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Concurrent Engineering of Robot Manipulators

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1. Introduction

Robot manipulators are good examples of complex engineering systems, where designers occasionally employ a subsystem-partitioning approach for their analysis and synthesis. The design methodology is traditionally based on the sequential decomposition of mechanical, electromechanical, and control/instrumentation subsystems, so that at each step a subset of design variables is considered separately (Castano et al., 2002). Although conventional *decoupled* or *loosely-coupled* approaches of design seem intuitively practical, they undermine the interconnection between various subsystems that may indeed play a crucial role in multidisciplinary systems. The necessity of communication and collaboration between the subsystems implies that such systems ought to be synthesized concurrently. In the concurrent design process, design knowledge is accumulated from all the participating disciplines, and they are offered equal opportunities to contribute to each state of design in parallel. The *synergy* resulting from integrating different disciplines in concurrent design has been documented in several case studies, to the effect that the outcome is a new and previously unattainable set of performance characteristics (Hewit, 1996). However, the challenge in a concurrent design process is that the multidisciplinary system model can become prohibitively complicated; hence computationally demanding. Plus, a large number of multidisciplinary objective and constraint functions must be taken into account, simultaneously, with a great number of design variables. As the complexity of the system model increases, in terms of the interactions between various subsystems, the coordination of all the constraints distributed in different disciplines becomes more difficult, in order to maintain the consistency between performance specifications and design variables.

Within the context of robotics, several *ad hoc* techniques of concurrent engineering have been reported in the literature. They are innovative design schemes for specific systems, such as Metamorphic Robotic System (Chirikjian, 1994), Molecule (Rus & McGray, 1998), Miniaturised Self-Reconfigurable System (Yoshida et al., 1999), Crystalline (Rus & Vona, 2000), and Semi-Cylindrical Reconfigurable Robot (Murata et al., 2000). But, more systematic approaches have been suggested by other researchers beyond the robotics community to tackle the challenge of high dimensionality in concurrent design. These approaches can be divided into two major groups. The first group translates the model complexity into a large volume of computations, and then attempts to find efficient algorithms or parallel

processing techniques to make these computations feasible. For example, parallel genetic algorithms were used for multi-objective optimizations (Coello, 1999), and later augmented with a penalty method to handle constraints (Kurapati et al., 2000). This approach was later adopted for the concurrent engineering of modular robotic systems (Bi & Zhang, 2001). Also, an integration of agent-based methods and simulated annealing was used for the modular configuration design (Ramachandran & Chen, 2000). The second group tries to alleviate the complexity by reducing the optimization space; either through breaking the optimization process into several stages (Paredis, 1996), or by approximating the space with the one with lower dimensions (Dhingra & Rao, 1995). Each group brings certain contributions to concurrent engineering, yet cannot avoid some drawbacks. While efficient algorithms, mostly taking advantage of parallel processing, can handle high computational demands in concurrent engineering, they tend to lose transparency, so that designers can no longer relate to the process. On the other hand, a better understanding of design may be achieved, should one be able to simplify the optimization model, but at a great cost of obtaining outcomes for an approximated version of the system that can be far from reality.

This chapter introduces a solution for the complexity of concurrent engineering, which in essence consists of two unique constituents, each relating to one of the above-mentioned groups. For the first part, it utilizes an efficient system modeling technique that not only does not compromise the transparency, but also accounts for complex phenomena such as sensor noise, actuator limitation, transmission flexibility, etc., which can hardly be captured by computational modeling. The model efficiency, in terms of both computation and accuracy, is due to the use of real hardware modules in the simulation loop and, hence, the real-time execution. In other words, the solution uses a Robotics Hardware-in-the-loop Simulation (RHILS) platform for "computing" the system model in the design process. And for the second part, the solution applies an alternative design methodology, namely Linguistic Mechatronics (LM), which not only formalizes subjective notions and brings the linguistic aspects of communication into the design process, but also transforms the multi-objective constrained optimization model into a single-objective unconstrained formulation. A combination of the above two techniques will ensure an efficient solution for concurrent engineering of robot manipulators, without simplifying the system model. Further, it facilitates communication between designers (of different background) and customers by including linguistic notions in the design process.

The chapter is organized as follows: Section 2 introduces Linguistic Mechatronics (LM). Section 3 details the Robotics Hardware-in-the-loop Simulation (RHILS) platform. Section 4 describes the LM-RHILS based concurrent engineering methodology and its application to an industrial robot manipulator. Some concluding remarks are made in Section 5.

2. Linguistic Mechatronics: An Alternative Approach to Concurrent Engineering

The premise of concurrent engineering is to provide a common language to fill in the communication gap between different engineering disciplines, and to devise a means for helping them collaborate towards a common goal. The need for communication and collaboration in concurrent engineering implies that, in addition to physical features, many subjective notions must be involved, which can hardly be captured by pure mathematical formulations. Both customers and designers need to communicate beyond the equations to

convey design requirements and specifications. Hence, there is a need for a communication means in concurrent engineering that can convey qualitative and subjective notions that are used frequently in human interactions, in addition to holistic criteria that finalize the design process based on objective performances in the real physical world. A few methodologies of concurrent design have attempted to include subjective notions in the design process (e.x., Dhingra et al., 1990). Amongst them, Method of Imprecision (MoI) is a notable attempt to take into account imprecision in design (Otto & Antonsson, 1995). This approach defines a set of designer's preferences 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 tradeoff strategies, and uses fuzzy-logic operators for tradeoff in the design space. This method offers a number of advantages that are crucial in concurrent engineering. However, it does not provide a systemic means to distinguish the constraints from the goals in the aggregation process; instead it simply offers two extreme designer's attitudes. Further, in the MoI methodology designer's attitudes are not justified with any objective performance criterion. While subjective notions can play a crucial role in concurrent engineering of multidisciplinary systems, their relevance must eventually be checked against the objective criteria of system performance.

