**Concept-based Design Space Exploration of Manipulators**

***Dithoto Modungwa\*, Amiram Moshaiov, Alon Snir***

*School of Mechanical Engineering, Tel Aviv University, Tel-Aviv, Israel*

A B S T R A C T

Determining the parameters of a manipulator for optimal performance is a challenging task. This is primarily due to the possible conflicting objectives, the various tasks that should be considered and the highly non-linear behavior that is involved. This work proposes to apply a novel method to the design of manipulators, which is termed the Concept-based Design Space Exploration (C-DSE) approach. According to the C-DSE approach, prior to the search, the designers divide the set of feasible solutions into meaningful subsets, which are termed concepts. The design space exploration involves a simultaneous search for optimal solutions within each of the pre-defined concepts. Here it is suggested to use the concept-based relaxed-Pareto-optimality, which involves pre-determination of a relaxation-zone in the objective space by the designers. Solutions with performance vectors within that zone are considered interesting to the designers. The C-DSE approach reveals not just interesting solutions but also the characteristics of the considered concepts, which are realized by the performances of their associated solutions. To demonstrate the proposed approach, a bi-objective serial manipulator design is investigated. The demonstration highlights the usefulness of the suggested method in providing an understanding of the design space both at the level of conceptual and particular solutions.

**Keywords:** Multi-objective optimization, Set-based Concepts, Pareto-optimality, Serial manipulators, Design space exploration

**Introduction**

Robotic manipulators are commonly used for industrial and other application areas. The decision on the best manipulator's configuration for a specific task has often been based on experience and intuition [1]. To make the design of manipulators optimal to their tasks, various design indices and optimization methods have been suggested by numerous researchers, as discussed in the sub-section 2.1 of the background. Of a particular interest for the design of a manipulator are its kinematic and dynamic performances. These are strongly influenced by the structural and dimensional synthesis of the manipulator.

As common to engineering design, when designing manipulators, the designers should consider tradeoffs due to the conflicting design objectives [2-6]. This makes the process of selecting a manipulator complicated. To support decision-making on the preferred manipulator design, under conflicting criteria, the use of Pareto-optimality has been suggested (see sub-section 2.1.4). In contrast to scalarization methods, such as the weighted-sum of objectives, the use of Pareto-optimality aims to provide the designers with alternative optimal solutions, without a pre-statement on the objective preferences.

One drawback of searching for the Pareto-optimal set of solutions is that the resulting set does not include alternatives, which might be selected if optimality conditions were somewhat relaxed. In general, multi-modal optimization was suggested as a means to reveal multiplicity of solutions, which might be considered for selection, based not only on their performances but also on their differences within the design space [7]. In such an approach, it is assumed that the designers are interested in finding near-optimal solutions and consider their selection due to aspects that are not necessarily included in the computational model of the problem. However, most studies on multi-modal optimization are restricted to single-objective problems.

As detailed in sub-section 2.2 of the background, studies such as in [8-11] suggest an alternative to multi-modal optimization, which is not restricted to single-objective optimization. These studies are-based on sets of particular designs, where each such set represents a different conceptual design. Of a particular interest here is the Concept-based Design Space Exploration (C-DSE), as described in [8]. As claimed here, this unique approach may provide manipulator designers with special insight on the design space, which is not available with common optimization approaches.

In this study, the algorithm presented in [8] is applied to the design of the Puma 560 serial robotic manipulator. To demonstrate the proposed approach, three concepts of the Puma 560 are simultaneously explored, which defer by the characteristics of their last link (short, medium and long length). The demonstration highlights the usefulness of the suggested method in providing an understanding of the design space both at the level of conceptual and particular solutions.

The rest of this paper is organized as follows. Section 2 provides the relevant background on optimization of manipulators and on C-DSE. In section 3, the C-DSE problem is formulated and its associated search algorithm is presented. Next, in section 4, the case study of Puma 560 manipulator is described. The results are presented and analyzed in section 5. Finally, section 6 concludes the study.

**Background**

***Optimization of Manipulators***

Developing alternative frameworks for optimal manipulator design has been a subject of research over several decades. Roughly speaking, research efforts have been divided between those concerning performance measures (indices), and those that deal with optimization approaches and techniques. The reader is referred to the work of Patel and Sobh [12] for an in-depth discussion on manipulators' performance measures, including a comprehensive literature survey on classification, scope, and limitations of the various indices. The following concentrates on reviewing research efforts concerning optimization approaches and techniques for the design of manipulators. This aims to highlight some important developments that took place after the 1989 survey of Rao and Bhatti [13]. In subsection 2.1.1 optimization studies, which are based on kinematic considerations, are presented, whereas in subsection 2.1.2 dynamic considerations are added. Next, in subsection 2.1.3 structural rigidity is considered. Finally, in subsection 2.1.4 various optimization methods, which have been suggested for the design of manipulators, are overviewed.

