactions for the design variables are modified such that they become zero out of the ranges C_j's. By using these satisfactions in the calculation of the overall satisfaction, as explained in Sub-section 2.2, one can employ any standard optimization method with the initial value $\boldsymbol{X}_0$ obtained from the primary phase:

$$\mu^{(p,q,\alpha)}(\boldsymbol{X}_s) = \max_{\boldsymbol{X}\in\mathbb{R}^n} T^{(p)}(\mu_M^{(p)}(\boldsymbol{X}), \mu_W^{(q,\alpha)}(\boldsymbol{X})) . \tag{23}$$

The solution $\boldsymbol{X}_s$ of (23) is called a *satisfactory design alternative*. In (23), various attitude parameters, i.e., p, q and α, result in different satisfactory design alternatives. Hence, $\boldsymbol{X}_s$ is implicitly a function of the attitude parameters. A set of satisfactory design alternatives that is generated by changing the attitude parameters is denoted by $C_s \equiv \{\boldsymbol{X}_s(p,q,\alpha) : p,q > 0, \alpha \in \mathbb{R}\}$.

Proposition: The solution to (23) is locally pareto-optimal for (1). In other words, the design state $\boldsymbol{X}_s$ that maximizes the overall satisfaction (a single function) is the locally unique pareto-optimal solution for the multi-objective, constrained optimization presented in (1).

Proof: The local pareto-optimality of the solution is a direct result of the way that the satisfactions are defined and aggregated throughout Sub-section 2.1&2. Assume that $\boldsymbol{X}_s$ is not locally pareto-optimal. Then, $\exists \boldsymbol{X}_1 \in \mathbb{R}^n$ such that

$$F_i(\boldsymbol{X}_1) \succeq F_i(\boldsymbol{X}_s) \quad \forall i = 1,\dots,N ,$$

particularly, there exists an i_0 such that

$F_{i_0}(\boldsymbol{X}_1) \succ F_{i_0}(\boldsymbol{X}_s)$.

According to Definition 1,

$a_{i_0}(\boldsymbol{X}_1) \geq a_{i_0}(\boldsymbol{X}_s)$,

Hence, if F_{i_0} corresponds to a *must* attribute, due to the monotonicity of the t-norm operator in (5),

$\mu_M^{(p)}(\boldsymbol{X}_1) \geq \mu_M^{(p)}(\boldsymbol{X}_s)$.

Similarly, if F_{i_0} corresponds to a *wish* attribute, due to the monotonicity and continuity of both the t-norm and the generalized mean operators in (11),

$\mu_W^{(q,\alpha)}(\boldsymbol{X}_1) \geq \mu_W^{(q,\alpha)}(\boldsymbol{X}_s)$.

Finally, the monotonicity of the t-norm in (12) leads to

$\mu^{(p,q,\alpha)}(\boldsymbol{X}_1) \geq \mu^{(p,q,\alpha)}(\boldsymbol{X}_s)$.

Obviously, the above equation contradicts with the fact that $\mu^{(p,q,\alpha)}(\boldsymbol{X}_s)$ is the maximum. ■

2.5. Performance Supercriteria

In the last phase of the LCD 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/costumer'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 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 for such systems 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 the introduction of *bond graphs* in the early 60s (Paynter 1961). Bond graphs are domain-independent graphical descriptions of dynamic behaviour 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*, *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 many references (for example, (Breedveld 2004; Borutzky 2009)) bond graph model of multidisciplinary systems is constructed for analysis, which is not the scope of this paper, whereas in (Chhabra and Emami 2011) this model is utilized for defining three design criteria, which are briefly reviewed in sequel.

2.5.1. 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, $CE(\boldsymbol{X})$ can be defined as a supercriterion, coined as *energy supercriterion*, which should be minimized. Based on the principle of conservation of energy, for a pre-defined effective work (i.e., *EW* is independent of $\boldsymbol{X}$),

$$SE(\boldsymbol{X}) = EW + CE(\boldsymbol{X}), \tag{24}$$

which shows minimizing the supplied energy 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 in C_s. That is, by changing the attitude parameters different satisfactory design alternatives are achieved whose corresponding value of energy criterion is optimized.

$$SE(\boldsymbol{X}^{\boldsymbol{*}}(p^{*},q^{*},\alpha^{*})) = \min_{p,q>0,\alpha\in\mathbb{R}} SE(\boldsymbol{X}_{s}(p,q,\alpha))\,. \tag{25}$$

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 (source of *effort* and *flow*) with the bonds coming out of them. For a time interval [0,t_f], where t_f is the final time for a bond graph simulation, $SE(\boldsymbol{X}_s)$ can be calculated by integrating the supplied power at all source elements in time (Chhabra and Emami 2011).