This section introduces *Linguistic Mechatronics* (LM) as an alternative concurrent design framework, which emphasizes on the designer's satisfaction, instead of pure performance optimization, and brings the linguistic aspects of communication into the design process. It not only formalizes subjective notions of design and simplifies the complicated multi-objective constrained optimization, but also resolves the above-mentioned deficiencies of the MoI methodology through **a)** dividing the design attributes into two inherently-different classes, namely *wish* and *must* attributes; and **b)** aggregating satisfactions using *parametric* fuzzy-logic operators so that the designer's attitude can be adjusted based on an objective performance criterion. Linguistic Mechatronics involves three stages of system modeling. First, a fuzzy-logic model is developed in the *primary* phase of design; secondly, a software and/or hardware simulation of the system is used for the *secondary* phase. And lastly, a bond graph model of the system assigns appropriate *supercriteria* that finalize the design. In the following sub-sections, the foundations of linguistic mechatronics, namely fuzzy modeling and fuzzy operators, will be reviewed first, and then a step-by-step formulation of the LM methodology will be presented.

2.1 Fuzzy-Logic Modeling

Fuzzy-logic modeling is an approach to forming a system model by using a descriptive language based on fuzzy-logic with fuzzy propositions. In (Emami, 1997), a systematic approach of fuzzy-logic modeling is developed, which is adopted in this work. In general, the clustered knowledge of a system can be interpreted by fuzzy models consisting of IF-THEN rules with multi-antecedent and multi-consequent variables (n antecedents, s consequents, and r rules):

IF U_1 is B_{11} **AND**…**AND** U_n is B_{1n} **THEN** V_1 is D_{11} **AND**…**AND** V_s is D_{1s}
ALSO
… (1)
ALSO
IF U_1 is B_{r1} **AND**…**AND** U_n is B_{rn} **THEN** V_1 is D_{r1} **AND**…**AND** V_s is D_{rs}

where U_j (j=1,…,n) is the j^{th} input variable and V_k (k=1,…,s) is the k^{th} output variable, B_{ij} (i=1,...,r, j=1,…,n) and D_{ik} (i=1,…,r, k=1,…,s) are fuzzy sets over the input and output universes of discourse, respectively. Constructing a fuzzy model can be divided into two major steps: **a)** fuzzy rule-base generation, and **b)** fuzzy inference mechanism selection.

A. Fuzzy Rule-base Generation

Assuming the existence of sufficient knowledge of the system, the process of rule-base generation can be performed in the following sequence: **a)** clustering output data and assigning output membership functions, **b)** finding the non-significant input variables and assigning the membership functions to the rest of them, and **c)** tuning the input and output membership functions. Clustering methods are occasionally based on the optimization of an objective function to find the optimum membership matrix, $\boldsymbol{U}=[u_{ik}]$, that contains the membership value of the k^{th} data point, $\boldsymbol{z}_k \in \boldsymbol{Z}$, to the i^{th} partition. In Fuzzy C-Means (*FCM*) clustering method, this function, J_m, is defined as the weighted sum of the squared errors of data points, and the minimization problem is formulated as:

$$\min_{(\mathbf{U},\mathbf{V})}\left[J_m(\boldsymbol{U},\boldsymbol{V};\boldsymbol{Z}) = \sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m (\boldsymbol{z}_k - \boldsymbol{v}_i)^T(\boldsymbol{z}_k - \boldsymbol{v}_i)\right]; \tag{2}$$

where $\boldsymbol{V} = \{\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_c\}$ is the set of unknown cluster centers, N and c are the number of data points and clusters, respectively, and m is the weighting exponent.

A prerequisite for *FCM* is assigning c and m. The optimal values of these numbers are calculated based on two requirements: **a)** maximum separation between the clusters; and **b)** maximum compactness of the clusters. Therefore, the *fuzzy within-cluster scatter matrix*,

$$\boldsymbol{S}_{\boldsymbol{W}} = \sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m (\boldsymbol{z}_k - \boldsymbol{v}_i)(\boldsymbol{z}_k - \boldsymbol{v}_i)^T \tag{3}$$

and *between-cluster scatter matrix*,

$$\boldsymbol{S}_{\boldsymbol{B}} = \sum_{i=1}^{c}\left(\sum_{k=1}^{N}(u_{ik})^m\right)(\boldsymbol{v}_i - \bar{\boldsymbol{v}})(\boldsymbol{v}_i - \bar{\boldsymbol{v}})^T \tag{4}$$

are defined to reflect the two criteria (Emami et al., 1998). Note that the fuzzy total mean array, $\bar{\boldsymbol{v}}$, is defined as:

$$\bar{\boldsymbol{v}} = \frac{1}{\sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m}\sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m \boldsymbol{z}_k \ . \tag{5}$$

The matrix $\boldsymbol{S}_{\boldsymbol{B}}$ represents the separation between the fuzzy clusters, and $\boldsymbol{S}_{\boldsymbol{W}}$ is an index for the compactness of fuzzy clusters. For obtaining the best clusters the trace of matrix $\boldsymbol{S}_{\boldsymbol{W}}$, $tr(\boldsymbol{S}_{\boldsymbol{W}})$, should be minimized to increase the compactness of clusters and $tr(\boldsymbol{S}_{\boldsymbol{B}})$ should be

maximized to increase the separation between clusters. Alternatively, $s_{cs} = tr(\boldsymbol{S}_W) - tr(\boldsymbol{S}_B)$ can be minimized to identify the optimum number of clusters, *c*. The weighting exponent, *m*, varies in $(1,+\infty)$ and indicates the degree of fuzziness of the assigned membership functions. In order to have a reliable index for s_{cs}, *m* should be far enough from both extremes. Hence, the reliable value of *m* is what holds the trace of *fuzzy total scatter matrix* ($\boldsymbol{S}_T$),

$$s_T = tr(\boldsymbol{S}_T) = tr(\boldsymbol{S}_W + \boldsymbol{S}_B), \tag{6}$$

somewhere in the middle of its domain. Since s_T and s_{cs} are both functions of *m* and *c*, the process of choosing the parameters should be performed by a few iterations.

In systems with a large number of variables, there occasionally exist input variables that have less effect on the output, in the range of interest. In order to have an efficient fuzzy-logic model, an index, π_j, is defined as an overall measure of the non-significance of input variable x_j as:

$$\pi_j = \prod_{i=1}^{n} \frac{\Gamma_{ij}}{\Gamma_j}; \qquad (j=1,\ldots,r) \tag{7}$$

where Γ_{ij} is the range in which membership function $B_{ij}(x_j)$ is one, and Γ_j is the entire range of the variable x_j. The smaller the value of π_j is, the more effect the j^{th} variable has in the model, and vice versa.

