Evolutionary Multi-objective Optimization for Bulldozer and its Blade in Soil Cutting

Synopsis report submitted

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Synopsis Report

The real-world problems often consist of multiple objectives that are to be optimized simultaneously. When such problems are solved using any evolutionary multi-objective (EMO) technique, a set of Pareto-optimal (PO) solutions are generated that show trade-off among the objectives. These PO solutions provide multiple choices to a practitioner that can be used for a relative comparison and also, for appropriate selection of a solution. In this thesis, a real-world optimization problem is targeted from the domain of construction equipment, that is, bulldozer for soil cutting.

A bulldozer is a construction equipment which has a tractor for supplying power and a metallic blade in its front for soil cutting (Peurifoy et al. 2006). When the soil cutting operation is modeled for a bulldozer and its blade, an emphasis is given to make the operation economical and productive. The operation can be made economical when the variable cost of a bulldozer can be reduced. The variable cost depends on the operating conditions which involve many parameters, such as power required from a bulldozer, speed of a bulldozer, depth of a blade inserted in soil, dimensions of a blade, etc. The operation can be made productive when a bulldozer can finish soil cutting task as early as possible. However, any productive soil cutting operation with a large size blade operating at a larger speed and higher cutting depth requires more power from the bulldozer. Such conflicting scenario involves multiple objectives to achieve for optimal soil cutting operation.

In the literature, most of the earlier studies focused on determining the cutting force on a bulldozer blade at different cutting depths (McKyes 1985). For example, many analytical and numerical models have been developed that can determine the cutting force with a desired accuracy. The numerical models were developed using finite element methods and discrete element methods which were found to be efficient by considering the effect of parameters, such as blade dimensions, cutting depth and cutting angle, etc., on the cutting force. However, the numerical models always demand higher computation time. On the other hand, the analytical models can determine the cutting force quickly on a blade with a decent accuracy. Experimental studies have also been done to determine the accurate cutting force on a bulldozer blade. However, such studies need more time and economic support.

In the past, studies focused on determining the cutting force accurately by changing few parameters. However, to make the soil cutting operation economical and productive the optimal input parameters have to be chosen. This leads to the motivation of this thesis in which the soil cutting operation by a bulldozer and its blade is formulated as an optimization problem. In this thesis, three multi-objective optimization formulations are developed chronologically by making them realistic and practical for usage in every attempt. The first attempt is made by developing a bi-objective formulation, which is given in (1). The problem is formulated using the decision variables on operating conditions, such as cutting depth (D), blade cutting angle (α), bulldozer velocity (v), and on dimensions of a blade, such as blade width (B), blade height (H), blade curvature radius (R) and blade curvature angle (θ). The economic aspect is achieved by minimizing F which reduces power requirement from a bulldozer thereby reducing fuel consumption. The operation is made productive by maximizing V which can cut and fill more soil, and finish the operation at the earliest.

$$
\begin{aligned}
\textbf{Min.} \quad & F \text{ (Cutting Force)},\\
\textbf{Max.} \quad & V \text{ (Blade Capacity)},\\
\text{sub. to} \quad & P_R \geq 0 \text{ (Remaining power)},\\
& 0.01 \leq D \leq 0.5,\\
& 0.785 \leq \alpha \leq 1.309,\\
& 0.278 \leq v \leq 1.389,\\
& 3 \leq B \leq 5,\\
& 1 \leq H \leq 2.5,\\
& 0.9 \leq R \leq 1.5,\\
& 1.047 \leq \theta \leq 1.309.
\end{aligned}
\tag{1}
$$