2.5.2. 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. Therefore, 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, i.e., *R* 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, i.e.,

$$t_{eq}(\boldsymbol{X}) = Inf\{t_0 : \forall t > t_0 \ \frac{\partial Q_{irr}}{\partial t}(t,\boldsymbol{X}) < \varepsilon\}\,. \tag{26}$$

The $Q_{irr}(t_{eq}(\boldsymbol{X}),\boldsymbol{X})$ can also be considered as a performance supercriterion, and it is called *entropy supercriterion*. Using this supercriterion, the best design can be attained in the set of optimally satisfactory solutions by

$$Q_{irr}(t_{eq}(\boldsymbol{X}^{\boldsymbol{*}}),\boldsymbol{X}^{\boldsymbol{*}}(p^{*},q^{*},\alpha^{*})) = \min_{p,q>0,\alpha\in\mathbb{R}} Q_{irr}(t_{eq}(\boldsymbol{X}_s),\boldsymbol{X}_s(p,q,\alpha)). \tag{27}$$

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

2.5.3. Agility

For multidisciplinary systems whose response time is a crucial factor, the rate of energy transmission through the system, or *agility*, can be a 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*

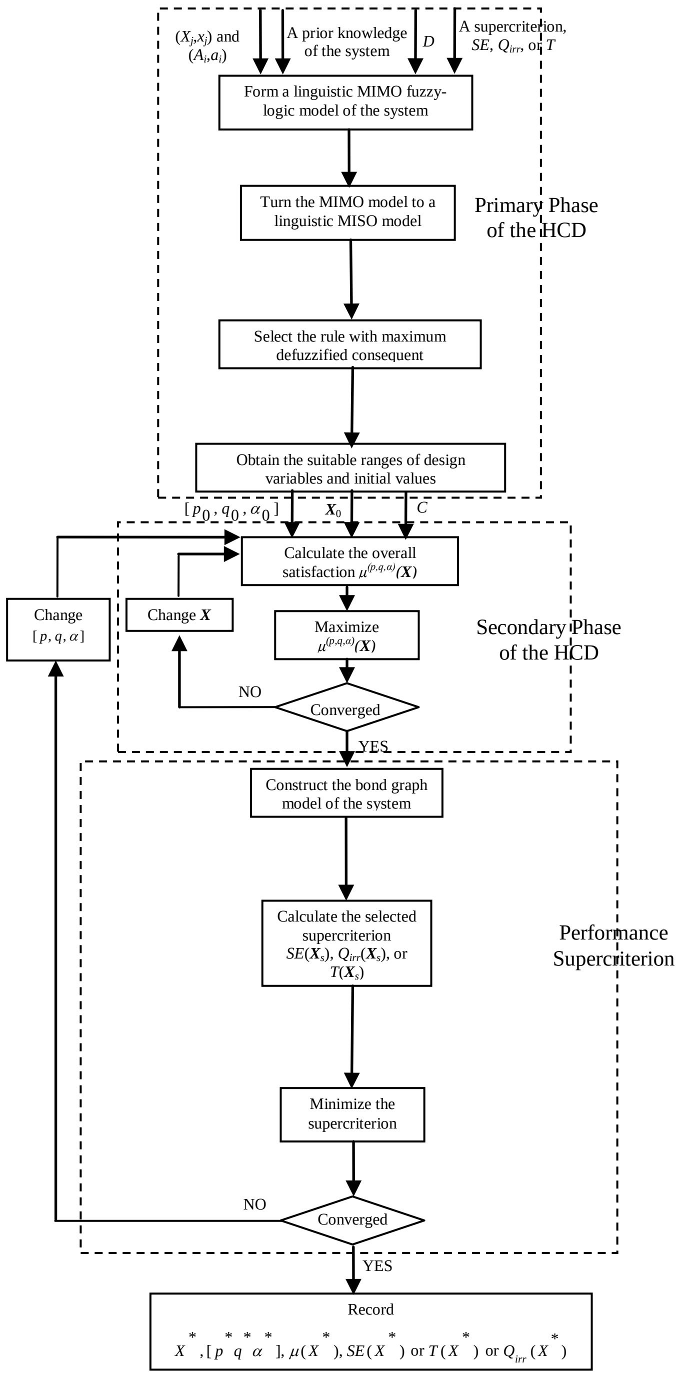


Fig. 3. The Linguistic Concurrent Design flowchart

energy $K(t, \boldsymbol{X})$ is zero. 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 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, i.e.,

$$T(\boldsymbol{X}) = Inf\{t_0 : \forall t > t_0 \ \frac{\partial K}{\partial t}(t, \boldsymbol{X}) < \delta\} . \tag{28}$$

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, i.e.,

$$T(\boldsymbol{X}^{*}(p^{*}, q^{*}, \alpha^{*})) = \min_{p,q>0,\alpha\in\mathbb{R}} T(\boldsymbol{X}_s(p, q, \alpha)) . \tag{29}$$

The complete flowchart of the LCD methodology is presented in Fig. 3.

3. Application to Robot Manipulators

In this section, the LCD methodology is implemented to develop an efficient design architecture for generic serial-link robot manipulators, as an example of multidisciplinary engineering systems. For the primary phase, existence of a database is assumed based on the existing design of similar systems. Accordingly, a fuzzy-logic modeling approach presented in (Emami et al. 1998) is adopted to construct the linguistic MISO fuzzy-logic rule-base in (14). In order to evaluate the design attributes in the secondary phase a robot simulation package is integrated with the LCD 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 a detailed description of which is presented in (Chhabra and Emami 2011). The resulting design architecture, shown in Fig. 4, is employed to concurrently improve the design of a five d.o.f. industrial manipulator, namely CRS-CataLyst 5, to follow a number of pre-defined trajectories, including step, ramp, pick-and-place, and periodic, subject to one kilogram payload at the end-effector.