Finally, to map the output membership functions onto the input spaces, a clustering method, called *line fuzzy clustering*, is employed. This method works based on the distance of each data point located on the axis x_j, to the interval of the j^{th} input variable corresponding to the output membership function equal or close to one (Emami, 1997).

B. Fuzzy Reasoning Mechanism

To interpret connectives in fuzzy set theory, there exist a number of different classes of triangular norm (*t-norm*) and triangular conorm (*t-conorm*), 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 is shown in (Emami, 1997) that for any arbitrary *t-norm* (*T*) and *t-conorm* (*S*) and for all $a_i \in [0,1]$:

$$\begin{aligned} T_W(a_1,\ldots,a_n) &\le T(a_1,\ldots,a_n) \le T_{\min}(a_1,\ldots,a_n), \\ S_W(a_1,\ldots,a_n) &\le S(a_1,\ldots,a_n) \le S_{\max}(a_1,\ldots,a_n). \end{aligned} \tag{8}$$

Various types of parameterized operators have been suggested in the literature to cover this range. In particular, a class of operators for fuzzy reasoning is introduced in (Emami et al., 1999), which is adopted here for aggregating the satisfactions, as explained in the next sub-section:

$$S^{(p)}(b_1,b_2,\ldots,b_n) = [b_1{}^p + (1-b_1{}^p)[\ldots[b_{n-2}{}^p + \ldots + (1-b_{n-2}{}^p)[b_{n-1}{}^p + (1-b_{n-1}{}^p)b_n{}^p]]\ldots]]^{1/p}; \tag{9}$$

where $b_i \in [0,1]$ and $p \in (0,+\infty)$. Consequently, the corresponding *t-norm* operator is defined based on De Morgan laws using standard complementation operator, as:

$$T^{(p)}(a_1, a_2, ..., a_n) = 1 - S^{(p)}((1-a_1),(1-a_2),...,(1-a_n)) . \quad (10)$$

In the extreme cases, this class of parameterized operators approaches (T_{min},S_{max}) as $p \to +\infty$, (T_{prod} S_{sum}) as $p \to 1$, and (T_W, S_W) as $p \to 0$.

The meaning of an aggregation operator is sometimes neither pure AND (*t-norm*) with its complete lack of compensation, nor pure OR (*t-conorm*). This type of operator is called *mean aggregation* operator. For example, a suitable parametric operator of this class, namely *generalized mean operator*, is defined in (Yager & Filev, 1994) as:

$$G^{(\alpha)}(a_1, a_2, ..., a_n) = \left(\frac{1}{n} \sum_{i=1}^{n} a_i^{\alpha} \right)^{1/\alpha} ; \quad (11)$$

where $\alpha \in (-\infty,+\infty)$. It appears that this type of aggregation monotonically varies between *Min* operator while $\alpha \to -\infty$ and *Max* operator as $\alpha \to +\infty$. Subsequently, an appropriate inference mechanism should be employed to combine the rules and calculate the output for any set of input variables. Takagi-Sugeno-Kang (*TSK*) reasoning method is associated to a rule-base with functional type consequents instead of the fuzzy sets and the crisp output, y^*, is defined by the weighted average of the outputs of individual rules, y_i's, as:

$$y^* = \sum_{i=1}^{r} \frac{\tau_i}{\sum_{j=1}^{r} \tau_j} y_i = \sum_{i=1}^{r} \frac{\tau_i}{\sum_{j=1}^{r} \tau_j} (b_{i0} + b_{i1} x_1 + ... + b_{in} x_n) ; \quad (12)$$

where τ_i is the degree of fire of the i^{th} rule:

$$\tau_i = T(\mathrm{B}_{i1}(x_1),...,\mathrm{B}_{in}(x_n)) . \quad (13)$$

Since the *TSK* method of reasoning is compact and works with crisp values, it is computationally efficient; and therefore, it is widely used in fuzzy-logic modeling of engineering systems, especially when tuning techniques are utilized. Ultimately, the parameters of input membership functions and output coefficients are tuned by minimizing the mean square error of the output of the fuzzy-logic model with respect to the existing data points.

2.2 The LM Formulation

A design problem consists of two sets: *design variables* $\boldsymbol{X} \equiv \{X_j : \forall j = 1,..., n\}$ and *design attributes* $\boldsymbol{A} \equiv \{A_i : \forall i = 1,..., N\}$. Design variables are to be configured to satisfy the *design*

requirements assigned for design attributes, subject to the design availability $\boldsymbol{D} \equiv \{D_j : \forall j = 1,...,n\}$. Each design attribute stands for a design function providing a functional mapping $F_i : \aleph \to \Im_i$ that relates a state of design configuration $\boldsymbol{X} \in \aleph$ to the attribute $A_i \in \Im_i$, i.e., $A_i = F_i(\boldsymbol{X})$ (i=1,…,N). These functional mappings can be of any form, such as closed-form equations, heuristic rules, or set of experimental or simulated data.

Given a set of design variables and a set of design attributes along with an available knowledge that conveys the relationship between them, the process of Linguistic Mechatronics is performed in two phases: **a)** *primary* phase in which proper intervals for the design variables are identified subject to design availability, and **b)** *secondary* phase in which design variables are specified in their intervals in order to maximize an overall design satisfaction based on the design requirements and designer's preferences. Thus, the secondary phase involves a single-objective optimization, yet it is critically dependant on the initial values of a large number of design variables. The primary phase makes the optimization more efficient by providing proper intervals for the design variables from where the initial values are selected. The *overall satisfaction* is an aggregation of satisfactions for all design attributes. The satisfaction level depends on the designer's attitude that is modeled by fuzzy aggregation parameters. However, different designers may not have a consensus of opinion on *satisfaction*. Therefore, the system performance must be checked over a holistic *supercriterion* to capture the objective aspects of design considerations in terms of physical performance. Designer's attitude is adjusted through iterations over both primary and secondary phases to achieve the enhanced system performance. Therefore, this methodology incorporates features of both human subjectivity (i.e., designer's intent) and physical objectivity (i.e., performance characteristics) in multidisciplinary system engineering.

