Optimum design of a hand-tractor handlebar through metaheuristic algorithms

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Optimum design of a hand-tractor handlebar through metaheuristic algorithms

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Abstract. This paper presents simultaneous topology shape and sizing design of a walking-tractor handlebar based on using many-objective metaheuristics (MnMHs) in order to reduce vibration transmission, which to some extent causes vibration syndrome disease. The design problem is posed to maximise natural frequencies of the first 5 modes, minimise structure mass and minimise construction cost subjected to stress and displacement constrains with bending and torsion loading conditions. Design variables include topology of side bar stiffeners, shape, and size of all bars. Several MnMHs are used to solve the problems while the results are compared. With this study, the performances of MnMHs for solving optimum design of a walking-tractor handlebar is examined whereas the optimal structures are obtained.

1. Introduction

Nowadays, a walking tractor (also known as a power tiller, a hand tractor, or a behind tractor) is used worldwide particularly in developing countries due to compact, cheap and affordability for small and medium agriculture farms. Moreover, it can be applied to many purposes in the farm such as irrigation, transportation, and tillage [1]. Under working conditions, the walking tractor is subject to several mechanical phenomena such as bending stress, torsion stress, and vibrations [2, 3, 4, and 5] while some of such phenomena e.g. vibration is the cause of an operator injuring issue. Various disorders associated with vibration are vascular, musculoskeletal neurological, and articular which know as hand-arm vibration syndrome (HAVS) [6].

Generally, design of a walking tractor is mostly concerned with improving structural strength based on static analysis [5, 7 and 8]. For the dynamic analysis, the walking tractor handlebar was optimised [2] with two objectives to minimise structural mass and maximise natural frequency. The work was extended to be many-objective optimisation in [9]. This work presented many objective optimisation that minimises structural mass, maximises structural strength in two loading conditions and maximises natural frequencies. Although, many-objective optimisation has been proposed [2 and 9] to serve several requirements of walking tractor handle bar design, it was found that the results obtained in the previous study are difficult to apply in real situations due to expensive and complicated-to-manufacture handlebars being obtained. In this regard, improving design optimisation of a walking tractor handle bar with manufacturing requirements is still a challenge.

This work presents many-objective optimisation of a walking tractor handlebar. The considered design variables include topology of side bar stiffeners, shape, and sizes of all bars. For more practical use, the sizing variables are set to be discrete to fit with the commercialised bar sizes available. The
design problem is posed to maximise natural frequencies of the first 5 modes, minimise structure mass and minimise construction cost subjected to stress and displacement constrains with 2 loading conditions, bending and torsion. To deal with the many-objective problem, several MnMHs including, Differential Evolution for Multi-objective Optimisation (DEMO) [10], Multi-objective Harmony Search (MOHS) [11], Hybrid multi-objective real-code population based incremental learning and differential evolution algorithm (MORPBII) [2], Multi-objective Particle Swarm Optimisation (MOPSO) [12], Unrestricted Population Size Evolutionary Multi-objective Optimisation Algorithm (UPS-EMOA) [13], Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [14] and real-code population-based incremental learning and differential evolution algorithm (RPBILDE) [15] are employed to tackle the problem. The MnMHs performances are investigated and optimal walking tractor handlebar structures are obtained.

2. Design problem

In order to design taking account of ergonomic effect or human factors simultaneously with optimum structural strength, a walking tractor handlebar should have maximised natural frequencies so as to avoid vibration resonance from external excitation that may transmit to a user. Besides, minimising bending and torsion deflection can, to some extent, increase structural reliability. The minimisation of structural mass or volume will affect structural c...
where $\mathbf{x}$ is a vector of design variables. $f_1$ and $f_2$ are the maximum displacements in the $y$-direction (vertical direction) due to the bending load and the torsion load, respectively, while $f_3$ and $f_4$ are the inverse of the sum of natural frequencies in the first five modes and the structural mass, respectively.

$$\mathbf{x} = \{ y_1, y_2, y_3, y_4, z_1, z_2, r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9, r_{10}, t_1, t_2, t_3, t_4, A, B, C, D, E, F, G, H, I, \text{ and } J \}^{T}$$

$$f_1 = \text{max displacement due to the bending load}$$

$$f_2 = \text{max displacement due to the torsion load}$$

$$f_3 = \frac{1}{\omega \omega \omega \omega \omega}$$

$f_4 = \text{structure mass}$

$$\sigma_{\text{bending max}} = \text{maximum von Mises stress due to the bending load}$$

$$\sigma_{\text{torsion max}} = \text{maximum von Mises stress due to the torsion load}$$

$$\sigma_{\text{allow}} = \text{allowable stress} \ (450 \times 10^6 \text{ N/m}^2)$$

Structural analyses are conducted to find the stiffeners matrix, natural frequency, bending and torsion stress of structure. The handlebar structure is modeled as 3D beams and shells. Influence each node in finite element analysis has 6 degrees of freedom.

![Figure 1. The Design variables.](image-url)
Figure 2. Available cross-sections

Figure 3. Topology design select of cross-section H, I and J
(a) diagonal left (b) diagonal right and (c) none.