Fig. 4. The LCD design architecture for serial-link robot manipulators

The LCD process is divided into five major steps: **a)** choosing the design variables and attributes, **b)** assigning satisfactions, **c)** primary phase, **d)** secondary phase, and **e)** performance supercriterion. In the following, these steps are detailed for improving the existing design of CRS-CataLyst 5.

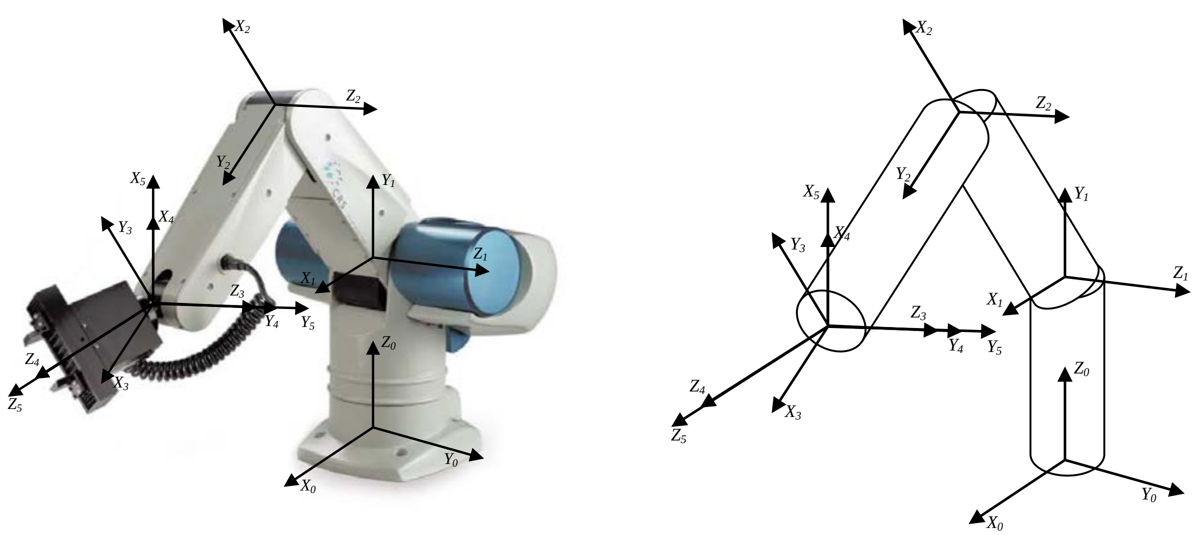
3.1. Design Variables and Attributes

The kinematic, dynamic and control parameters of a five d.o.f. manipulator with rotary joints are considered as the design variables. Kinematic parameters of the robot, i.e., its geometry, are defined based on standard Denavit-Hartenberg convention (Denavit and Hartenberg 1955). Length l_i, offset d_i, and twist

α_i (Fig. 5) are deemed as the kinematic design variables of the i^{th} 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 i^{th} link, i.e., mass, moment of inertia and the position of the centre of mass, knowing the density of link material. A schematic of a five d.o.f. serial-link manipulator is depicted in Fig. 5. 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 i^{th} 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 forty design variables, in total, to identify the best kinematic, dynamic and control design parameters for a five d.o.f. serial-link manipulator.

In the LCD methodology, design attributes are divided into *must* and *wish* attributes. As *must* attributes, a number of constraints are considered in the case study, which are listed below:

M1) Design availabilities, i.e., a set of inequalities for the design variables X_j's,



$l_i \equiv$ The length of common normal between Z_{i-1} and Z_i along X_i
$\alpha_i \equiv$ The angel between Z_{i-1} and Z_i measured about X_i
$d_i \equiv$ The distance from X_{i-1} to X_i measured along Z_{i-1}
$\theta_i \equiv$ The angel between X_{i-1} and X_i measured about Z_{i-1}

Fig. 5. The CRS CataLyst-5 manipulator, its schematic and link coordinate frames and D-H parameters

$$X_j^{\min} \le X_j \le X_j^{\max} \qquad (j=1,\ldots,40). \tag{30}$$

M2) Joint restrictions, i.e., a set of inequalities for the i^{th} joint variable at instant t, $\theta_i(t;\boldsymbol{X})$,

$$\theta_i^{\min} \le \theta_i(t;\boldsymbol{X}) \le \theta_i^{\max} \qquad (i=1,\ldots,5). \tag{31}$$

M3) Torque restrictions, i.e., a set of inequalities for the absolute torque of the joint i at instant t, $\tau_i(t;\boldsymbol{X})$,

$$\left|\tau_i(t;\boldsymbol{X})\right| \le \tau_i^{\max} \qquad (i=1,\ldots,5). \tag{32}$$

M4) The restriction on the farthest point of the end-effector reachable workspace, i.e., $Ri(\boldsymbol{X}) \le Ri^{\max}$.