Definition 1 - Satisfaction: A mapping μ such that $\mu : \boldsymbol{Y} \to [0,1]$ for each member of $\boldsymbol{Y}$ is called satisfaction, where $\boldsymbol{Y}$ is a set of available design variables or design attributes based on the design requirements. The grade one corresponds to the ideal case or the most satisfactory situation. On the other hand, the grade zero means the worst case or the least satisfactory design variable or attribute.

Satisfaction on a design attribute, $a_i \equiv \mu_{A_i}(\boldsymbol{X})$, indicates the achievement level of the corresponding design requirement based on the designer's preferences. The satisfaction for a design variable, $x_j \equiv \mu_{X_j}(\boldsymbol{X})$, reflects the availability of the design variable. In the conceptual phase, design requirements are usually subjective concepts that imply the costumer's needs. 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. Therefore, in *LM* the design attributes are divided into two subsets, labeled *must* and *wish* design attributes.

Definition 2 - *Must* design attribute: A design attribute is called *must* if it refers to costumer's demand, i.e., the achievement of its associated design requirement is mandatory with no room for compromise. These attributes form a set coined ***M***.

Definition 3 - *Wish* design attribute: A design attribute is called *wish* if it refers to costumer's desire, i.e., its associated design requirement permits room for compromise and it should be achieved as much as possible. These attributes form a set coined ***W***.
Therefore,

$$\boldsymbol{M} \cap \boldsymbol{W} = \phi, \qquad \boldsymbol{M} \cup \boldsymbol{W} = \boldsymbol{A}\,. \tag{14}$$

The satisfaction specified for *wish* attribute W_i is $w_i(\boldsymbol{X}) \equiv \mu_{W_i}(\boldsymbol{X})$ (i=1,…,N_W), and the satisfaction specified for *must* attribute M_i is $m_i(\boldsymbol{X}) \equiv \mu_{M_i}(\boldsymbol{X})$ (i=1,…,N_M)**.** Therefore, for each design attribute A_i (corresponding to either M_i or W_i), there is a predefined mapping to the satisfaction a_i (m_i or w_i), i.e., $\{(A_i, a_i) : \forall i = 1,..., N\}$. Fuzzy set theory can be applied for defining satisfactions through fuzzy membership functions and also for aggregating the satisfactions using fuzzy-logic operators.
Remark: $[F_i(\boldsymbol{X}_1) \succeq F_i(\boldsymbol{X}_2)] \Leftrightarrow [a_i(\boldsymbol{X}_1) \geq a_i(\boldsymbol{X}_2)]$ for monotonically non-decreasing satisfaction. More specifically, if $0 < a_i(\bullet) < 1$ then $[F_i(\boldsymbol{X}_1) \succ F_i(\boldsymbol{X}_2)] \Leftrightarrow [a_i(\boldsymbol{X}_1) > a_i(\boldsymbol{X}_2)]$ and if $a_i(\bullet) = 0 \text{ or } 1$ then $[F_i(\boldsymbol{X}_1) \succ F_i(\boldsymbol{X}_2)] \Leftrightarrow [a_i(\boldsymbol{X}_1) = a_i(\boldsymbol{X}_2)]$, where $\succeq$ denotes loosely superior and $\succ$ represents strictly superior. In other words, the better the performance characteristic is the higher the satisfaction will be, up to a certain threshold.
Definition 4 - Overall satisfaction: For a specific set of design variables ***X***, overall satisfaction is the aggregation of all *wish* and *must* satisfactions, as a global measure of design achievement.

A. Calculation of Overall Satisfaction
Must and *wish* design attributes have inherently-different characteristics. Hence, appropriate aggregation strategies must be applied for aggregating the satisfactions of each subset.

1) Aggregation of Must Design Attributes
Axiom 1: Given *must* design attributes, $\{(M_i, m_i) : \forall i = 1,..., N_M\}$, and considering component availability, $\{(D_j, x_j) : \forall j = 1,..., n\}$, the overall *must* satisfaction is the aggregation of all *must* satisfactions using a class of *t-norm* operators.

Must attributes correspond to those design requirements that are to be satisfied with no room of negotiation, and, linguistically, it means that all design requirements associated with *must* attributes have to be fulfilled simultaneously. Therefore, for aggregating the satisfactions of *must* attributes an AND logical connective is suitable. Considering satisfactions as fuzzy membership degrees, the AND connective can be interpreted through a family of *t-norm* operators. Thus, the overall *must* satisfaction is quantified using the *p*-parameterized class of *t-norm* operators, i.e.,

$$\mu_{\boldsymbol{M}}{}^{(p)}(\boldsymbol{X}) = T^{(p)}(m_1, m_2, ..., m_{N_M}, x_1, x_2, ..., x_n). \quad (p > 0) \tag{15}$$

The parametric *t-norm* operator $T^{(p)}$ is defined based on (9) and (10).

Parameter p can be adjusted to control the fashion of aggregation. Changing the value of p makes it possible to obtain different tradeoff strategies. The larger the p, the more pessimistic (conservative) designer's attitude to a design will be, and vice versa.

2) Aggregation of Wish Design Attributes

Definition 5 - Cooperative *wish* attributes: A subset of *wish* design attributes is called cooperative if the satisfactions corresponding to the attributes all vary in the same direction when the design variables are changed.

Therefore, *wish* attributes can be divided into two cooperative subsets:

a) Positive-differential *wish* attributes ($\boldsymbol{W}^+$): In this subset the total differential of the satisfactions for the *wish* attributes (with respect to design variables) are non-negative.

$$\boldsymbol{W}^+ = \{(W_i, w_i) : W_i \in \boldsymbol{W}, \quad dw_i(\boldsymbol{X}) \geq 0\}. \tag{16}$$

This subset includes all attributes that tend to reach a higher satisfaction when all design variables have an infinitesimal increment.

b) Negative-differential *wish* attributes ($\boldsymbol{W}^-$): In this subset the total differential of the satisfactions for the *wish* attributes (with respect to design variables) are negative.

$$\boldsymbol{W}^- = \{(W_i, w_i) : W_i \in \boldsymbol{W}, \quad dw_i(\boldsymbol{X}) < 0\}. \tag{17}$$

This subset includes all attributes that tend to reach a lower satisfaction when all design variables have an infinitesimal increment.

$$\boldsymbol{W}^+ \cap \boldsymbol{W}^- = \phi, \quad \boldsymbol{W}^+ \cup \boldsymbol{W}^- = \boldsymbol{W}. \tag{18}$$

Since in each subset all *wish* attributes are cooperative, their corresponding design requirements can all be fulfilled simultaneously in a linguistic sense. Hence, according to **Axiom 1**, similar to *must* satisfactions, a q-parameterized class of *t-norm* operators is suitable for aggregating satisfactions in either subsets of *wish* attributes.

$$\mu_{\boldsymbol{W}^\pm}{}^{(q)}(\boldsymbol{X}) = T^{(q)}(w_1, w_2, ..., w_{N_{W^\pm}}) \quad (q > 0); \tag{19}$$

where $N_{W^\pm}$ are the number of positive-/negative-differential *wish* attributes.

