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Optimum design of a walking tractor handlebar through many-objective optimisation

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Abstract. In this work, a comparative study of multi-objective meta-heuristics (MOMHs) for optimum design of a walking tractor handlebar is conducted in order to reduce the structural mass and increase structural static and dynamic stiffness. The design problem has objective functions as maximising structural natural frequencies, minimising structural mass, bending deflection and torsional deflection with stress constraints. The problem is classified as a many-objective optimisation since there are more than three objectives. Design variables are structural shape and size. Several well established multi-objective optimisers are employed to solve the proposed many-objective optimisation problems of the walking tractor handlebar. The results are compared whereas optimum design solutions of the walking tractor handlebar are illustrated.

Keywords: many-objective optimisation; natural frequency; walking tractor handlebar; structural stiffness; vibration suppression

1. Introduction

Nowadays, agricultural machinery has increasingly become a necessary tool in various farming countries because it can respond to the problem of human comfort, labour force shortage and working hours. A walking tractor is one of the most used terrain vehicles in various farming countries including Thailand, the country in which the majority of people are related to agriculture in one way or another. The handlebar is the main part of the walking tractor used to control the walking tractor. Under working conditions, the structure is subjected to several mechanical phenomena such as; bending stress failure, torsion stress failure, and vibration issues (Fabbri *et al.* 2017, Kanyakam and Bureerat 2007). In addition, some of the mechanical phenomena such as vibration transmissibility can cause human injury such as complex vascular, neurological and musculoskeletal disorder, which are collectively named as hand-arm vibration syndrome (Bovenzi 1998). To our best knowledge, the design of walking tractor is mostly focused on structural strength while the ergonomic effect is rarely considered in the design. Therefore, design optimisation for optimum ergonomic effect and structural mass simultaneously with maximum structural strength of the handlebar is needed.

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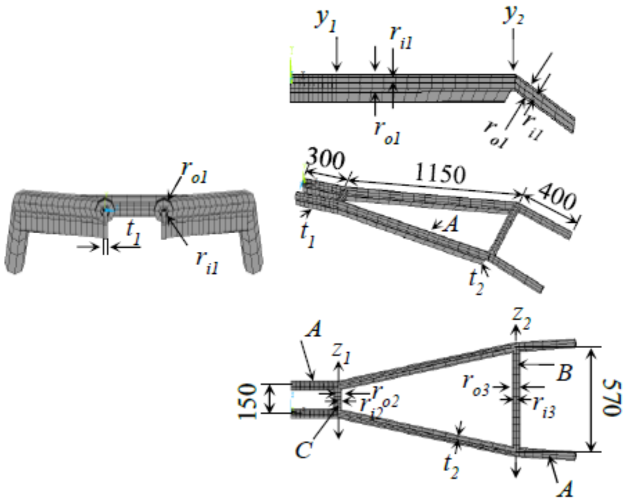

Fig. 1 Design variables

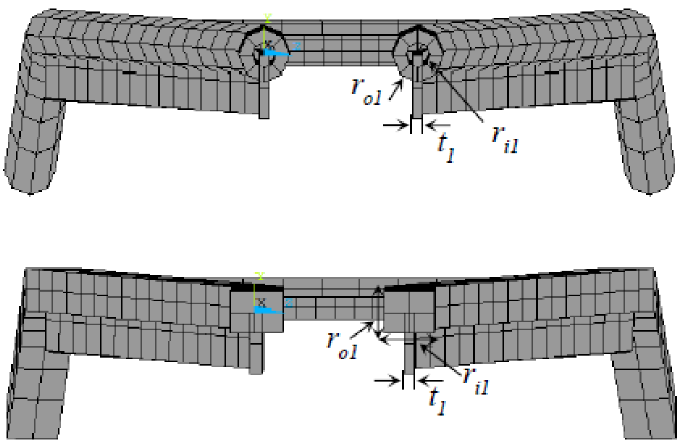

Fig. 2 Available cross-sections

Design optimisation is a special mathematical problem which is posed to find a set of design variables leading to minimising or maximising objective function (s) while fulfilling constraints. Generally, optimisation methods can be classified into two categories; gradient based method and meta-heuristics (MHs) where the latter is also known as evolutionary algorithms (EAs). The use of MHs is more popular than the gradient based methods in real engineering applications since there is no requirement of function derivative implying that they can possibly deal with any kind of objective function and design variable. Moreover, the MHs can explore Pareto fronts within a single run in cases of multi-objective optimisation. However, the MHs have some disadvantages in terms of search convergence rate and consistency. Therefore, development of MHs for a new type of engineering design is always required (Kanyakam *et al.* 2008, Robic and Filipic 2005, Sivasubramani and Swarup 2011, Deb *et al.* 2002, Yildiz and Solanki 2012, Pholdee and Bureerat 2013, Aittokoski and Miettinen 2010, Kaveh and Rezaei 2016, Tejani *et al.* 2016, Kaveh and Bakhshpoori 2016a, Kaveh and Bakhshpoori 2016b, Pham 2016, Pholdee and Bureerat 2016,