* + 1. ***Kinematics***

Studies involving numerical optimization for manipulator design are dated back to the 80's (e.g., [14-15]). Such studies focused on serial manipulators with the aim to optimize their kinematic design. Studies that focused on kinematics continued during the 90's. For example, Paredis and Khosla [16] dealt with Reconfigurable Modular Manipulator Systems (RMMS). The RMMS idea allows accomplishing a large set of tasks through reconfiguration based on an inventory of modules such as links and joints. In [16], it was suggested that the effective utilization of the RMMS concept would need optimization of the manipulator configuration based on task requirements. The approach in [16] is based on solving the kinematic design problem (i.e., the determination of the Denavit-Hartenberg (DH) parameters of a non-redundant manipulator with joint limits that can reach a set of specified points/orientations), in conjunction with a global optimization procedure. Studies on manipulators' optimization using kinematic considerations, continued into the 21 century. Kim and Ryu, [17], proposed a new Jacobian formulation, which they used to design an optimal parallel manipulator for optimum dexterity. Later on, Sobh and Toudonsky, [18], considered the optimal kinematic design problem of a serial manipulator that attains high manipulability at a given set of task points. Kucuk and Bingul, [19], studied the manipulability measure and condition number performance criteria with the aim of optimizing the kinematic design of serial manipulators. They further compared the structural configuration of such mechanisms based on the structural length index and global conditioning index (GCI). Nektarios and Aspragathos, [20], studied the optimal or suboptimal relative position and orientation of a non-redundant robot’s base to a position and orientation path-following task. The optimization is aimed at achieving the maximum possible end-effector velocity with the most efficient joint velocities of the end-effector. Valsamos et al., [21], studied design optimization of reconfigurable manipulators for both point-to-point and trajectory tasks. More recently, Wang et al., [22], proposed a solution for the kinematic optimization problem of a cyclical parallel manipulator.

* + 1. ***Kinematics and Dynamics***

In 1999, Snyman and Berner, [23], studied the optimization of planar manipulators based on torque considerations. Rout and Mittal, [24], presented an approach to determine factors responsible for performance variation and identification of the optimum kinematic and dynamic parameters of serial manipulators. Their technique involves an analysis of variance (ANOVA) for understanding complex physical phenomenon using a design of experiments approach. The work of Hammond, [25], considered both kinematics and dynamics in designing a redundant manipulator that is optimized for fault-tolerance. Hammond introduced a Relative Weight Global Isotropy Index (RWGII) as a performance measure, taking into account the primary manipulation goal of maintaining kinematic dexterity and the secondary goals of collision avoidance, torque minimization and fault tolerance capability. Al Dios et al., [26], optimized the task duration and link lengths and masses of serial manipulators under kinematic and dynamic constraints. Wu et al., [2], optimized the design of spherical parallel manipulators with the aim of enhancing both the kinematic and dynamic performances. Recently, Hwang et al., [27], also considered both the kinematic and dynamic performances. They proposed an approach for optimizing the design configuration of serial 7 DOF manipulators.

* + 1. ***Structural Rigidity***

The addition of structural considerations is important for manipulators that should meet high accuracy requirements. In such a case, commonly either a SCARA or a parallel manipulator is employed, which is in accordance with their ability to offer better manipulation accuracy, as compared with other types of manipulators.

Liu et al., [28], studied and optimized the dexterity and structural stiffness of a spherical parallel manipulator. Later on, Shiakolas et al., [29], proposed to include structural considerations, in addition to kinematics and dynamics, when searching for an optimal design of SCARA manipulators. Kim and Tsai, [30], also looked at structural considerations for the optimal design of parallel manipulators. Dash et al., [31], considered optimization of parallel manipulators based on the RMMS approach. They proposed a task-to-robot mapping for determining suitable parallel manipulator configurations and optimized the parameters for a specific task. Shirazi et al., [32], solved the kinematic problem of parallel manipulators using a new stiffness index termed Geometric Mean of Eigenvalues (GME). Recently, Badu et al., [33], determined the optimal configuration of parallel manipulator that yielded minimal structural compliance with larger workspace volume and improved dexterity.