Axiom 2: Given the satisfactions corresponding to positive- and negative-differential *wish* attributes, $\mu_{W^+}{}^{(q)}(\boldsymbol{X})$ and $\mu_{W^-}{}^{(q)}(\boldsymbol{X})$, the overall *wish* satisfaction can be calculated using an a-parameterized *generalized mean* operator.

The two subsets of *wish* attributes cannot be satisfied simultaneously as their design requirements compete with each other. Therefore, some compromise is necessary for

aggregating their satisfactions, and the class of *generalized mean* operators in (11) reflects the averaging and compensatory nature of their aggregation.

$$\mu_{\boldsymbol{W}}^{(\alpha,q)}(\boldsymbol{X}) = \left[\frac{1}{2}\left(\left(\mu_{\boldsymbol{W}^+}^{(q)}(\boldsymbol{X})\right)^{\alpha} + \left(\mu_{\boldsymbol{W}^-}^{(q)}(\boldsymbol{X})\right)^{\alpha}\right)\right]^{1/\alpha}. \tag{20}$$

This class of *generalized mean* operators is monotonically increasing with respect to *a* between *Min* and *Max* operators; therefore, offers a variety of aggregation strategies from conservative to aggressive, respectively. The overall *wish* satisfaction is governed by two parameters *q* and *a,* representing subjective tradeoff strategies. They can be adjusted appropriately to control the fashion of aggregation. The larger the *a* or the smaller the *q*, the more optimistic (aggressive) one's attitude to a design will be, and vice versa.

3) Aggregation of Overall Wish and Must Satisfactions

Axiom 3: The overall satisfaction is quantified by aggregating the overall *must* and *wish* satisfactions, $\mu_{\boldsymbol{M}}^{(p)}(\boldsymbol{X})$, and $\mu_{\boldsymbol{W}}^{(q,\alpha)}(\boldsymbol{X})$, with the *p*-parameterized class of *t-norm* operators, i.e.,

$$\mu^{(p,q,\alpha)}(\boldsymbol{X}) = T^{(p)}(\mu_{\boldsymbol{M}}^{(p)}(\boldsymbol{X}), \mu_{\boldsymbol{W}}^{(q,\alpha)}(\boldsymbol{X})). \quad (p>0). \tag{21}$$

The aggregation of all *wish* satisfactions can be considered as one *must* attribute, i.e., it has to be fulfilled to some extent with other *must* attributes with no compromise. Otherwise, the overall *wish* satisfaction can become zero and it means none of the *wish* attributes is satisfied, which is unacceptable in design. Therefore, the same aggregation parameter, *p,* that was used for *must* attributes should be used for aggregating the overall *wish* and *must* satisfactions. In (21), three parameters, i.e., *p, q* and *a,* called *attitude parameters*, govern the overall satisfaction.

B. Primary Phase of LM

Once the overall satisfaction is calculated, in order to obtain the most satisfactory design, this index should be maximized. The optimization schemes are critically dependent on the initial values and their search spaces. Therefore, to enhance the optimization performance, suitable ranges of design variables are first found in the primary phase of *LM*. In linguistic term, primary phase of *LM* methodology provides an *imprecise* sketch of the final product and illustrates the decision-making environment by defining some ranges of possible solutions. For this purpose, the mechatronic system is represented by a fuzzy-logic model based on (1). This model consists of a set of fuzzy IF-THEN rules that relates the ranges of design variables as fuzzy sets to the overall satisfaction; i.e.,

IF X_1 is B_{11} **AND**…**AND** X_n is B_{1n} **THEN** μ is D_1
ALSO
…
ALSO
IF X_1 is B_{r1} **AND**…**AND** X_n is B_{rn} **THEN** μ is D_r (22)

where μ is the overall satisfaction and B_{lj} and D_l (j=1,…,n and l=1,…,r) are fuzzy sets on X_j

and μ, respectively, which can be associated with linguistic labels.
The fuzzy rule-base is generated from the available data obtained from simulations, experimental prototypes, existing designs or etc., using fuzzy-logic modeling algorithm as detailed in the previous section. The achieved consequent fuzzy sets, D_l's, can be further defuzzified by (23) to crisply express the level of overall satisfaction corresponding to each rule.

$$\mu^*_l = \frac{1}{N}\sum_{i=1}^{N}\mu^i_l = \frac{1}{N}\sum_{i=1}^{N}(b_{l0} + b_{l1}X_1^i + ... + b_{ln}X_n^i); \tag{23}$$

where μ^i_l (l=1,2,…,r, i=1,2,…,N) is the overall satisfaction corresponding to the i^{th} data point in l^{th} rule, N is the number of data points in the existing database, b_{lj} (j=1,2,…,n) is the *TSK* consequent coefficient corresponding to the j^{th} design variable in the l^{th} rule, X_j^i is the j^{th} design variable in the i^{th} data point and μ^*_l corresponds to the overall satisfaction of rule l. The rule with the maximum μ_l^* is selected, and the set of its antecedents represents the appropriate intervals for the design variables. The set of these *suitable* intervals is denoted as $\boldsymbol{C} = \{C_j : \forall j = 1,...,n\}$ and the corresponding fuzzy membership functions are labeled as $c_j(X_j)\,(j = 1,...,n)$. Finally, these fuzzy sets are defuzzified using *Centre of Area* (*CoA*) defuzzification method (Yager & Filev, 1994) to introduce the set of initial values $\boldsymbol{X_0} = \{X_{j0} : \forall j = 1,...,n\}$ for design variables in the secondary phase of optimization process.