The considered *wish* design attributes are:

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 pre-defined end-effector trajectories at instant t is

$$E_{av}(t;\boldsymbol{X}) = \frac{1}{N_t}\sum_{m=1}^{N_t}\sqrt{(x_m(t;\boldsymbol{X}) - x_{d,m}(t))^2 + (y_m(t;\boldsymbol{X}) - y_{d,m}(t))^2 + (z_m(t;\boldsymbol{X}) - z_{d,m}(t))^2}\ ; \tag{33}$$

where $(x_{d,m}(t), y_{d,m}(t), z_{d,m}(t))$ are the desired coordinates of the end-effector in the m^{th} pre-defined 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 m^{th} pre-defined trajectory at instant t. The time average of $E_{av}(t;\boldsymbol{X})$ is considered as the end-effector overall position error, i.e.,

$$E_{tot}(\boldsymbol{X}) = \frac{1}{t_f}\int_0^{t_f} E_{av}(t;\boldsymbol{X})dt\ . \tag{34}$$

where t_f is the final simulation time.

W2) The robot manipulability $Man(\boldsymbol{X})$,

$$Man(\boldsymbol{X}) = \frac{1}{t_f}\int_0^{t_f}\left(\frac{1}{N_t}\sum_{m=1}^{N_t} cond(\boldsymbol{J}_0^m(t;\boldsymbol{X}))\right)dt\ ; \tag{35}$$

where $cond(\boldsymbol{J}_0^m(t;\boldsymbol{X}))$ is the condition number of the Jacobian matrix of the five d.o.f. serial-link manipulator with respect to the base coordinate frame at time t for the m^{th} pre-defined trajectory. At the singular points this condition number approaches infinity, and its minimum value is one (Bi and Zhang 2001).

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

$$Q_L(\boldsymbol{X}) = \sum_{i=1}^{5}(d_i + l_i) / \sqrt[3]{Vol(\boldsymbol{X})}\,; \tag{36}$$

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

W4) The average of the overall required torque at time t on the pre-defined end-effector trajectories $\tau_{tot}(t;\boldsymbol{X})$,

$$\tau_{tot}(t;\boldsymbol{X}) = \frac{1}{N_t}\sum_{m=1}^{N_t}\sum_{i=1}^{5}\left|\tau_i^m(t;\boldsymbol{X})\right|\,; \tag{37}$$

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

The above-mentioned design attributes are further detailed in (Chhabra and Emami 2009; Emami and Chhabra 2010).

3.2. Satisfaction Assignment

Satisfactions are defined as fuzzy membership functions over the range of values of the design variables and attributes. The *must* attributes (including the availability constraints) should often satisfy inequalities while *wish* attributes should be as satisfactory as possible. With the help of fuzzy set theory, the LCD methodology redefines the notions of inequality and optimization, and attempts to turn their strict binary nature into a flexible behaviour. A form of fuzzy membership functions is the trapezoidal function that is utilized in this case study to define satisfactions for the design variables and attributes (see Fig. 6). These functions are identified by their four corners that are specified by the designer based on the design availabilities and requirements, and the designer/customer's interpretation of inequality and optimization. The first and last points of the trapezoid corresponding to a *must* satisfaction are the

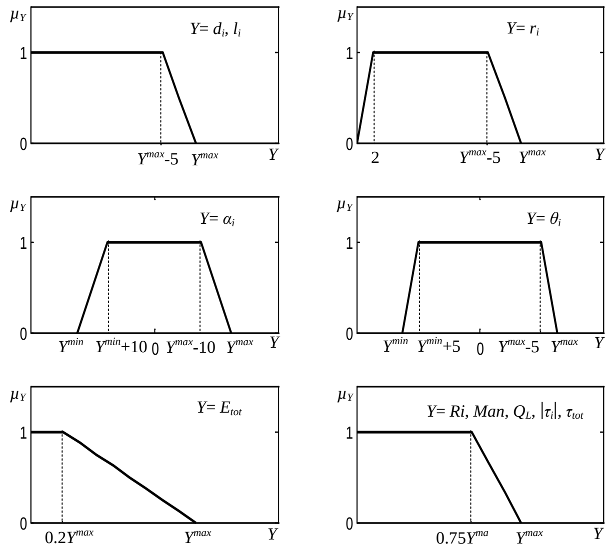


Fig. 6. Satisfactions defined on design variables and attributes

minimum and maximum values of the inequality, respectively. The middle points are chosen such that the definition of the inequality is neither too fuzzy nor too crisp, and it obeys the design requirements. For a *wish* satisfaction that needs to be minimized, the last point (of the trapezoid) is the maximum allowable value of the attribute, and as the attribute decreases the satisfaction approaches to one. The middle point is selected based on the designer/customer's interpretation of the notion of minimum. All acceptable ranges of values corresponding to the design variables and attributes in this case study are listed in Table I.

3.3. Primary Phase

The primary phase of the LCD methodology attempts to sketch the final design and search for a pareto-optimal design solution, and introduces the initial values for the optimization in the secondary phase. In this case study, the five d.o.f. robot manipulator is modeled by a set of fuzzy IF-THEN rules using the

Table I. Accepted ranges of design variables and attributes

i	1	2	3	4	5
$r_i\,(mm)$	[0,200]	[0,200]	[0,200]	[0,200]	[0,200]
$l_i\,(mm)$	[0,500]	[0,500]	[0,500]	[0,500]	[0,500]
$d_i\,(mm)$	[0,500]	[0,500]	[0,500]	[0,500]	[0,500]
$\alpha_i\,(^{o})$	[-180,180]	[-180,180]	[-180,180]	[-180,180]	[-180,180]
$\theta_i\,(^{o})$	[-180,180]	[-110,10]	[-100,70]	[-110,110]	[-180,180]
$\lvert\tau_i\rvert\,(N.m)$	[0,5.5]	[0,16.2]	[0,5.5]	[0,4.8]	[0,2.4]
$Ri(m)$			[0,0.87]		
E_{tot}			[0,2]		
Man			[1,24]		
Q_L			[0,1.6]		
$\tau_{tot}\,(N.m)$			[0,16.5]		
Control Gains			[0.01,1000]		

TABLE II. Antecedent and consequent memberships of the most satisfactory rule
(*a*, *b*, *c*, and *d* are the left-to-right corners of the trapezoidal function.)