* + 1. ***Optimization Methods***

Most studies on optimizing manipulators employ numerical methods, with some exceptions, such as the analytical work by Paden and Sastery [34]. Early attempts to numerically optimize manipulators employed gradient-based methods (e.g., [14, 23, 35]). Nevertheless, according to Shirazi et al., [32], using gradient-based methods for optimizing manipulators is very difficult. The alternative of Genetic Algorithms (GAs) has become popular since the 90's for solving such optimization problems (e.g., [3, 20-22, 25, 36-38]).

Some studies employed enhancements of the optimization process for manipulators. For example, Gao et al., [39], employed GA with neural networks. Kordjazi et al., [40], claimed to improve the performance of GA search by the introduction of an adaptive search range mechanism that is based on fuzzy logic. Mansour et al., [41], amended their GA-based study with the use of quasi-Newton algorithm and constraint handling methods. Shiakolas et al., [29], employed GA, but amended their study with another type of evolutionary algorithm, namely Differential Evolution (DE).

Other types of bio-inspired methods have been used. For example, Shirazi et al., [32], as well as An et al., [42], employed Particle Swarm Optimization (PSO). Xu and Li, [43], used three different approaches to optimize manipulators including the Nelder–Mead simplex (NMS) algorithm of [44], GA, and PSO. Patel and Sobh, [45], employed Simulated Annealing (SA) to search for the optimal configuration of a non-redundant serial manipulators from task descriptions.

Many works, such as described above, posed the optimization problem of manipulators as a single objective problem. Yang and Lee, [46], who maximized the manipulator workspace, pointed out that: *"This investigation deals with only one of many possible objectives for the optimization of manipulator design. Some other important engineering aspects, such as the dexterity of the workspace, the dynamics of the structure, and the controllability of the manipulator etc., need to be considered as well."* In the 1989 review, in [13], on optimization in the design and control of robotic manipulators, Rao and Bhatti pointed out that: *"If a robot is to perform satisfactorily in all aspects, different criteria must be optimized simultaneously in the design process, which can be handled by using a multiobjective optimization procedure. However, no work has been reported in the literature that applies multiobjective optimization techniques to robot design."*

Traditionally, some scalarization approach has been used to transform a multi-objective problem into a surrogate single objective problem. Such scalarization techniques are also evident in the literature on optimal design of manipulators (e.g., [4, 20, 25, 32, 38, 47-48]). Some references, such as [27], suggest that transforming multi-objective manipulator optimization problems into scalarized problems is still prevalent. However, given that in such problems the design objectives could be conflicting, e.g., [49], it is desired to have an understanding of the performance tradeoffs. Such an understanding can be achieved using Pareto-based optimization.

According to the Pareto-based optimization approach, the designers perform optimization without a-priori declaration on their objective preferences. This means that the entire Pareto-optimal set of solutions and the associated front in the objective space, or their approximations, are sought before multi-criteria decision-making on a preferred solution is employed. The main advantage of the Pareto-based approach is that the performance tradeoffs are exposed, which supports rationalizing the selected solution. In recent years, with the availability of reliable multi-objective evolutionary algorithms, studies on the use of the Pareto optimality approach for the design of manipulator have flourished.

The first attempt to use a Pareto-based approach for multi-objective optimization of manipulators should probably be attributed to Koski and Osyczka [50]. Their work concerned a serial manipulator with counterweight balancing. The optimization problem involved four objectives including the minimization of maximal torques and reactions. Koski and Osyczka employed multiple searches, each with a different weighted-sum of the objectives to obtain an approximated Pareto-front. Their work was followed by Coello et al., [51], who employed multiple GA-based searches to solve the same problem. In fact, the possibility of using evolutionary algorithms to obtain approximated Pareto-fronts has been known over several decades. During the 90's Multi-Objective Evolutionary Algorithms (MOEAs) were developed and formally tested to numerically prove their ability to cope with various numerical difficulties. NSGA-II is one such example [52]. It is a well-known MOEA, which has been employed successfully for solving a wide range of real-life multi-objective problems. Surprisingly, attempts to use such well-known algorithms to the optimal design of manipulators have become popular only since 2010 (e.g., [33, 53-64]). While evolutionary computation is considered as the most common technique for finding Pareto-optimal set and fronts, other approaches, such as a hybrid GA and PSO, have also been employed by robotic researchers for this purpose (e.g., [65-66]).