$$X_{j0} = \frac{\int_{C_j} X_j c_j(X_j)dX_j}{\int_{C_j} c_j(X_j)dX_j}. \quad (j = 1,...,n) \tag{24}$$

C. Secondary Phase of LM
In the secondary phase, *LM* employs regular optimization methods to perform a single-objective unconstrained maximization of the overall satisfaction. The point-by-point search is done within the suitable intervals of design variables obtained from the primary phase. Therefore, the locally unique solution $\boldsymbol{X_s}$ is obtained through:

$$\mu^{(p,q,\alpha)}(\boldsymbol{X}_s) = \max_{\boldsymbol{X}\in\boldsymbol{C}} T^{(p)}(\mu_{\boldsymbol{M}}{}^{(p)}(\boldsymbol{X}), \mu_{\boldsymbol{W}}{}^{(q,\alpha)}(\boldsymbol{X})). \tag{25}$$

It can be shown that the pareto-optimality of the solution is a result of how the satisfactions are defined: Assume that $\boldsymbol{X_s}$ is not locally pareto-optimal. Then $\exists \boldsymbol{X_1} \in \boldsymbol{C}$ such that

$$F_i(\boldsymbol{X_1}) \succeq F_i(\boldsymbol{X_s}), \quad \forall i = 1,...,N \tag{26}$$

particularly, there exists an i_0 that:

$$F_{i_0}(\boldsymbol{X_1}) \succ F_{i_0}(\boldsymbol{X_s}). \tag{27}$$

Thus, according to the **Remark**,

$$a_{i_0}(\boldsymbol{X}_1) > a_{i_0}(\boldsymbol{X}_s), \tag{28a}$$

or

$$a_{i_0}(\boldsymbol{X}_1) = a_{i_0}(\boldsymbol{X}_s) = 1. \tag{28b}$$

Hence, if F_{i_0} corresponds to a *must* attribute, due to the monotonicity of *t-norm* operator in (15),

$$\mu_{\boldsymbol{M}}{}^{(p)}(\boldsymbol{X}_1) \geq \mu_{\boldsymbol{M}}{}^{(p)}(\boldsymbol{X}_s)\,. \tag{29}$$

And if F_{i_0} corresponds to a *wish* attribute, due to the monotonicity of both *t-norm* and *generalized mean* operators in (20),

$$\mu_{\boldsymbol{W}}{}^{(q,\alpha)}(\boldsymbol{X}_1) \geq \mu_{\boldsymbol{W}}{}^{(q,\alpha)}(\boldsymbol{X}_s)\,. \tag{30}$$

Finally, the monotonicity of *t-norm* in (21) lead to:

$$\mu^{(p,q,\alpha)}(\boldsymbol{X}_1) \geq \mu^{(p,q,\alpha)}(\boldsymbol{X}_s)\,. \tag{31}$$

Obviously, (31) contradicts the fact that $\boldsymbol{X_s}$ is a locally optimal solution. Note that in (29), (30) and (31) the equality holds when both satisfactions are 1. Thus, in order to avoid the equality, the satisfactions can be defined monotonically increasing or decreasing on the set of suitable intervals, $\boldsymbol{C}$.

As indicated in (25), various attitude parameters, *p, q* and *a*, result in different optimum design values for maximizing the overall satisfaction. Consequently, a set of satisfactory design alternatives ($\boldsymbol{C_s}$) is generated based on subjective considerations, including designer's attitude and preferences for design attributes.

D. Performance Supercriterion

From the set of optimally satisfactory solutions, $\boldsymbol{C_s}$, the best design needs to be selected based on a proper criterion. In the previous design stages, decision making was critically biased by the designer's preferences (satisfaction membership functions) and attitude (aggregation parameters). Therefore, the outcomes must be checked against a supercriterion that is defined based on physical system performance. Indeed, such a supercriterion is used to adjust the designer's attitude based on the reality of system performance. A suitable supercriterion for multidisciplinary systems should take into account interconnections between all subsystems and consider the system holistically, as the synergistic approach of mechatronics necessitates.

Although mechatronic systems are multidisciplinary, 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 notions that are proper for mechatronics. A successful attempt in this direction is the conception of *bond graphs* in the early 60's (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, store or dissipate, and reversibly or irreversibly transform. In (Breedveld, 2004; Borutzky, 2006) bond graphs are utilized to model mechatronic systems. This generic modeling approach provides an efficient means to define holistic supercriteria for mechatronics based on the first and second laws of thermodynamics (Chhabra & Emami, 2009).

1) Energy Criterion

Any mechatronic system is designed to perform a certain amount of work on its environment while the input energy is supplied to it. Based on the first law of thermodynamics, this *supplied energy* (S) does not completely convert into the *effective work* (E) since portions of this energy are either stored or dissipated in the system by the system elements or alter the global state of the system in the environment. This *cost energy* (f) should be paid in any mechatronic system in order to transfer and/or convert the energy from the suppliers to the effective work. Therefore, a supercriterion, coined *energy criterion*, can be defined as minimizing $f(\boldsymbol{X})$ for a known total requested effective work from the system. Based on the principle of conservation of energy:

$$S(\boldsymbol{X}) = E + f(\boldsymbol{X}), \tag{32}$$

which shows that minimizing the supplied energy is equivalent to the energy criterion. Therefore, by minimizing the supplied energy or cost function, depending on the application, with respect to the attitude parameters the best design can be achieved in the set of optimally-satisfied solutions ($\boldsymbol{C}_s$).

$$S(\boldsymbol{X}^*) = \min_{\boldsymbol{X}_s \in \boldsymbol{C}_s} S(\boldsymbol{X}_s; p, q, \alpha). \tag{33}$$

In bond graphs the supplied energy is the energy that is added to the system at the source elements, which are distinguishable by S_e and S_f with the bonds coming out of them. Hence, by integrating the supplied power at all of the source elements during the simulation $S(\boldsymbol{X})$ can be calculated.

