Optimization of a Robot Used for a Solid Waste Selection System

Catalin Boanta and Cornel Brisan

***Abstract*—Solid waste selection is a common problem of the cities in emerging economies. In order to overcome this problem, a concept of smart selection of solid waste system has been developed, composed by a transportation system, a sensorial systems and a robotic system for selection of the solid waste. This paper focuses of the robotic system, the aim of this paper being the multi -objective optimization of a parallel robotic system in order to achieve maximal workspace and dexterity. Hence, the paper illustrates a small introduction in the concept of the new solid waste selection system and presents a recent literature review regarding the optimization of robots. Then, the structure and formal analysis of the robotic systems that has application for a smart selection of solid waste. The optimization is carried out using Genetics Algorithms and the objective function of the optimizations that takes into consideration the volume of the constant orientation workspace alongside with the average isotropy index within the workspace.**

***Index Terms*—Robots, optimization, genetic algorithms, workspace, isotropy.**

I. Introduction

Unsorted waste (UW) produced by the inhabitants of cities from emerging economies has become one of the most relevant problem in the middle and low income regions in the past years. The quantity of plastic, metal, paper, leather, glass or other type of solid waste is growing exponentially, aspect that generates environmental and public health issues[1], [2].

The concept of the Automated Solid Waste Selection System has been presented extensively in the papers [3] and [4] and is composed by a ramified Transportation System (TS) , such as set of conveyors that transport the unsorted waste (UW) from the loading point up to the unloading point, a waste Image Recognition and Sensorial System (IRS) , that identifies the type of waste that passes beneath, and a waste selective Robot Disposal System (RDS), that extracts a specific waste from the conveyor and places it in a specific container. If necessary, a more detailed description of the Automated Solid Waste Selection System is presented in the papers [3], [4].

This paper focuses on the development of the Robot Disposal System (the Robots from 1 to N from the Fig. 1, by optimizing the architecture of a parallel robot that may be used to dispose a solid waste from a conveyor. Therefore, the robot is optimized in order to achieve the maximal workspace and very good kinematic performance within the workspace. The optimization is implemented using Genetic Algorithms.

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Cătălin Boanta and Cornel Brișan are with the Technical University of Cluj-Napoca, Romania (e-mail boanta_catalin@yahoo.com, cornel.brisan@mdm.utcluj.ro).

In the following, a literature review is presented, regarding the key topics of this paper: solid waste selection system, workspace and performance criteria of the parallel robots and optimization algorithms. The rest paper is organized as follows. The Section II illustrates the architecture of the robot, the Section III presents the design vector, objective function and constraints and the Section IV the numerical results are illustrated. In the end, the Section V presents the conclusions of the presented optimization.

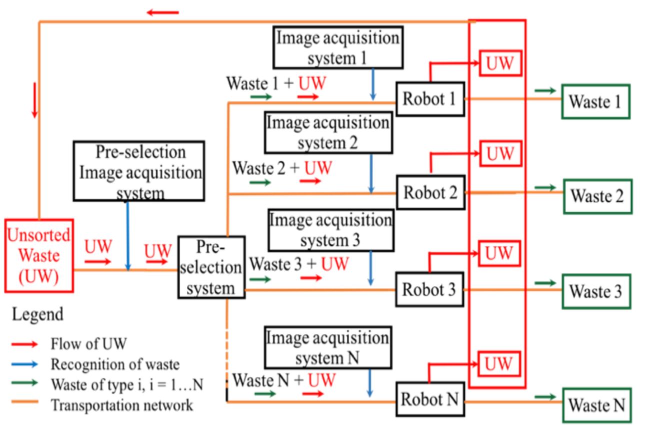

Fig. 1. Concept of automated solid waste selection system.

Automated selection of the solid waste is a public health problem that has drawn attention to researchers in the past years. Therefore, there are already published examples of solid waste selection system, as presented in [5]-[7], that propose the use of robots, image recognition system or fluids to select several types of solid waste. On the other hand, the concept presented in [4], integrates both transportation, image recognition using CCTVs and smart selection using robots.

Parallel robots are mainly used in industrial application due to their advantages regarding high operational speeds, high accuracy and stiffness. On the other hand, the workspace of a parallel robot is reduced in comparison to its dimensions. This is why, in the process of designing a parallel robot is desired to take into consideration to maximize workspace, while preserving other kinematic characteristic as high as possible.

The kinematic performance of parallel robots has been expressed in several forms in the scientific literature, mostly by evaluating the condition number [8], the inverse of the condition number[9], manipulability[10] or isotropy (with average condition number) [11], [12].