Figure 4. (a) Bending load and (b) Torsion load
Table 1. Available cross-section A, B, C, D, E, F and G subject to $r_1$, $r_2$ and $r_3$

| Set | $\sum_{i=1}^{3} r_i$ (mm.) | $\sum_{i=1}^{3} t_i$ (mm.) |
|-----|-----------------------------|-----------------------------|
| 1   | 10.85                       | 2                           |
| 2   | 13.6                        | 2.3                         |
| 3   | 17                          | 2.3                         |
| 4   | 21.35                       | 2.3                         |
| 5   | 24.3                        | 2.3                         |

Table 2. Available cross-section H, I and J subject to $r_4$, $r_5$, $r_6$, $r_7$, $r_8$, $r_9$ and $r_{10}$

| Set | $\sum_{i=4}^{10} r_i$ (mm.) |
|-----|-------------------------------|
| 1   | 3                             |
| 2   | 4                             |
| 3   | 4.5                           |
| 4   | 5                             |
| 5   | 6                             |
| 6   | 7.5                           |
| 7   | 9.5                           |
| 8   | 11                            |
| 9   | 12.5                          |

3. Numerical Experiment

The proposed many-objective design problem will be solved by several MOEAs including [9]:
- Differential evolution for multi-objective optimisation (DEMO) [10] using real codes with crossover probability, scaling factor and probability of choosing an element from an offspring in crossover for DE operators being 0.7, 0.8, and 0.5, respectively.
- Multi-objective harmony search (MOHS) [11] using harmony memory considering rate, minimum pitch adjustment rate, maximum pitch adjustment rate and minimum bandwidth rate being 0.5, 0.2, 2, 0.45, and 0.9, respectively.
- Multi-objective population-based incremental learning (MOPBIL) [2] using binary code. The learning rate, mutation probability, and mutation shift are set as 0.25, 0.05, and 0.2, respectively.
- Multi-objective Particle Swarm Optimisation (MOPSO) [12] using starting inertia weight, ending inertia weight, cognitive learning factor and social learning factor being 0.75, 0.1, 0.75 and 0.75, respectively.
- Unrestricted population size evolutionary multi-objective optimisation algorithm (UPS-EMOA) [13] using crossover probability, scaling factor, probability of choosing element from offspring in crossover, minimum population size, and burst size being 0.7, 0.8, 0.5, 10, and 25 respectively.
- Non-dominated sorting genetic algorithm II (NSGA-II) [14] using real codes with crossover mutation probabilities of 1.0 and 0.1 respectively.
- Real-code population-based incremental learning and differential evolution algorithm (RPBILDE) [15] using real codes with NI = 40 where each probability tray produces 5 design solutions. Crossover probability, scaling factor and probability of choosing an element from an offspring in crossover for DE operators are set as 0.7, 0.8, and 0.5 respectively.

Each algorithm is used to solve the problem stated in Section 2 for five optimisation runs. The population size is set to be 100 while the number of iterations is 250. One optimisation run takes $100 \times 250$ function evaluations. It should be noted that the total number of function evaluations used in this study can be considered insufficient for some meta-heuristics according to the literature; nevertheless, this value is set so as to look for only really powerful algorithms. The hypervolume indicator as detailed in [16 and 17] will be used to measure the optimisers’ performance. Note that the optimisation parameter settings detailed above are obtained from using several settings for each optimiser and selecting the one that gives the best results.

### 4. Results and Discussion

After performing 5 optimisation runs of the five MnMHS on solving the proposed walking tractor handlebar optimisation problem, comparison results based on hypervolume indicator is shown in table 3. The mean value of hypervolume is used to measure algorithm’s search convergence while the standard deviation (STD) value is used to measure algorithm’s search consistency. The higher mean hypervolume values is the better convergence while the lower STD is the better consistency. From Table 3, the best performer based on mean hypervolume value is UPS-EMOA while the second best and the third best are MODE and RPBILDE, respectively. For the measure of search consistency based on STD of hypervolume values, the best performer is MODE while the second best, which obtained slightly higher STD, is UPS-EMOA. Overall, the UPS-EMOA is said to be the best performer for solving the proposed walking tractor handlebar optimisation problem in this study in terms of both search convergence and search consistency. Figure 5 shows some of the optimum structures obtained from using UPS-EMOA.

| Algorithm   | Runs         |
|-------------|--------------|
|             | 1  | 2  | 3  | 4  | 5  | Mean | STD   |
| MODE        | 0.831 | 0.834 | 0.833 | 0.833 | 0.834 | 0.833 | 0.00110 |
| MOHS        | 0.814 | 0.815 | 0.815 | 0.812 | 0.818 | 0.8148 | 0.00194 |
| MOPBIL      | 0.807 | 0.793 | 0.793 | 0.799 | 0.8 | 0.7988 | 0.00483 |
| MOPSO       | 0.819 | 0.813 | 0.819 | 0.816 | 0.819 | 0.8172 | 0.00240 |
| UPS-EMOA    | 0.835 | 0.835 | 0.833 | 0.833 | 0.836 | 0.8344 | 0.00120 |
| NSGA-II     | 0.831 | 0.823 | 0.831 | 0.824 | 0.828 | 0.8274 | 0.00338 |
| RPBILDE     | 0.832 | 0.835 | 0.832 | 0.832 | 0.831 | 0.8324 | 0.00136 |

#### Table 3. Comparison results based on hypervolume indicator
Figure 5. Some of the optimum structures obtained from the best performer UPS-EMOA.

5. Conclusions

In this work, simultaneous topology, shape and size design of a walking-tractor handlebar based on using many-objective metaheuristics (MnMHs) is presented. The design problem is posed to maximise the sum of natural frequencies of the first 5 modes, minimise structure mass and minimise construction cost subject to stress and displacement constrains with 2 loading conditions, bending and torsion. Design variables include the topology of side bar stiffeners, shape, and size of all bars. Several MnMHs are used to solve the problem while the results are compared to based on the hypervolume indicator. With this study, the best algorithm of the five implemented MnMHs is UPS-EMOA. For future work, more important parameters for ergonomic design will be added while a more advanced many-objective optimiser will be developed.

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