2) Entropy Criterion

Based on the second law of thermodynamics, after a change in supplied energy, a mechatronic system reaches its equilibrium state once entropy generation approaches its maximum. During this period the system loses its potential of performing effective work, constantly. Therefore, if the loss work of the system is less, available work from the system or, in other words, the aptitude of the system to perform effective work on the environment is more. This is equivalent to minimizing the entropy generation or the irreversible heat exchange at the dissipative elements of the bond graphs, i.e., $Q_{irr}(t; \boldsymbol{X})$, with respect to $\boldsymbol{X}$ and accordingly it is called *entropy criterion*. Given a unit step change of supplied energy, the equilibrium time, denoted by $t_{eq}(\boldsymbol{X})$, is the time instant after which the rate of change of dissipative heat remains below a small threshold, ε,

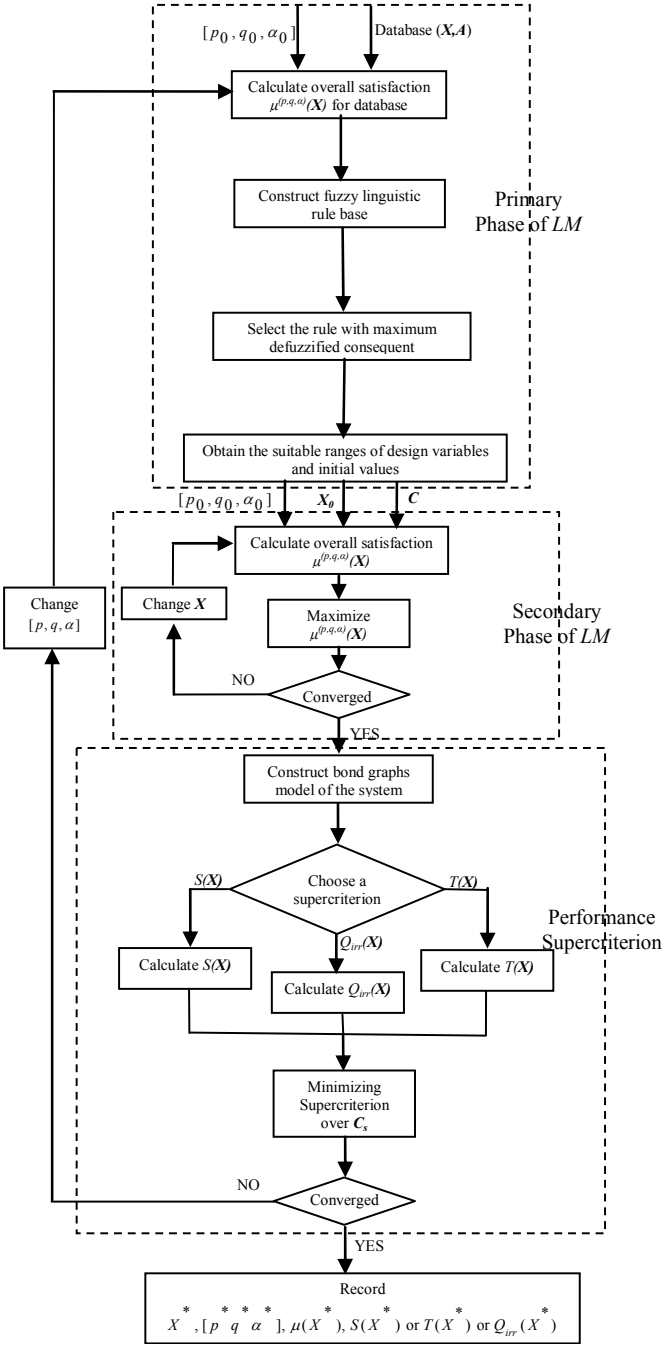


Fig. 1. The flow chart of Linguistic Mechatronics

$$t_{eq}(\boldsymbol{X}) = Inf\{t_0 : \forall t > t_0 \ \dot{Q}_{irr}(t, \boldsymbol{X}) < \varepsilon\} . \tag{34}$$

Consequently, the best design is attained in the set of optimally satisfactory solutions,

$$Q_{irr}(t_{eq}(\boldsymbol{X}^*)) = \min_{\boldsymbol{X}_s \in \boldsymbol{C}_s} Q_{irr}(t_{eq}(\boldsymbol{X}_s); p, q, \alpha) . \tag{35}$$

3) Agility Criterion

Alternatively, for systems where response time is a crucial factor the rate of energy transmission through the system, or *agility*, can be used for defining the performance supercriterion. Thus, the supercriterion would be to minimize the time that the system needs to reach a steady state as the result of a unit step change of all input parameters at time zero. A system reaches the steady state when the rate of its *internal dynamic energy*, *K*, becomes zero. Internal dynamic energy is equivalent to the kinetic energy of masses in mechanical systems or the energy stored in inductors in electrical systems. Masses and inductors resist the change of velocity and current, respectively. In terms of bond graph modeling, both velocity and current are considered as *flow*. Consequently, internal dynamic energy is defined as the energy stored in the elements of system that inherently resist the change of *flow*. Therefore, 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 internal dynamic energy, $\dot{K}$, remains below a small threshold, δ.

$$T(\boldsymbol{X}) = Inf\{t_0 : \forall t > t_0 \ \dot{K}(t, \boldsymbol{X}) < \delta\} . \tag{36}$$

As a design supercriterion, when the response time reaches its minimum value with respect to attitude parameters the best design is attained in $\boldsymbol{C}_s$.

$$T(\boldsymbol{X}^*) = \min_{\boldsymbol{X}_s \in \boldsymbol{C}_s} T(\boldsymbol{X}_s; p, q, \alpha) . \tag{37}$$

The complete flowchart of *LM* is presented in Fig. 1.