Since it is desired that the robot designed for waste selection to have best kinematic performance along the

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workspace, this paper will focus on enlarging as much as possible the workspace of the robot and, at the same time, preserving the kinematic performance as high as possible. The kinematic perfomance [11], [12] will be expressed in terms of average isotropy, presented in the scientific literature as the average condition number within the workspace (that expresses the local isotropy that varies with the robot configuration and parameters), expressed in the eq.1.

$$\eta_j = \frac{\int_W k_j dW}{\int_W dW}. \tag{1}$$

where, W is the workspace of the robot, and k_j is the local isotropy index, dependent by the Jacobian matrix of a robot, given by the eq. 2 .

$$k_j = \left\| J^{-1} \right\| \cdot \left\| J \right\| \tag{2}$$

The optimization of the robot in order to achieve both is implemented using Genetic Algorithms, an evolutionary type algorithm, that mimics the genetics of real life beings. The algorithms evolve from an initial state to its final solution (called populations) and preserves best the best solution from all the population, usually this one being the solution of the optimized problem. As seen in the scientific literature, this type of algorithms have been successfully implemented in several other studies regarding optimization problems, as presented in [13]-[15].

The main purpose of this paper is to develop an optimization method of a parallel robot used for a solid waste selection system, taking into consideration both to maximize the workspace and to attain very good kinematic performance within the workspace. Since more than one performance criteria are evaluated in the cost function, the optimization may be considered as multi-objective (even though a Paretto diagram is not presented). On the other side, if more than one cost function is evaluated in an optimization problem, there are more viable solution of the optimized problem. The approach from this paper eliminates the evaluation of two cost functions at once by calculating two performance factors of a parallel robot (size of the workspace and the kinematic performance) in a single equation (a proper tradeoff between these factors is realized).

II. Robot to Be Optimized

The robots that is optimized is a 6 DOF parallel robot with rotational actuators, composed by six identical rotational-universal-spherical kinematic open loops (RUS – from the bottom fixed plate to the top mobile plate). The architecture of the robot is presented in the Fig. 2.

The robot shall be used as a translational robot in order to select the unsorted waste from a moving conveyor. The waste is taken from the moving conveyor and placed in a specific waste container, based on prior information received by and Image Acquisition System (see the Fig. 3) as presented in the concept from [3] and [4] (this aspect being beyond the scope of this paper).

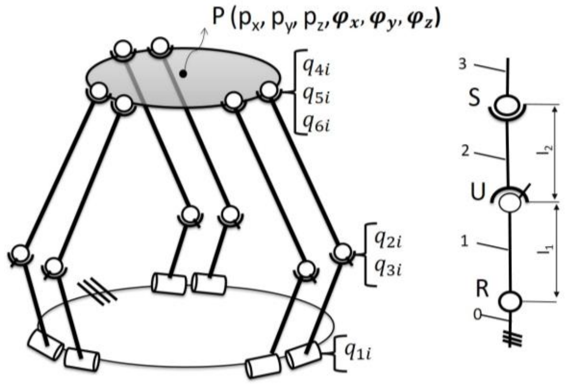

Fig. 2. Parallel robot to be optimized.

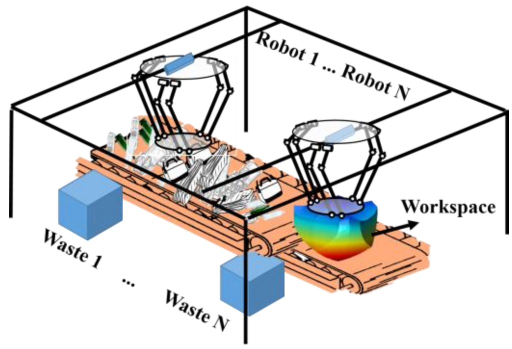

Fig. 3. Parallel robot to select unsorted waste from a conveyor.

III. Optimization Setup

In order to maximize both the workspace and the global dexterity, the setup of the optimization using Genetics Algorithms has to be properly defined. Firstly, de design variables are selected, the constraints are imposed, and the cost function is defined. All of these steps are crucial in order to achieve proper results of the optimization, so a human designer shall attach the same importance to all of these steps

A. Design Vector

The design vector shall contain the geometrical characteristics of the robot that influence the most the results of the optimization. Since the time demanded to compute an optimization problem evolves exponentially with respect with the number of variables in the design vector, it is desired to exclude from the deign vector the variables that have less influence in the results of the optimization or that may be expressed as a function of other variables.