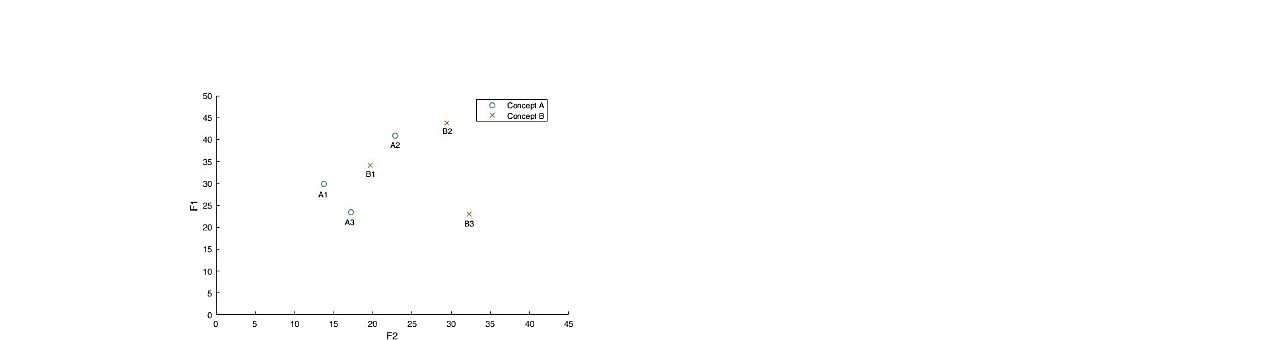
Only a few studies have attempted to compare results, which were obtained using different algorithms, including [54], and [56-57]. It should be noted that evolutionary algorithms are stochastic in nature. Hence, different runs commonly end with different results. Surprisingly none of the cited references reports results from multiple runs. Only Bahrami and Nikkhah, [65], attempted to address this issue using a hybrid search technique.

Given the above observations, it appears that further studies should be carried out to tailor and compare MOEAs to the optimal design of manipulators. Given the multi-objective nature of manipulator design problems, MOEAs can be used to find alternative solutions of interest to the designers, which result from not declaring any objective preferences. For some problems, and particularly those with increasing number of objectives, computational resources may be too restrictive when aiming to find the entire Pareto optimal set. In such a case, one may need to consider advanced MOEAs, which allows better control of the computational efforts. Reviews, such as in [67-69], may provide some insight on different MOEAs that have been developed in recent years to allow solving problems with many objectives and to articulate some partial objective preferences to better utilize the available computational resources.

The use of MOEAs by manipulator designers aims to provide them with a set of Pareto-optimal solutions. The observed tradeoffs can be used for the final selection of a solution. For real-world problems due to physical and other possible constraints, which are not necessarily included in the computational model, the best results cannot always be realized. Tacit knowledge and other considerations, such as the need for a robust solution, may suggest that rather than searching for optimal solutions, engineers should explore additional alternatives. In fact, such arguments have been made to justify the need for multi-modal optimization (e.g., [70, 71]). Studies on multi-modal optimization commonly deal with optima in single-objective problems. Moshaiov [9] has recently suggested considering the concept-based approach, which is applied here, as a kind of a mixture of multi-objective and multi-modal optimization. This alternative, for finding multiplicity of meaningful solutions is described in the following.

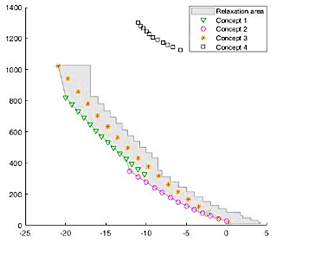
* 1. The Concept-based Approach

Recently, the Concept-based Design Space Exploration (C-DSE) approach has been suggested as a tool to explore design spaces [8]. Moreover, it has been argued that the use of the concept-based approach can be viewed as an alternative to multi-modal optimization both for single and multi-objective problems [9]. In the concept-based approach, a concept is a meaningful subset of solutions. The notion of a concept is quite flexible with this respect. For example, a concept may be defined as all manipulators with the first joint being a revolute one, or it may be defined as all manipulators with the last link having a length that is smaller than 0.5 meters, and so on. The main idea behind the use of concepts is that designers are expected to be able to determine, prior to the search, what constitutes a meaningful division of the set of all feasible solutions. Once determined, then a simultaneous search within all concepts may take place.

In the concept-based approach the solutions of the concepts are compared in a mutual objective space. While based on similar idea to Pareto-optimality, the notion of concept-based domination relation is somewhat different. This is illustrated in Fig. 1, which shows several performance vectors from two different concepts in a bi-objective space with respect to a min-min problem. The figure depicts performance vectors of solutions of concept A and concept B, denoted as A1-A3, and B1-B3, respectively. It is noted that A1 dominates A2 and also A3 dominates A2. However, A1 and A3 are non-dominated solutions. Furthermore, by the domination relation A1 would have been considered as also dominating B1 and B2. However, in the concept-based approach it does not. This is because B1 and B2 do not belong to concept A. It is also noted that B1 dominates B2. Furthermore, B1 and B3 are non-dominated. In other words, in the concept-based approach domination holds only within each concept.