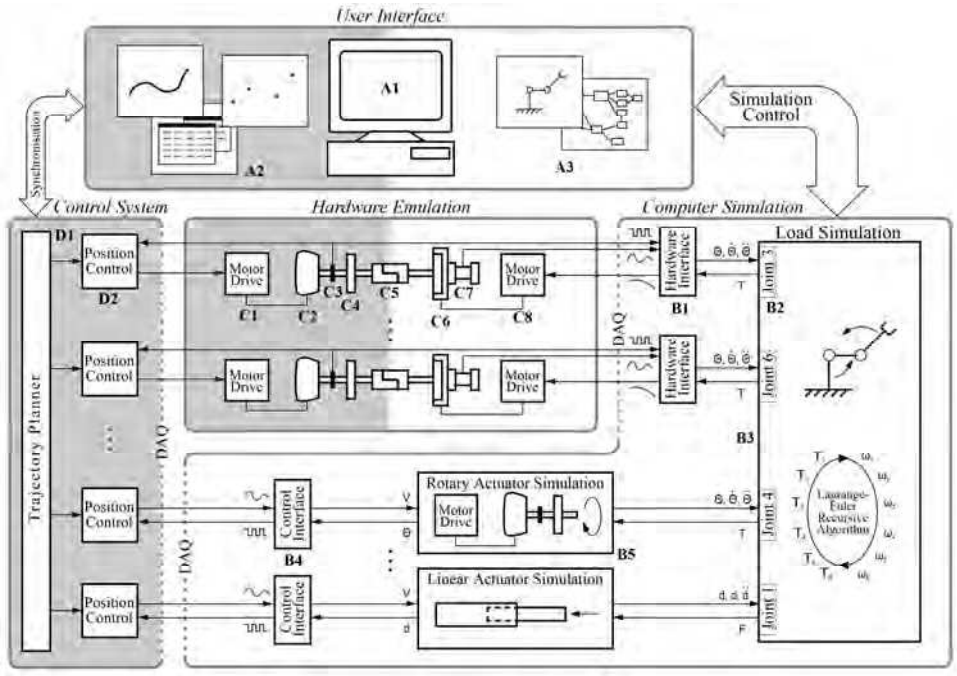
3. Robotic Hardware-in-the-loop Simulation Platform

The increasing importance of several factors has led to an increase in the use of HIL simulation as a tool for system design, testing, and training. These factors are listed in (Maclay, 1997) as: reducing development time, exhaustive testing requirements for safety critical applications, unacceptably high cost of failure, and reduced costs of the hardware necessary to run the simulation. By using physical hardware as part of a computer simulation, it is possible to reduce the complexity of the simulation and incorporate factors that would otherwise be difficult or impossible to model. Therefore, HIL simulations can play an effective role in systems concurrent engineering. The HIL simulations have been successfully applied in many areas, including aerospace (Leitner, 1996), automotive (Hanselman, 1996), controls (Linjama et al., 2000), manufacturing (Stoeppler et al., 2005), and naval and defense (Ballard et al., 2002). They have proven as a useful design tool that

reduces development time and costs (Stoeppler et al.; 2005; Hu, 2005). With the ever improving performance of today's computers it is possible to build HIL simulation without specialized and costly hardware (Stoeppler et al., 2005).
In the field of robotics, HIL simulation is receiving growing interest from researchers, and has been applied from a number of different perspectives. These approaches include: *robot-in-the-loop* simulations, such as the platform used for the task verification of the special-purpose dexterous manipulator at the Canadian Space Agency (Piedboeuf et al., 1999) or the use of both real and simulated mobile robots interacting with a virtual environment (Hu, 2005); *controller-in-the-loop* simulations, where a real control system interacts with a computer model of the robot (Cyril et al., 2000); and *joint-in-the-loop* simulations, which use a computer model to compute the dynamic loads seen at each joint and then emulate those loads on the real actuators (Temeltas et al., 2002). Each of these approaches applies the HIL concept slightly differently, but all have produced positive results. In a recent work (Martin & Emami, 2008), a modular and generic Robotic HIL Simulation (RHILS) platform was designed and developed for the industrial manipulators, and its performance was verified using the *CRS-CataLyst-5* manipulator from Thermo Fisher Scientific Inc. (Thermo, 2007). The RHILS platform was used in this work as the second constituent of robotic concurrent engineering, next to Linguistic Mechatronics. The architecture of the RHILS platform is illustrated in Fig. 2, and an overview of its modules is presented below:

3.1 RHILS Architecture

The RHILS platform architecture allows for simultaneous design and testing of both the joint hardware and control system of a robot manipulator. The architecture is designed to be adequately generic so that it can be applied to any serial-link robot manipulator system, and focuses on modularity and extensibility in order to facilitate concurrent engineering of a wide range of manipulators. This section presents a detailed breakdown of the main blocks of the architecture.
The architecture is separated into four subsystems: (a) the *User Interface*, (b) the *Computer Simulation*, (c) *Hardware Emulation*, and (d) the *Control System*, which are described below with reference to Fig. 2. These subsystems are further partitioned into two major categories: RHILS Platform components (indicated with a white background), and Test System components (indicated with a grey background). The RHILS Platform components are generic and should remain largely consistent over multiple applications, while the Test System components are part of the system being designed and/or tested on the platform. Depending on how much of the system is implemented in hardware versus how much is simulated it is possible to tailor the setup to all phases of the design cycle, and the architecture is designed to make adjusting this ratio as easy as possible.



A1 User interface host computer
A2 Control system user interface and trajectory setup
A3 Simulation user interface and scheduler
B1 Motor interface block, converts between actual hardware signals and the standardized form used in the simulation
B2 Joint assignment for the module
B3 Inverse dynamics simulation
B4 Control interface block, converts between actual control signals and the standardized form used with simulated actuators
B5 Simulated model of an actuator, for cases where the hardware module is unavailable, impractical, or unnecessary
C1 Drive electronics for Test Motor
C2 Test Motor
C3 Differential rotary encoder
C4 Harmonic drive transmission
C5 Detachable coupling to allow test hardware to be swapped in and out
C6 Load Motor
C7 Reaction torque transducer, for closed loop control and data acquisition
C8 Drive electronics for Load Motor
D1 Trajectory planner
D2 Position controller

A gray background indicates that section is part of the system being designed and tested using the RHIL platform

Fig. 2. RHILS Platform Architecture

A. User Interface Block

This block contains the most overlap between the RHILS Platform and the Test System. Because it is necessary to synchronize initial conditions before starting a simulation, this block acts as an intermediary between the custom control system and the generic simulation. On the RHILS Platform side robot configurations and parameters are chosen, as well as specifying any external conditions, for example zero-gravity or end-effector payloads, that will be used during a simulation. For the Test System side any configurable