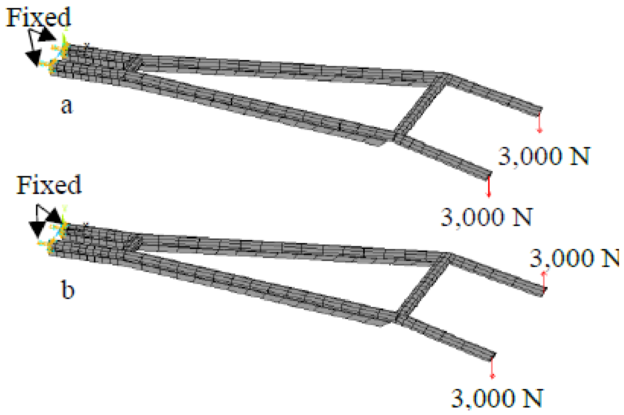

Fig. 3(a) Bending loads and (b) Torsion loads

Pholdee *et al.* 2017, Medeiros and Kripka 2016). For optimisation design of walking tractor, MH named multi-objective population-based incremental learning (MOPBIL) was successfully applied by Kanyakam and Bureerat in 2007. This work only presents the successful use of MOPBIL for this application, however, the performance of the used MH is not investigated thoroughly. As numerous MHs have been developed and reported worldwide for various real engineering design problems and there is no single MH that can perform well for all types of problems, it is always interesting to investigate the search performance of those well-established MHs for a newly proposed engineering design problem.

This work presents a comparative study of multi-objective MHs for many-objective design optimisation of a walking tractor handlebar. The objective functions of the design problem include maximising structural natural frequencies (Qing-zu *et al.* 2007), minimising structural mass, bending deflection, and torsional deflection (Yıldız and Lekesiz 2017) resulting in a many-objective optimisation problem with stress constraints. The design variables are structural shape and sizes.

There are several well-established optimisers including; differential evolution for multiobjective optimisation (DEMO) (Robic and Filipic 2005), multiobjective harmony search (MOHS) (Sivasubramani and Swarup 2011), multi-objective population-based incremental learning (MOPBIL) (Bureerat and Sriworamas 2007), multiobjective particle swarm optimisation (MOPSO) (Reyes-Sierra and Coello Coello 2006, Yildiz and Solanki 2012), unrestricted population size evolutionary multiobjective optimisation algorithm (UPS-EMOA) (Aittokoski and Miettinen 2010), non-dominated sorting genetic algorithm II (NSGA-II) (Deb *et al.* 2002) and real-code population-based incremental learning and differential evolution algorithm (RPBILDE) (Pholdee and Bureerat 2013).

2. Design problem

The vibration of a walking tractor handlebar causes complex vascular, neurological and musculoskeletal disorder, collectively named as hand-arm vibration syndrome (Bovenzi 1998). To alleviate such undesirable vibration, a walking tractor handlebar should have maximised natural frequencies so as to avoid vibration resonance from external excitation. Also, minimising bending and torsion deflection can, to some extent, increase structural reliability. The minimisation of structural mass or volume will affect structural cost. These criteria should be all taken into account when designing the structure. With such four design objectives, the optimisation is called many-objective optimisation. Stress constraints should be added to the problem for safety requirements.

Figs. 1 and 2 show an initial handlebar structure which comprises of the main handlebars and stiffeners. In this study, design variables will determine shape and sizes of the structure. In Fig. 1, y_1, z_1, y_2, and z_2 are shape design parameters while r_{1o}, r_{1i}, r_{2o}, r_{2i}, r_{3o}, r_{3i}, t_1, and t_2 are sizing parameters. The structure can have either a circular or a square cross-section which is controlled by the parameters A, B and C as shown in Figs. 1-2.

Two static load cases are applied to the structure as shown in Fig. 3. The first load case is bending load, which is caused by a user controlling the tractor. The second load case is torsion acting on the handlebar tips (Fig. 3(b)). These types of loads are caused by the vehicle having unequal loads on both wheels under real working conditions. Material properties, density, and young modulus are set to be 200 GPa, and 7800 Kg/m^3, respectively.