**Fig. 1:** Dormination Relation

Fig. 2, which is adapted from [10], illustrates a possible result from a simultaneous search by the aforementioned approach. It concerns four concepts. The figure shows the obtained four Pareto-fronts of the considered concepts, which are represented by the different shapes. Normally, one may argue that the designers are interested only in the so called s-Pareto front (see [11]). For the illustrated case, the s-Pareto front is a “combined front” including part of the front of the 1st concept and all of the front of the 2nd concept. However, as claimed in [8], one should not ignore the front of the 3rd concept, since that its pair-wise comparisons, with the front of the 1st concept and independently with that of the 2nd concept, are not conclusive. One may declare that the 3rd concept is neither dominated by the 1st nor by the 2nd concept, when set domination relation is used rather than vector domination. On the other hand, the 4th concept is dominated by all others, therefore it may be viewed as of no relevance for selection. Using algorithms that aims at the s-Pareto front will not reveal the front of the 3rd concept. To overcome this problem, the concept-based relaxed-Pareto-optimality technique has been suggested [10].



**Fig. 2:** s-Pareto and Relaxation approach

The current study employs the concept-based relaxed-Pareto-optimality technique. More specifically it uses the Concept-based Design Space Exploration (C-DSE) approach as in [8]. This method allows the designers to determine a relaxation-zone in the objective space. Solutions with performance vectors within that zone are considered interesting to the designers, as long as they are not dominated by other solutions belonging to the same concept. This results with alternative solutions, either from all concepts or from some superior concepts. The idea of the relaxation zone is presented in Fig. 2. It shows a relaxation zone, which is marked by the gray area, that is determined by the use a relaxation vector relative to the s-Pareto front. In comparison with the s-Pareto approach, in the considered case of Fig. 2, the results of the 3rd concept are also revealed within the specified relaxation.

In contrast to the use of the classical Pareto-optimality, and in-contrast to the s-Pareto approach, the search by the aforementioned relaxation technique provides optimal and near-optimal solutions possibly belonging to different concepts. This means that using the C-DSE approach the designer will gain better insight on possible solutions to choose from.

**Methodology**

***Problem Description***

As explained in the introduction, this paper proposes to consider the Concept-based Design Space Exploration (C-DSE) approach as a support tool for the design of manipulators. The C-DSE problem is defined as follows.

Let:

be the dimension of the objective-space and the number of concepts.

be the feasible design space of the -th concept, and

be the vector of objective functions of the *m*-th concept.

be the dimension of .

be any specific design while and represent the concept index and design vector of respectively.

represents the -th element of ,

represents the performance vector of , with represent the -th element of

First, without loss of generality, we define a complete C-DSE, which sets out to find all feasible Pareto-optimal solutions and fronts for each independent problems:

and x (1)

Let be the union of all the solutions of the complete C-DSE problem, and also let be the set of all feasible designs from all the concepts. Following Mattson and Messac 2003 [10], the s-Pareto set, denoted as , is defined as:

(2)

where refers to is dominating . The concept-based relaxed Pareto-optimal set is defined as:

(3)

where is termed as the relaxation vector, which is predefined by the designers.

The s-Pareto set is associated with the s-Pareto front.

***The Evolutionary Search Technique***

The C-DSE aims at finding the concept-based relaxed-Pareto-optimal set (see Eq. 3), and the associated performance vectors. To search for these sets, we adopted the evolutionary algorithm of Moshaiov et al. [8]. As pointed out in Moshaiov and Snir [72], concept-based algorithms may suffer from premature concept-convergence. Namely, the search may prematurely reduce resources to concepts which may wrongly be considered as inferior. For such reasons one should be careful when designing algorithms that simultaneously search within various concepts. The computational study in (Moshaiov et al. [8]) investigated and demonstrated the ability of the suggest algorithm to cope with various numerical difficulties, while simultaneously searching the decision spaces of many concepts. The following outline the principles by which that algorithm searches for the concept-based relaxed-Pareto-optimal set and the associated performance vectors (details can be found in Moshaiov et al. [8]).

A major difficulty in finding and the associated performance vectors is that it is defined based on the s-Pareto front. Yet, the s-Pareto set and front is unknown prior to the search. The search approach taken in (Moshaiov et al. [8]) accommodates this difficulty using a dynamic relaxation vector. This vector changes during the evolution according to a predefined function of the generation. The process starts without any restriction (infinite relaxation) and ends with a predefined relaxation vector, which represents the sub-optimal zone that is of interest to the designers.