X_j	Antecedent Parameters			
	a	*b*	*c*	*d*
$r_1\,(mm)$	6.531E+1	6.561E+1	6.561E+1	6.607E+1
$r_2\,(mm)$	2.768E+1	2.776E+1	2.776E+1	2.836E+1
$r_3\,(mm)$	2.404E+1	2.406E+1	2.410E+1	2.458E+1
$r_5\,(mm)$	1.000E+1	1.004E+1	1.025E+1	1.051E+1
$\alpha_1\,(^o)$	-9.327E+1	-8.984E+1	-8.909E+1	-8.846E+1
$l_1\,(mm)$	-9.279E-4	3.108E-3	3.370E-2	1.278E-1
$l_2\,(mm)$	2.539E+2	2.539E+2	2.542E+2	2.577E+2
$d_2\,(mm)$	0.000E+0	0.000E+0	4.355E-3	1.567E-1
$\alpha_3\,(^o)$	-4.074E-3	-2.763E-5	2.800E-3	5.546E-3
$d_3\,(mm)$	0.000E+0	2.584E-3	4.820E-2	2.292E-1
$\alpha_4\,(^o)$	-9.299E+1	-9.001E+1	-8.869E+1	-8.548E+1
$l_5\,(mm)$	9.976E-8	1.000E-7	1.001E-7	1.024E-7
P_1	1.993E+1	1.999E+1	2.100E+1	2.100E+1
$Kv_{fb,1}$	3.998E+1	4.035E+1	4.156E+1	4.251E+1
$Kv_{ff,1}$	4.278E+1	4.449E+1	4.504E+1	4.549E+1
P_2	2.200E+1	2.200E+1	2.215E+1	2.275E+1
$Kv_{fb,2}$	3.742E+1	3.859E+1	4.140E+1	4.271E+1
$Kv_{ff,2}$	4.740E+1	4.753E+1	4.800E+1	4.972E+1
$Kv_{fb,3}$	2.298E+1	2.362E+1	2.470E+1	2.503E+1
$Kv_{ff,3}$	3.256E+1	3.291E+1	3.352E+1	3.413E+1
P_5	9.878E+0	9.939E+0	1.009E+1	1.028E+1
I_5	9.863E-2	9.937E-2	1.010E-1	1.031E-1
μ	2.761E-1	2.783E-1	2.818E-1	2.838E-1
μ^*	0.280			

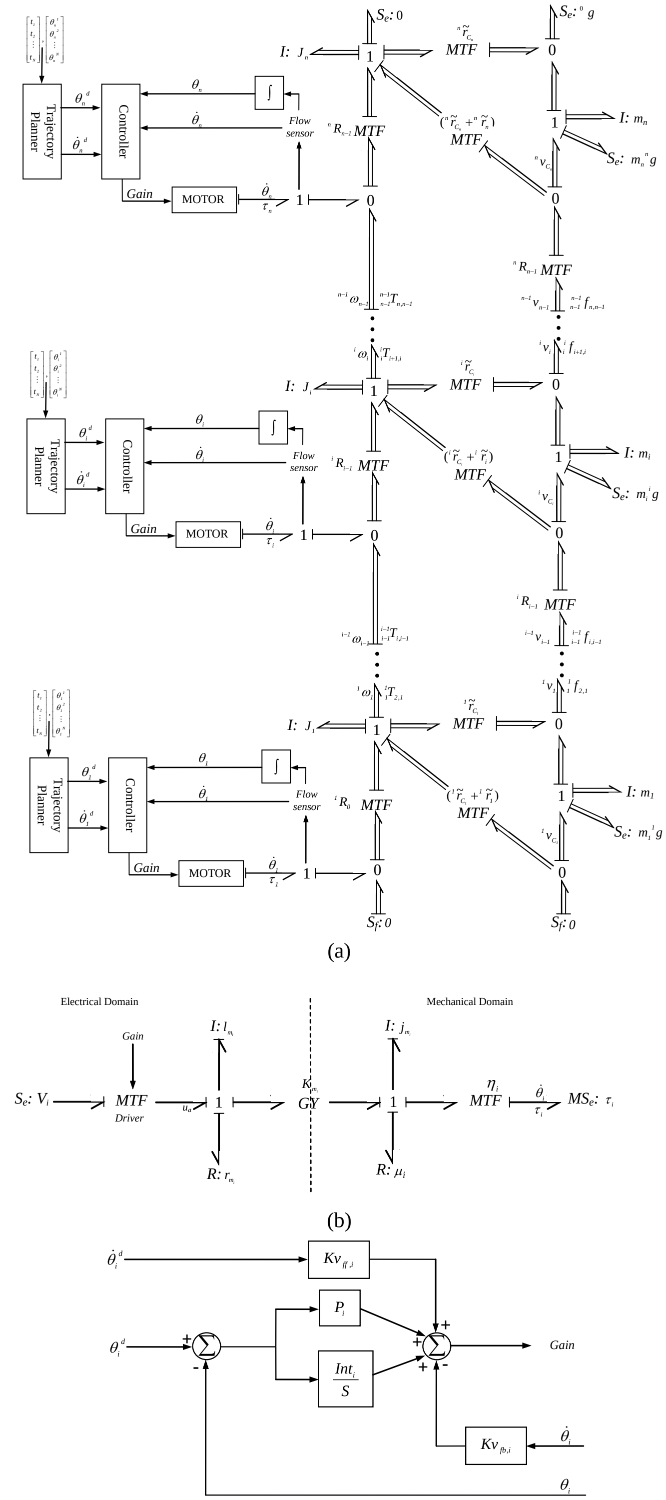
system knowledge extracted from a computer simulation of CRS-CataLyst 5. A MISO fuzzy rule-base was obtained from this model with the overall satisfaction as its consequent. A method of fuzzy-logic modeling presented in (Emami et al. 1998) is employed to build the rule-base. First, Fuzzy C-Means (FCM) clustering method (Bezdek 1981) is used to introduce membership functions on the universe of discourse of overall satisfaction that leads to 20 rules (clusters) for the system under study. Secondly, the 22 significant antecedents (design variables), which are shown in Table II, are identified by a non-significance measure (Emami et al. 1998). Finally, the output membership functions are projected to the input space to define the antecedent membership functions using line fuzzy clustering (Emami et al. 1998). The TSK inference mechanism is used to evaluate this model. In each rule, the overall satisfaction is presented by the centre of area of the consequent membership function, and the rule with the highest satisfaction is selected. The antecedent and consequent membership functions of the most satisfactory rule are depicted in Table II. In addition, the initial values for the optimization in the secondary phase, which are stated in Table IV, are identified by defuzzifying the antecedent membership functions. The initial values of the non-significant variables do not influence the secondary phase significantly; hence, their initial values are selected based on the existing design of CRS-CataLyst 5.