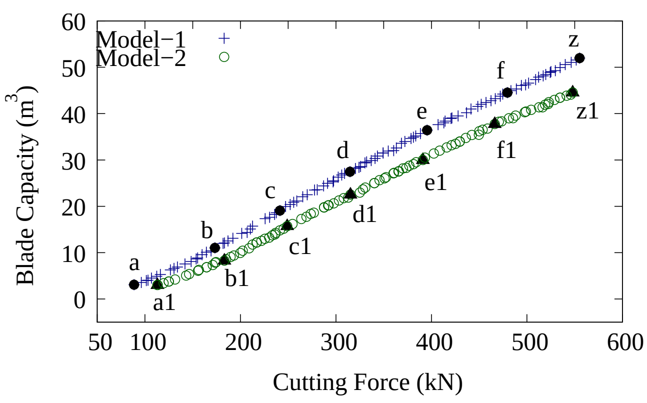

Figure 1: Pareto-optimal solutions of bi-objective problem for both the models.

For determining F, two analytical cutting force models from the literature have been adopted which are developed by considering different soil failure zones using the passive earth pressure theory. The cutting force model of Qinsen & Shuren (1994) is referred as model-1 and model of McKyes (1985) is referred as model-2. A systematic approach is followed for presenting results and discussion in which multiple EMO techniques, such as elitist non-dominated sorting genetic algorithm (NSGA-II), strength Pareto evolutionary algorithm-2 (SPEA2), etc., are used to solve the problem given in Eq. (1), and their results are compared based on the inverse generalized distance (IGD) and hypervolume (HV) statistical indicators. The performance of EMO techniques is found to be similar, therefore the PO solutions evolved by NSGA-II are considered for further study. It can be seen from Fig. 1 that a linear trend between F and V is evolved.

In the next step of the systematic approach, a closeness of the obtained PO solutions is validated by solving Eq. (1) using the $\epsilon-$constraint method. The variable-wise perturbation analysis is then performed in the close vicinity to observe sensitivity of each decision variable for F. Afterward, the post-optimal analysis of obtained PO solutions is performed to decipher design principles that are responsible for generating the PO solutions. Moreover, relationships among other variables are presented that are responsible for trade-off among the PO solutions. From the analysis, it is concluded that D, H, and B are the decision variables which generated many PO solutions. The other decision variables have been evolved at their lowest bounds. The guidelines have been suggested for choosing the optimal values of decision variables from obtained relationships in the post-optimal analysis.

From the results of the previous formulation, it was observed that the formulation lacks realistic objectives and constraints so that it cannot be used in practice. Moreover, maximizing V leads to higher time for cutting soil when a big size blade is used at a relatively lower cutting depth of soil. Therefore, a realistic bi-objective formulation is proposed which is given in Eq. (2). Now, P and T are minimized simultaneously by limiting power requirement for soil cutting, by limiting F on the blade in order to avoid its failure, and by keeping desired production rate. By following the same systematic approach discussed earlier, the obtained PO solutions for both cutting force models are shown in Fig. 2. The nature of PO solutions is changed now, and the PO font is evolved with the knee region. This is the preferred region from in which an optimal solution can be selected because solutions away from it show any gain in one objective with a higher loss in another objective. Thereafter, the $\epsilon-$constraint method is applied to solutions $a1 - z1$ and $a2 - z2$ which justified the closeness of the obtained PO solutions with the true PO solution. This observation is further supported by the variable-wise perturbation analysis. Moreover, it is found that v is the most sensitive decision variable followed by D, H, B, R and θ to the given problem. In the post-optimal analysis, the optimal values of B, H, R, θ, and α decision variables are evolved at their bounds. The other decision variables show relationship for trade-off among the obtained PO solutions. Since the knee region is preferable, the guidelines are presented for choosing an appropriate optimal solution. The present study is supported by validating the obtained PO solutions with the experiments from the literature.

$$
\begin{aligned}
\textbf{Min.} \quad & P \text{ (Power)}, \\
\textbf{Min.} \quad & T \text{ (Time)}, \\
\text{sub. to} \quad & P_R \geq 0 \text{ (Remaining power)}, \\
& F \leq F_{max} \text{ (Blade failure)}, \\
& P_d \geq P_{d_{min}} \text{ (Production rate)}, \\
& 0.01 \leq D \leq 0.5, \\
& 0.785 \leq \alpha \leq 1.309, \\
& 0.278 \leq v \leq 1.389, \\
& 3 \leq B \leq 5, \\
& 1 \leq H \leq 2.5, \\
& 0.9 \leq R \leq 1.5, \\
& 1.047 \leq \theta \leq 1.309.
\end{aligned}
\qquad (2)
$$