As suggested in Moshaiov and Snir [72], in principle any multi-objective evolutionary algorithm can be tailored to the concept-based approach. The algorithm in (Moshaiov et al. [8]) is inspired by ε-MOEA of Deb et al. [73]. Following ε-MOEA, the algorithm of [8] employs a steady-state evolution and a resolution vector concerning the objective space. The major modification is that subpopulations are used, where each subpopulation is associated with a concept. This resembles the island model, (Cantú-Paz [74]) which is a well-known concept that is used for parallel evolutionary algorithms. In contrast to the island model, given that the decision spaces of concepts may vary from one concept to another, there is no recombination done between individuals from different sub-populations. Yet, a simultaneous search is carried out. During the simultaneous evolutionary process computational resources are to be fairly allocated to the different subpopulations. In the proposed algorithm of (Moshaiov et al. [8]), such a justified resource allocation is based on the performances of the concepts by way of the dynamic relaxation vector. At the beginning, when the relaxation is infinite, all concepts are given an equal share of resources. When the relaxation zone starts to shrink, concepts that have no performances within the zone created by the dynamic relaxation vector are abandoned, whereas those inside are given an equal share of resources. In other words, less promising concepts are gradually abandoned, which means that more computational resources are made available to the more promising concepts.

**The Considered Concept-based Design Space Exploration Problem**

***Kinematic Representations***

The standard Denavit-Harterberg (DH) notation is used to represent the manipulator structure [75]. The DH parameters include the link's length and twist , as well as the link offset and the joint angle where the index *i ∈ {1,2,…,n}* and *n* is the number of joints. In general, for a manipulator that is structured as an open-chain, there are 4*n* parameters, out of which 3*n* parameters are fixed and *n* parameters are variable parameters that depend on the type of joints.

For such an -DOF manipulator, the joint variable vector is defined as:

(4)

where *qi* is the joint angle for a revolute joint and the link offset for a prismatic joint.

A unique configuration of such an - DOF manipulator can be represented by a vector of the DH parameters as follows:

(5)

Here, a manipulation task is defined as a set *P* of *t* task-points that the manipulator's end-effector should reach as follows:

(6)

where each such task-point is a vector that includes a description of the position and orientation of the end-effector. Using the Euler angles for describing the orientation, a task-point is defined as:

(7)

For a unique- DOF manipulator configuration vector DH, with the joint variable vector and a specified task-point , then the mapping between the spaces is:

(8)

In practice the joint variables will be constrained due to some mechanical limits such as link interferences. Such constraints are represented as follows:

(9)

* 1. ***Objective Functions/ Performance Measures***

Here, two conflicting criteria are used. The first criterion is based on the manipulability index [76]. According to [12] the manipulability index is widely used for manipulator synthesis, workspace optimization, task planning, motion control etc. Following [45], the criterion that is used here takes a summation of the calculated manipulability indices from all the task-points of the considered set of tasks as defined below.

(10)

where is the jacobian matrix of the manipulator [76]. It is noted that the first objective is to maximize this manipulability measure.

The second objective involves energy requirement. An energy efficient manipulator is a common requirement when there are energy limitations. According to [77], a trajectory, which is planned based on minimum energy, tends to be smooth and easy to track. Furthermore, minimizing joint torques leads to reduced stresses at the manipulator actuators and structure [78]. To determine the actuator effort, the generalized torques are computed by solving the inverse dynamics of the manipulator using the Recursive Newton-Euler (RNE) algorithm, which was introduced in [79]. The resulting equations of motion for an n-axis manipulator can be represented in a matrix form as:

(11)

where u is the vector of generalized forces, , and are the joint variables, velocities and accelerations vectors, is the inertia matrix, is a matrix that includes the Coriolis and centripetal effects, and is the gravity vector. Here, no friction is assumed.

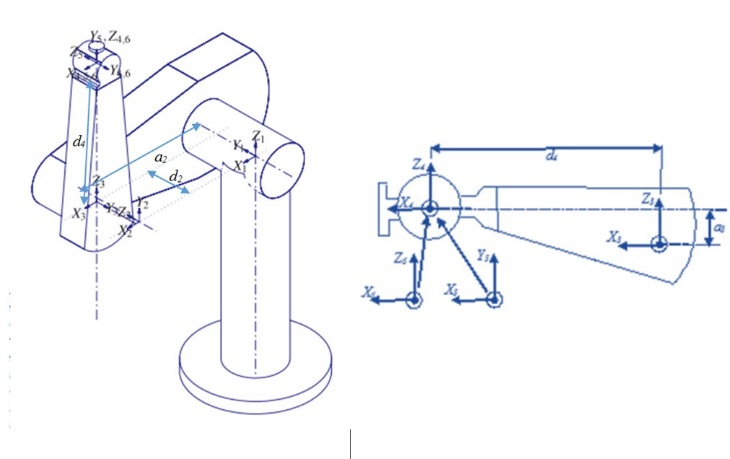
Minimizing the following measure of the actuator-effort is chosen as the second objective.