3.4. Secondary Phase

In the secondary phase, for each design state the robot simulation is first run for different trajectories specified in the design problem, and the required data are saved for post-processing. The *must* and *wish* design attributes, defined in **M1-4** and **W1-4**, are then computed for the design state, and satisfactions are evaluated using the membership functions shown in Fig. 6. Assuming small changes in the design variables in the successive optimization steps, the total differential of *wish* satisfactions are estimated using the satisfactions calculated in two consecutive steps of the optimization. The positive- and negative-differential *wish* attributes are specified, accordingly, and finally *wish* and *must* satisfactions are aggregated based on the procedure explained in Sub-section 2.2 to compute the overall satisfaction for the design state. This phase of design involves the maximization of the overall satisfaction starting with an initial design state determined in the primary phase. Although CRS-CataLyst 5 has already been optimized using the conventional design methodologies, it is shown in this section that one can further enhance the performance of this multidisciplinary system using the LCD methodology through considering all design variables concurrently. 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. Based on the definition of the overall satisfaction, the optimum design variables depend on the attitude parameters p, q and α.

3.5. Performance Supercriterion

In this phase of design, the energy supercriterion that is defined in Sub-section 2.5.1 is minimized over the set of satisfactory design alternatives. In the design loop, this supercriterion is determined for each satisfactory design candidate using a bond graph model of a five d.o.f. serial-link manipulator including its joint modules and controllers, which is illustrated in Fig. 7. In this figure, the *flows* and *efforts* are distinguished based on their location at the corresponding power bond. The symbol on the right-hand-side (at the bottom) of a vertical (horizontal) power bond is *effort* and the one on the left-hand-side (at the top)



(c)

Fig. 7. Bond graph representation of (a) a serial link manipulator, and (b) an electric motor; (c) the controller block diagram

of a vertical (horizontal) power bond is *flow*. A step-by-step construction of the bond graph model of a multidisciplinary system is detailed in (Borutzky 2009), and a complete description of the model shown in

Table III. CRS CataLyst-5 motor parameters used in the simulation

	V_i (V)	r_{m_i} (Ohm)	l_{m_i} (mH)	K_{m_i} (N.m/A)	j_{m_i} (g.cm^2)	η_i	μ_i (N.m.s/rad)
Link 1	4	3.3	3	0.2587	68	1/72	0.0001
Link 2	3.6	1.8	2.5	0.4414	300	1/72	0.0001
Link 3	3.6	1.8	2.5	0.4414	300	1/72	0.0001
Link 4	4	3.3	3	0.2587	68	1/19.6	0.0001
Link 5	4	3.3	3	0.2587	68	1/9.8	0.0001

Fig. 7 can be found in (Chhabra and Emami 2011). The bond graph model of the mechanical subsystem of the robot manipulator is derived based on the power and motion exchange between the constituents of the physical system, which result in an alternative representation of system dynamics to the Newton-Euler formulation for a generic serial link manipulator (Kamopp et al. 2006). The boundary conditions are zero angular and linear velocities (*flow*) at the base and constant force and zero moment (*effort*) at the end effector.