In the optimization problem addressed in this paper, it has been assumed that the robot is symmetrical, aspect that increases the kinematic performance, as seen in [16]. The design vector x, contains the parameters from the eq. 3.

$$x = (l_1, l_2, ratio_u, ratio_d, r, R) \tag{3}$$

The variables from the eq. 3, define geometrical parameters of the robot, as seen below:

1) l_1 and l_2 are the first and the second links from the RUS open kinematic loop, as seen in the Fig. 2
2) $ratio_u$ and $ratio_d$, are the ratios between two consecutive angles α_i and β_i, that define the position of

the spherical joints on the mobile platform and of the rotational joins on the fixed platform, as seen in the Fig. 4

3) R and r are the radiuses of the fixed and of the mobile platform (Fig. 4).

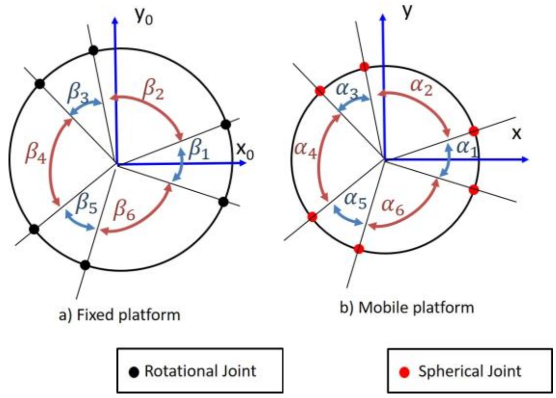

Fig. 4. Fixed (a) and mobile platform of the robot.

B. Constraints

The constraints play an important role, due to the fact that these sets the bonds of the interval in which the variables are searched, and, moreover, influence the computational time. For the design vector presented in the eq. (3) the constraints have been defined as follows:

$$\begin{aligned}
&l_1 > 0.001[m]\\
&l_2 > 0.001[m]\\
&l_1 < 0.6[m]\\
&l_2 < 2[m]\\
&ratio_u > 0.1\\
&ratio_u < 10\\
&ratio_d > 0.1\\
&ratio_d < 10\\
&r > 0.001\\
&R > 0.001\\
&r < 0.6[m]\\
&R < 2[m]
\end{aligned} \tag{4}$$

In order to express the constraints in a matrix form, we consider the following equation:

$$A \cdot x^t < b \tag{5}$$

where, *A* and *b* are given eq. (6) and (7)

$$A = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

$$b = \begin{bmatrix} -0.001 \\ -0.001 \\ 0.3 \\ 2 \\ -0.1 \\ 10 \\ -0.1 \\ 10 \\ -0.001 \\ -0.001 \\ 0.6 \\ 2 \end{bmatrix} \tag{7}$$

C. Cost Function

The cost or fitness function may represent the core of an optimization function, since the result of a cost function is the value that expresses mathematically the degree of validity of the current solution of the design vector (or, expressed in other terms, how close is the current solution to the optimal solution).

In the optimization presented in this paper, the cost function *fit* has to involve two dimensions: the size of the workspace (sub function *fit_WS* and the average dexterity of the robot, evaluated in each point of the workspace, sub function *fit_DEXT*, from the equation.

$$fit = fit\_WS + fit\_DEXT \tag{7}$$

The first sub function evaluates the size of the workspace by performing the kinematic analysis for a each point from predefined cube discretized in 50^3 points (50 for each dimensions). The cube is predefined in terms of number of points, not in dimensions (its dimensions variate proportionally to the geometrical dimensions of the robot, therefore, making it suitable for each set of the design vector).

In the kinematic analysis, the generalized coordinates q_i are evaluated (from the Fig. 2). If the kinematic analysis conducts to valid results (i.e. values of the generalized coordinates lie within the joints limits) the point form the cube is validated. In the end, the number of validated points compose the workspace. The value of the sub function (*fit_WS*) is given by the eq. (8) and for each valid case of the design vector (meaning that the has valid geometric length), fit_WS is lower than 1. In ideal case, *fit_WS* equals 1.

$$fit\_WS \in [0,1] \tag{8}$$

The second sub function evaluates an approximation of the average of local isotropy index from the eq. (1) within the workspace. For each identified point of the workspace from the first subfunction the local isotropy index from the eq is evaluated, then the resulted values are added togheter and divided with the total number of the points from the workspace (therefore, obtaining an approximation of the average of the local isotropy index). As presented in [15], the local isotropy index lies in the following limits:

$$k_j \in [1, \infty) \tag{9}$$

That means, that the average of the local isotropy index lies within the same interval.

$$\eta_j \in [1,\infty) \tag{10}$$

The eq. 7 assumes that both of the sub functions have the same range of returned values (in order to have same influence on the value of the fitness function). Since *fit_WS* returns values from 0 to 1, it is desired that *fit_DEXT* to return similar range values. Therefore, the sub function *fit_DEXT* return the value from the eq. 11.

$$fit\_DEXT = \frac{1}{\eta_j} \in [0,1] \tag{11}$$

IV. Numerical Results

The optimization has been implemented in Matlab, using the Global Optimization Toolbox. In order to decrease the computational time, all the equation has been implemented in a vectored manner (meaning that no for loops were used). Moreover, the Parallel Processing Toolbox has been used, in order to utilize all the threads available on an Intel i7 CPU.