(12)

where represents the generalized force/torque at joint *i*, is a task-point of the task set P (see Eq. 6) and is the maximum number of joints in the manipulator.

***4.3 The Design Concepts***

In this paper the application of the C-DSE approach to the design of manipulators is demonstrated based on PUMA 560, which is a six DOF serial manipulator. It is schematically depicted in Fig. 3, which is adopted from [80].

The DH parameters for each link of the Puma 560 manipulator are listed in Table 1 below. It is noted that many other industrial manipulators are designed according to the same manipulator type. It is therefore interesting to investigate a range of possible values for the DH parameters of the model including, , .

**Fig. 3.** Puma 560 kinematic configuration in standard DH parameter notation

**Table 1 -** Puma 560 6 DOF manipulator DH parameters

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  | 0 | 0 |  |
|  | 0 |  | 0 |
|  |  |  |  |
|  |  | 0 |  |
|  | 0 | 0 |  |
|  | 0 | 0 | 0 |

Here, the set of feasible solutions is divided into meaningful subsets, which are referred to as concepts. The three concepts in this study are made up of three subsets (categories) defined by three ranges of the values of the offset parameter (see section 4.4). These ranges are termed: short-length, medium-length and long-length. The first concept , which is marked as C1, includes all possible designs in which the offset is within the range of the short-length. Similarly, the second and third concepts, C2 and C3, include all possible designs in which the offset is within the medium and long lengths, respectively.

***4.4 Details of the Employed Search***

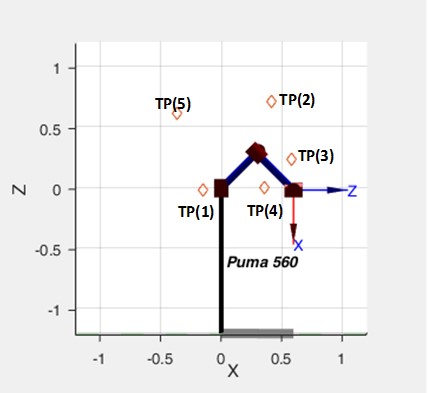
The C-DSE algorithm of [8], which is briefly described in section 3, was employed to explore the design space of the C-DSE problem that has been described above. Table 2 describes the range of the DH parameters that are used as design variables.

**Table 2:** Optimization parameters and ranges

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Lower Limit (*m*)** | **Upper Limit (*m*)** |
|  | 0.0 | 0.450 |
|  | 0.0 | 0.080 |
|  | 0.0 | 0.200 |
|  | 0.0 | 0.500 |

It is noted that the range of the offset parameter is partitioned into three ranges including [0, 0.2], [0.200, 0.4], and [0.400, 0.500], where these ranges are given in meters. During the evolutionary process, within each concept, if a solution is generated out of the permitted ranges, it is considered infeasible. Such a solution is simply eliminated and an alternative solution is generated. All the simulations, which were needed for the optimization process, were performed using MATLAB software and the Robotics Toolbox for Matlab [81].

As explained in section 4.1 a set of task-points is used to define the performance of the manipulator. The task-points that were used in the considered problem are illustrated in Fig. 4, and their coordinates are given in Table 3. The parameters for the evolutionary search are given in Table 4.

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**Fig. 4.** The applied task-points shown in the x-z plane of the task space

NEED TO ADD THE DYNAMIC PARAMETERS

**Table 3:** Coordinates of the task-points

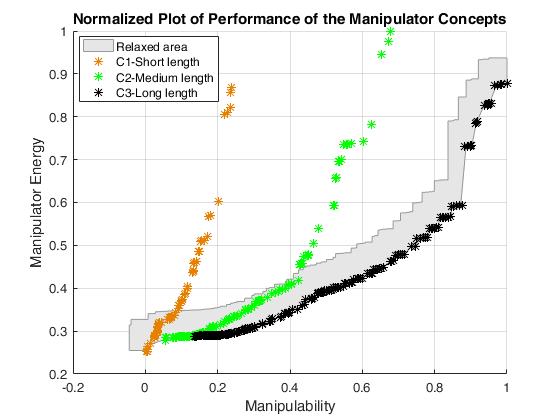
|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Task Points** | **X**  **meters** | **Y**  **meters** | **Z**  **meters** | **radians** | **radians** | **radians** |
| **TP(1)** | -0.15 | -0.5963 | -0.0144 | 0 | 0 | 0 |
| **TP(2)** | 0.4149 | 0.2027 | 0.7172 | 0 | 1.565 | 0 |
| **TP(3)** | 0.5797 | -0.15 | 0.2405 | -3.142 | 0 | -3.142 |
| **TP(4)** | 0.3586 | 0.6414 | 0 | 1.784 | -1.571 | 0.213 |
| **TP(5)** | -0.365 | -0.15 | 0.6241 | 0 | -1.565 | 0 |