The bond graph representation of the electric motors consists of two physical domains, i.e., electrical and mechanical. A gyrator element, using the torque coefficient of the motor K_{m_i} as the gyrator ratio, relates these two domains. The electrical part includes a voltage supply V_i, a motor driver that is modeled by an amplification gain, and a simple *RL* circuit (r_{m_i} and l_{m_i} are the resistor and inductor coefficients). The mechanical domain consists of the motor shaft moment of inertia j_{m_i}, viscous friction at the bearings μ_i, and transmission system with ratio η_i. The actuators parameters of the CRS CataLyst-5 have been used in this simulation, as listed in Table III.

The energy criterion of the manipulator for a pre-defined end-effector trajectory is the time integral of the inner product of *flow* and *effort* at the source elements. 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

$$SE(\boldsymbol{X}_s;p,q,\alpha) = \frac{1}{N_t}\sum_{m=1}^{N_t}\sum_{i=1}^{5}\left(V_i\int_0^{t_f}\left|I_i^m(t;\boldsymbol{X}_s,p,q,\alpha)\right|dt\right); \tag{38}$$

where $I_i^m(t;\boldsymbol{X}_s,p,q,\alpha)$ is the current at the i^{th} electric source while the manipulator is following the m^{th}

Table IV. 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				

pre-defined end-effector trajectory, and $\boldsymbol{X}_s \in C_s$ is a satisfactory solution of design identified in the secondary phase. By minimizing this criterion over C_s the best design is achieved, i.e.,

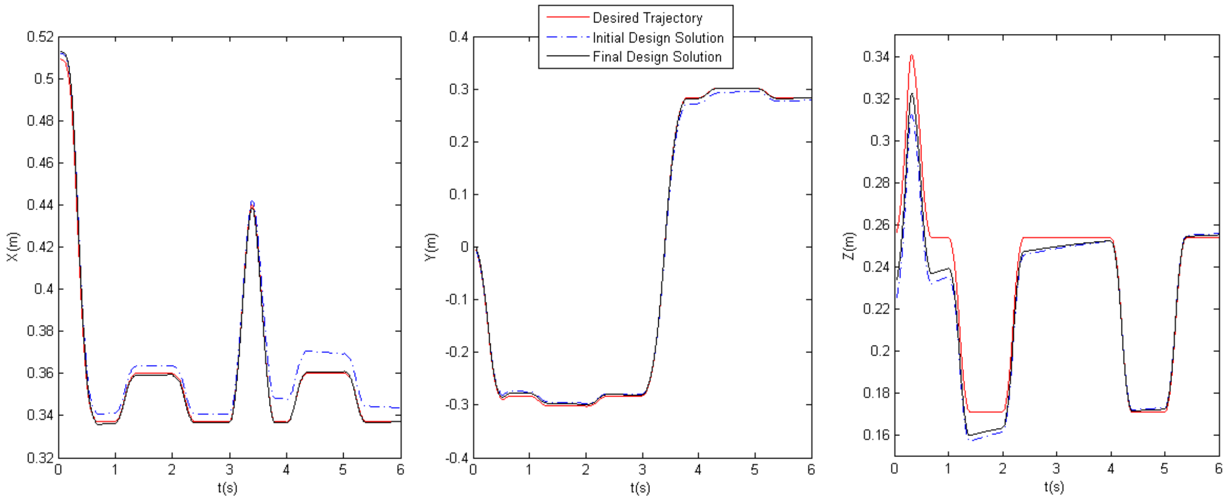
$$SE(\boldsymbol{X}^{*};p^{*},q^{*},\alpha^{*}) = \min_{X_s \in C_s} SE(\boldsymbol{X}_s;p,q,\alpha)\,. \tag{39}$$

The bond graph model of the robot manipulator was programmed in MATLAB® Simulink and a gradient-based, constrained non-linear optimization algorithm, called *fmincon*, was employed to optimize the energy supercriterion. In each optimization loop, the designer's attitude parameters are changed and the energy criterion is evaluated for a satisfactory design candidate by calculating the power transmission at the constituents of the system.