The many-objective design problem is set to find shape and sizes of the structure for maximising natural frequency, minimising structural mass and displacements due to bending and torsion loads. The design constraints are assigned in such a way that the maximum stresses due to the bending and torsion loads do not exceed the allowable stress. The optimisation problem can be written as

Min: $f_1(\mathbf{x})$, $f_2(\mathbf{x})$, $f_3(\mathbf{x})$, $f_4(\mathbf{x})$

Subject to

$\sigma_{\text{bending max}} \leq \sigma_{\text{allow}}$

$\sigma_{\text{torsion max}} \leq \sigma_{\text{allow}}$

$-0.05 \leq y_1 \leq 0.06$, m

$-0.025 \leq z_1 \leq 0.025$, m

$0.05 \leq y_2 \leq 0.06$, m

$-0.06 \leq z_2 \leq 0.09$, m

$0.01 \leq r_{1o} \leq 0.025$, m

$0.005 \leq r_{1i} \leq 0.009$, m

$0.01 \leq r_{2o} \leq 0.025$, m

$0.005 \leq r_{2i} \leq 0.009$, m

$0.01 \leq r_{3o} \leq 0.025$, m

$0.005 \leq r_{3i} \leq 0.009$, m

$0.005 \leq t_1 \leq 0.02$, m

$0.005 \leq t_2 \leq 0.02$, m

$A, B, C \in \{0, 1\}$

where $\mathbf{x}$ is a vector of design variables.; f_1 is maximum displacement in y-direction (vertical direction) due to the bending load.; f_2 is maximum displacement in y-direction due to the torsion load.; f_3 is set to minimise the first five natural frequencies.; f_4 is structural mass.

$\mathbf{x} = \{y_1, z_1, y_2, z_2, r_{1o}, r_{1i}, r_{2o}, r_{2i}, r_{3o}, r_{3i}, A, B, C, t_1, t_2\}^T$

f_1 = max displacement due to the bending load

f_2 = max displacement due to the torsion load

$$f_3 = \frac{1}{\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5} \tag{1}$$

f_4 = structure mas
$\sigma_{\text{bending max}}$ = maximum von Mises stress due to the bending load
$\sigma_{\text{torsion max}}$ = maximum von Mises stress due to the torsion load
σ_{allow} = allowable stress (450 MPa)

Structural analyses are carried out using the finite element method. During an optimisation process, static and free vibration analyses are performed. The main handlebar is modelled as 3D beams while the stiffeners are modelled as shell elements. This means that each node of the finite element model has 6 degrees of freedom.

3. Implemented meta-heuristics

In this work, the comparative study of several MOMHs is conducted. Brief details of the used algorithms are expressed as follows:

Differential evolution for multiobjective optimisation (DEMO) (Robic and Filipic 2005) is a multiobjective version of the original differential evolution algorithm. The search process starts with a randomly generated set of solutions which is traditionally called population and then update those solutions using two operators, mutation, and crossover. Then, the next generation will be selected based on non-dominated score similarly to NSGAII. Non-dominated solutions of the final iteration are regarded as an approximate Pareto front.

Multiobjective harmony search (MOHS) (Sivasubramani and Swarup 2011) is a multi-objective version of the harmony search algorithm which was developed and inspired by the improvisation process of jazz musicians. The search process starts by randomly generating a population and then update the population using two operators called memory consideration and pitch adjustment. The next generation will be selected based on non-dominated scores and non-dominated solutions of the final population are set as a Pareto front similarly to DEMO.

Multi-objective population-based incremental learning (MOPBIL) is a binary based algorithm. The search process starts with an initial probability matrix while the binary population according to the initial probability matrix is then created. The binary population is decoded and objective values are evaluated. The best binary solutions based on non-dominated scores are chosen to update the probability matrix for the next iteration. The updating process is completed when all rows of the probability matrix are changed. The process is repeated until a termination criterion is fulfilled.

Multiobjective Particle Swarm Optimisation (MOPSO) (Reyes-Sierra and Coello Coello 2006) is a multiobjective version of particle swarm optimisation (PSO), developed from mimicking a group of birds behavior. Then, the particles will be updated by randomly tracking best particles (non-dominated solutions). Current non-dominated solutions are then saved to an external archive. The archive is updated iteratively until reaching the maximum iteration.

For unrestricted population size evolutionary multiobjective optimisation algorithm (Aittokoski and Miettinen 2010), the search process starts by randomly generating a population and a burst size of parents is selected randomly. The population will be updated based on the selected burst size parents using DE mutation and crossover. Then, the current population is selected based on non-dominated sorting. Non-dominated solutions of the final iteration are regarded as Pareto optimal solutions.

Non-dominated sorting genetic algorithm II (NSGA-II) (Deb *et al.* 2002) is a multiobjective version of a genetic algorithm. Its search starts by randomly generating a population. In this work, real code crossover and real code mutation are used for updating a population. The next generation is selected based on a non-dominated sorting scheme and a crowding distance archiving technique.

Real-code population-based incremental learning and differential evolution algorithm (RPBILDE) (Pholdee and Bureerat 2013) is a real code version of MOPBIL hybridised with DE crossover and mutation. The search process starts with an initial probability matrix. Then, a population according to the initial probability matrix is generated. The population is further modified by using DE mutation and crossover to maintain population diversity. The best solutions or non-dominated solutions are saved to an external Pareto archive. The archive is updated iteratively until meeting the stopping condition.