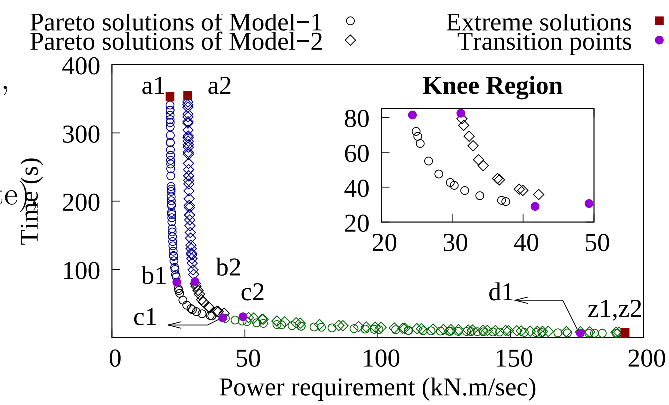

Figure 2: Pareto-optimal solutions of modified bi-objective problem for both the models.

From the previous study, it was observed that the PO solutions were evolved with B, H, R, θ, and α at their lower bounds. It means that a smaller size blade can minimize P and T simultaneously, which lacks variation in blade dimensions for generating the PO solutions. Therefore in the next chronological attempt, a three-objective optimization formulation is proposed in Eq. (3). A new objective on a number of passes to cut a fixed amount of soil is included in this study. Rest of the objectives, constraints, and variables remain same as given Eq. (2).

$$
\begin{aligned}
&\textbf{Min.} && P \text{ (Power requirement)} \\
&\textbf{Min.} && N \text{ (Number of passes)}, \\
&\textbf{Min.} && T \text{ (Time)}, \\
&\text{sub. to} && \text{same constraints and decision variables given in Eq. (2).}
\end{aligned}
\tag{3}
$$

In the systematic approach for presenting results and discussion, the obtained PO solutions from two cutting force models are shown in Fig. 3. For discussion, these solutions are categorized into three groups. The first group of the obtained PO is referred as the surface solutions (blue color symbols) in which most of the solutions are generated at lower P values. The second group of solutions (black color filled symbols) is referred as the knee-solutions that show a decent trade-off among the objectives. The third region is referred as the extension solutions in which the solutions do not show much trade-off between T and N, but objective P increases to a higher value. This study is also supported by the results of the $\epsilon-$constraint method and perturbation analysis for closeness of the obtained PO solutions with the true PO front.

In the post-optimal analysis of the obtained PO solutions, θ and R are evolved at their lowest values for all PO solution. Other decision variables are responsible for trade-off among the solutions. The surface solutions are evolved with smaller to bigger size of the blades that are operated at a smaller cutting depth. The knee solutions are evolved with wide ranges of D, α, B and H thereby showing a decent trade-off among the obtained PO solutions. For extension solutions, the decision variables B, H, v, and α are varying from their lower to upper limits. Moreover, D remains at its upper bound. The three objective study is validated using the experimental results