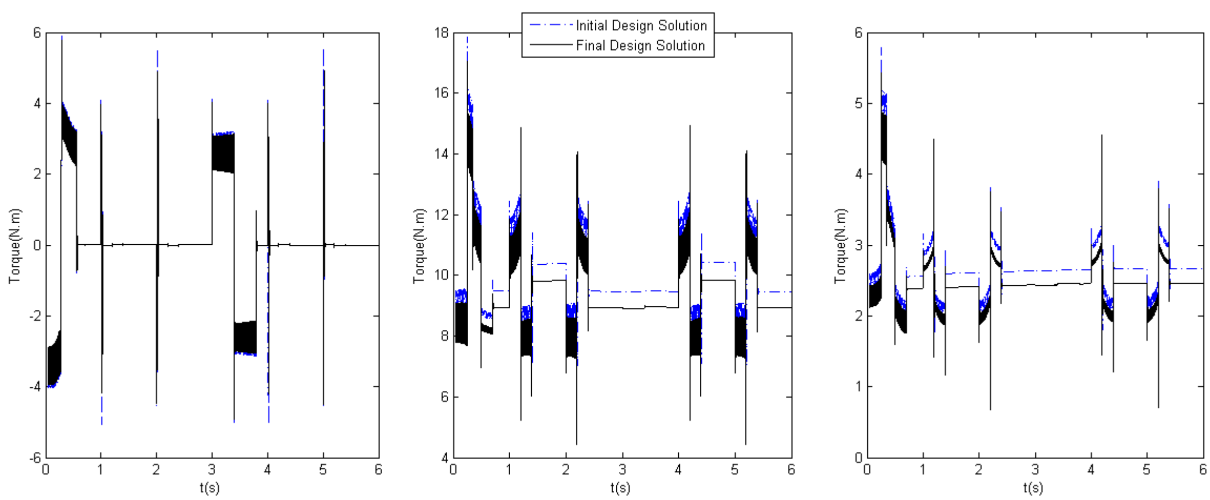
3.6. Discussion of Results

The initial and final design solutions of CRS CataLyst-5 are presented in Table IV. Since the design problem was to improve the existing design of a system, whose design has already been refined conventionally, some of the design variables did not change from their initial values notably. The minimum modifications are observed in the non-significant design variables that were identified in the primary phase of the LCD. However, for the dynamic parameters, the radius of the third link has changed most notably by almost 5%. Also, for the kinematic parameters the length of the second and third links have changed by nearly 1% and -0.5%, respectively. For the link offsets, only the first link shows a considerable adjustment. None of the twist variables have significantly changed. 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 to 1.5% to enhance the system performance.

An improvement in all *wish* attributes is noticeable in Table IV, which indicates that the existing design was not a pareto-optimal solution for the design attributes described in **M1-4** and **W1-4**. Hence, the LCD 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 concurrent synthesis and analysis strategy, which considers interconnection between different disciplines. The most important *wish* design attribute is the end-effector overall position error E_{tot} defined by (34). From Table IV, a significant improvement in E_{tot} is achieved, i.e., the final value of E_{tot} is almost 3.25 times smaller than its initial value. For instance, Fig. 8(a) demonstrates that for a pick-and-place end-effector trajectory, which was considered as one of the pre-defined trajectories in the design process, the final design solution follows the desired trajectory with less error at all times, comparing to the initial design solution. In this figure the x, y, and z components of the end-effector trajectory are shown separately. According to the designer/customer's preference, the corresponding *wish* satisfaction has reached to 0.417 from the initial value of zero. The manipulability measure indicates how close to singularity the manipulator configuration is while following different pre-defined trajectories. The ideal value for this *wish* design attribute is one. Table IV shows 4% improvement for this 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 a less overall amount of material. The average of the



(a)



(b)

Fig. 8. Performance comparison of the initial and final design solutions in terms of
(a) following a pick-and-place end-effector trajectory, and (b) torque at the first three joints (from left to right)

overall required torque in the manipulator for pre-defined end-effector trajectories is shown in Table IV at seven different times, each of which is considered as a *wish* design attribute. All of them have decreased by almost 6-7%, which means that the final manipulator consumes less energy. For example, Fig. 8(b) demonstrates that for a pick-and-place trajectory the torque at the first three joints is always less than the corresponding torque for the initial design solution. Further, the overall *must* satisfaction has also increased, which indicates an improvement in satisfying the constraints and design availabilities; therefore, the final design is more fault-tolerant.

All satisfactory design alternatives were checked against a purely-objective supercriterion, as part of the LCD methodology, to adjust the designer's attitude in the aggregation process and confirm the designer/customer's preference. The energy supercriterion introduced in Sub-section 2.5.1 was used to finalize the design process. The state with the minimum energy consumption was picked as the final design. According to Table IV, the energy consumption has decreased by nearly 6%, which is consistent with the change of the total input torque in the manipulator. Comparing the final designer's attitude with the initial parameters shows a 5% decrease in the *must* aggregation parameter p. This change indicates that the designer was initially slightly conservative in aggregating *must* attributes. 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, i.e., 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 the initial designer's attitude was too aggressive (optimistic) for the aggregation of the cooperative *wish* attributes. Thus, the designer should not try to enhance all cooperative *wish* attributes at once, and should instead focus more on improving the minimum attribute. Overall, this case study shows that implementation of the LCD can not only result in a system with a better performance, but it also helps the designer gain a better understanding of his/her actions.

4. Conclusion

A concurrent design methodology for multidisciplinary systems was formalized that effectively employs notions of fuzzy logic and fuzzy set theory, such as membership functions, fuzzy connectives and fuzzy-logic modeling, to systematically take into account subjective aspects of design and offer a practical approach to the multidisciplinary design problem. Its implementation to the design of robot manipulators was illustrated through a case study involving the re-design of a five d.o.f. industrial manipulator. It was shown that an existing design based on traditional methodologies can be further improved by considering the notions of *satisfaction* in the synthesis and *energy* in the analysis, and accordingly taking into account all design variables concurrently. The LCD methodology is naturally divided into three phases. The primary phase, which emulates the conceptual phase of design, considers all possible design solutions and qualitatively searches for a region of the design space that corresponds to the highly satisfactory design attributes. The secondary phase that is analogous to the detailed phase of design attempts to locally find the most satisfactory design solutions. Finally, a performance supercriterion determined through a bond graph model of the system is used to adjust the designer's attitude and find the ultimate design solution based on a system performance.

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