**Table 4:** The parameters used in the evolution

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **# of Concepts** |  | **# of Resolution Intervals** | **The Resolution**  **Range** | **Final Relaxation** | **# of Iterations** |
| 3 | 4 | 40 | [0.01,400] | [0.03,1200] | 9000 |

**Results and Discussion**

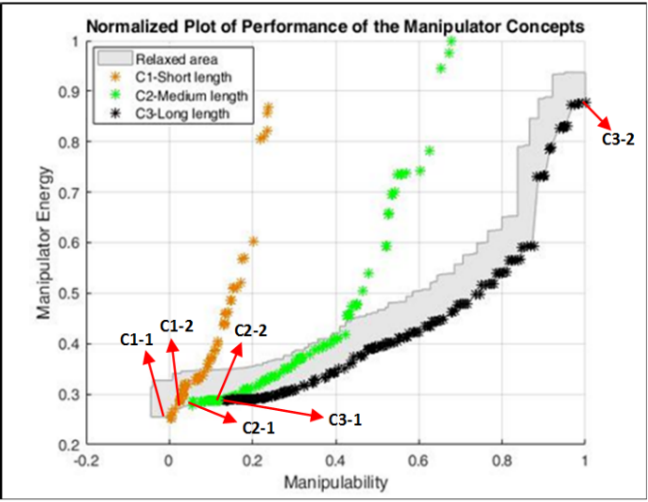
Fig. 5 shows the Pareto-front for each of the three concepts. The employed relaxation-zone is shown as the gray area on the graph. In general, for all concepts, a tradeoff between manipulability and actuator-effort can be observed. It is noted that all the performances that are presented in the figure of this section are normalized.



**Fig. 5.** The obtained fronts of the concepts

In addition, it can be easily observed that the third concept C3 with the long-length of the offset has the best front. In fact, the majority of the s-Pareto solutions belong to this concept. This suggests that for this specific application the designer should consider a configuration in which the offset is long. However, if the designer is willing to relax the optimization requirement, she may select the other concepts, which do have solutions within the relaxation zone. Suppose that a manipulator design is composed of modules, and the designer knows that currently there are only medium size links in the available inventory. Furthermore, the designer knows that it may take a month to obtain a long link. In such a case the results of a search such as demonstrated here, will provide the designer with an understanding of the optimality implications of making a decision to use the medium-size link, rather than waiting for the supply of the long link.

Next, to further examine the results, several performance vectors along the s-Pareto are selected as representatives, and their associated designs are analyzed. The representative vectors are marked by red arrows in Fig. 6. They constitute, for each concept, the extreme performances along the s-Pareto. The associated designs are denoted as C*i*-1 and C*i*-2 for the *i*-th concept. Also shown on the figure is the performance vector of the Puma 560. The details of the representative designs and their performances are given in Table 5. As a reference, the table includes also the relevant details of Puma 560.



**Fig. 6.** The performances of the representative designs (marked by the red arrows)

**Table 5:** Details of the representative designs

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Design** | | **Performance Measures** | | | **Design Variables (*m*)** | | | | |
|  | **Manipulability Measure** | | **Actuator-Effort** |  | |  |  |  |
| C1-1 | 0.0047 | | 0.2560 | 0.1350 | | 0.0740 | 0.0350 | 0.1990 |
| C1-2 | 0.0135 | | 0.2722 | 0.16875 | | 0.0560 | 0.0550 | 0.0398 |
| C2-1 | 0.0759 | | 0.2854 | 0.1575 | | 0.0380 | 0.0250 | 0.3990 |
| C2-2 | 0.1299 | | 0.2884 | 0.13500 | | 0.0560 | 0.0 | 0.3642 |
| C3-1 | 0.1485 | | 0.2887 | 0.3150 | | 0.0 | 0.0250 | 0.4850 |
| C3-2 | 1.0 | | 0.8780 | 0.1350 | | 0.0160 | 0.0050 | 0.5000 |

**TO BE CONTINUED**

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