4. Numerical experiment

The proposed many-objective design problem will be solved by several MOMHs including:

- Differential evolution for multiobjective optimisation (DEMO) (Robic and Filipic 2005) 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.
- Multiobjective harmony search (MOHS) (Sivasubramani and Swarup 2011) 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) (Bureerat and Sriworamas 2007) using binary code. The learning rate, mutation probability, and mutation shift are set as 0.25, 0.05, and 0.2, respectively.
- Multiobjective Particle Swarm Optimisation (MOPSO) (Reyes-Sierra and Coello Coello 2006) 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 multiobjective optimisation algorithm (UPS-EMOA) (Aittokoski and Miettinen 2010) 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) (Deb *et al.* 2002) 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) (Pholdee and Bureerat 2013) using real codes with $N_I = 40$ 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 method is used to solve the problem for 5 optimisation runs. The population size is set to be 100 while the number of iterations is 250. For the optimisers using different population sizes, their search processes are terminated with the total number of function evaluations equal to 100×250. 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 (Zitzler and Thiele 1998, Bandyopadhyay and Mukherjee 2014) 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.

Table 1 Comparison results based on hypervolume indicator

Algorithm	Runs						
	1	2	3	4	5	Mean	STD
MODE	0.444	0.445	0.424	0.437	0.447	0.439	0.0084
MOHS	0.409	0.411	0.421	0.413	0.419	0.415	0.0046
MOPBIL	0.351	0.386	0.298	0.410	0.352	0.359	0.0379
MOPSO	0.375	0.310	0.348	0.363	0.376	0.354	0.0244
UPS-EMOA	0.400	0.438	0.303	0.404	0.415	0.392	0.0464
NSGA-II	0.445	0.444	0.420	0.444	0.447	0.440	0.0101
RPBILDE	0.442	0.441	0.447	0.432	0.444	0.441	0.0050

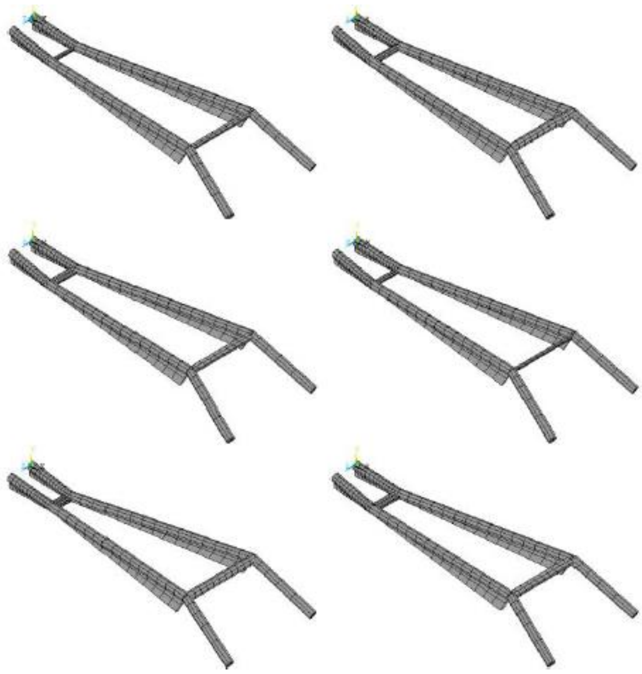

Fig. 4 some of the optimum structures obtained from the best performer RPBILDE

5. Results and discussion

After solving the problems using various multi-objective MHs as detailed in section 3, the comparative results based on the hypervolume indicator are shown in Table 1. 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. For mean values, the higher is the better while, for STD, the lower is the better. From the table, the best according to the convergence rate is RPBILDE while the second best and the third best are NSGA-II and DEMO, respectively. For the measure of search consistency based on STD value, the most consistent optimiser is MOHS while the second and third most consistent methods are RPBILDE and DEMO respectively. Overall, RPBILDE is the best performer for solving many-objective optimisation of walking tractor handlebar design. Fig. 4 shows some of the optimum structures obtained from using RPBILDE

6. Conclusions

In this work, a comparative study of multi-objective MHs for the many-objective designs of a walk-tractor handle bar is conducted. The proposed design problem has objective functions as maximising structural natural frequencies, minimising structural mass, bending deflection and torsional deflection with stress constraints while the design variables include structural shape and sizes. After solving the proposed many-objective optimisation problem using several well-established MOMHs, the results are compared based on the hypervolume indicator. It was found that the RPBILDE is the best performer among the several MOMHs used in this study. This work is a start for ergonomic design of farm machinery for lower class farmers. More important design criteria will be added in research future while a more advanced many-objective optimiser will be developed.

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