The evolution of the fitness value of the optimization is presented in the Fig. 5 and the final value is presented in the eq. 12. The algorithm has passed through 142 iterations until the final solution has been achieved. A population of 200 members has been used.

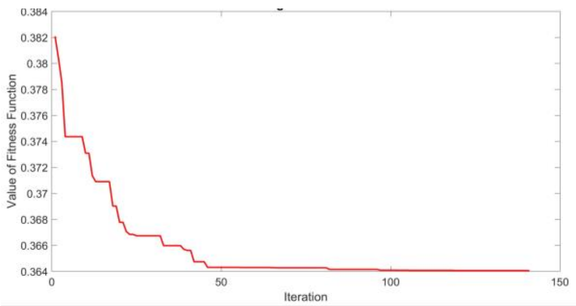

Fig. 5. Convergence of the objective function.

$$fit = 0.3641 \tag{12}$$

In order to achieve this final value, the algorithm has modified the design vector on each iteration (the Fig. 6 illustrates the best values for each iteration). The first 20 iterations present high modification in the best values of design vector, in accordance with the descent in the value of the fitness function (Fig. 6).

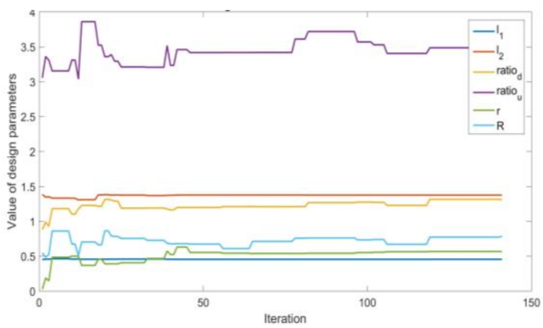

Fig. 5. Variation of the best values of the design vector.

The best values of the design vector are presented below.

$$x_{best} = [0.49, 1.45, 1.39, 3.45, 0.59, 0.76] \tag{12}$$

The optimal values of the design vector are correspondent to the minimal value of the fitness function. Therefore, the workspace of the robot is as large as possible, and presents the best kinematic performance for that configuration of the robot. The final workspace of the robot is presented in the Fig. 7

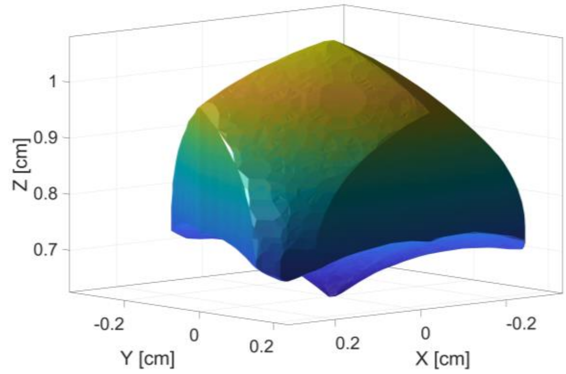

Fig. 7. Workspace of the optimized robot

V. Conclusions

This paper presents an optimization of a parallel robotic system used for solid waste selection, in order to achieve maximal workspace and dexterity. The main contribution of this paper regards the evaluation of a tradeoff between the size of the workspace and of the dexterity, both of these being evaluated in the same equation. This is why, it may be considered that the optimization takes into account more than one performance factors, hence it has performed in a similar manner to a multi-objective optimization. The future outlook regards the optimization of a reconfigurable parallel robotic system, in the case that fewer DOFs are necessary in an application.

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Catalin Boanta after finishing his master thesis in 2016 from mechatronics at Technical University of Cluj Napoca, Mr. Boanta continues his studies, curently being in his third year of Ph.D. studies in the field of Industrial Engineering.

Cornel Brisan after obtaining a degree in mechanical engineering at the Technical University of Cluj Napoca, Mr. Brisan continues his studies in the field of industrial engineering, obtains a Ph.D. degree in 1995. In the period 2000–2001 Mr. Brisan was researching in Duisburg, Germany as an alexander von humboldt fellow. From 2003 he is professor at the Technical University of Cluj Napoca, Department of Mechanisms, Precision Mechanics and Mechatronics.