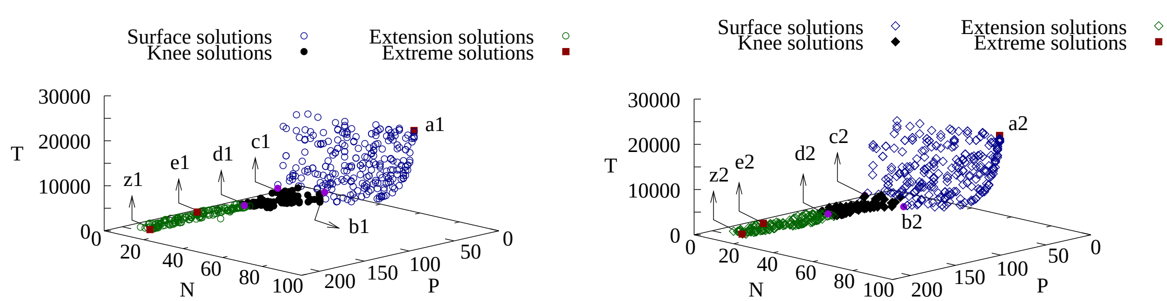

Figure 3: The obtained Pareto-optimal solutions from NSGA-II for model-1 (LHS) and model-2 (RHS).

from the literature which shows the closeness of the obtained PO solutions with the experiments.

In the previous studies, the proposed formulations were solved using five existing EMO techniques. These EMO techniques can be made faster by coupling them with the local search. In the last phase of the thesis, a hybrid EMO procedure is proposed to address three challenges of implementing local search with EMO techniques. The challenges are (i) `Frequency`: When to execute the local search?, (ii) `Number`: How many solutions are selected for performing a local search?, (iii) `Choice`: What are those solutions which are selected for the local search? An approach for `number` and `choice` of solutions is proposed which is based on the objective space decomposition using the reference points. First, the current population of NSGA-II is normalized using the Ideal and Nadir points. The non-dominated solutions which are closest to each reference line are selected for the local search. It is noted that the reference lines are drawn from the origin and the reference points. The number of the reference points is determined as $K = C_p^{m+p-1}$, where p is the number of division for each axis. We set $p = 2^n$, where $n \in (1, 2, 3, 4, 5)$. `Frequency` challenge is addressed by adaptively deciding the local search execution in every generation that is based on IGD values. The IGD value for each generation is stored and the statistical values of IGD over past q generations are used as $(IGD_{max} - IGD_{min})/q \leq \delta$, where IGD_{min} and IGD_{max} are the minimum and maximum IGD values over past q generations. δ is the user-defined value. When the condition gets satisfied in any generation, the local search is executed on the chosen non-dominated solutions. The local search is executed by using the $\epsilon-$constraint method. *fmincon* solver of MATLAB is chosen in which the SQP technique is selected. The local search was implemented on NSGA-II framework for testing on the bi-objective optimization problem given in Eq. (2).

Different variants of local search are implemented with NSGA-II such as, case 1: executing local search at the beginning on the initial population only, case 2: executing local search after regular interval of generations, case 3: executing local search adaptively as defined earlier, and case 4: executing local at the beginning on the initial population and also adaptively. It is found that case 1 and case 4 improve the convergence of NSGA-II framework. Except for the small number of reference points (RPs), the convergence was independent of the number of RPs. Also, the convergence was independent of q as well. The results of case 4 also suggest that the hybrid EMO is converged in less than half of NSGA-II generations. Other cases show the dependency of convergence on a number of RPs and q.

The major findings/contributions of this thesis are as follows

1. Soil cutting operation is made economical and productive by proposing three formulations in a chronological order. The three-objective formulation emerges as the most realistic that can be used in practice.

2. The solutions obtained from the proposed formulation showed the closeness to the experimental results from the literature. Therefore, it can be used by a practitioner.

3. The post-optimal analysis has been done for the obtained PO solutions from the proposed formulations. It was observed that a few decision variables can be fixed at their bounds for generating PO solutions. Other decision variables like velocity, cutting depth, width and height of blade, etc., can be varied to generate trade-off among the solutions.

4. This study takes forward the relationships obtained using the post-optimal analysis and guidelines have been suggested to choose an appropriate PO solution. Accordingly, the optimal decision variables value can be found that can make the soil cutting operation economical and productive.

5. For further improving the convergence of existing EMO technique, three challenges on `number`, `choice` and `frequency` of implementing the local search have been addressed and the proposed approach was coupled with NSGA-II. The hybrid EMO technique was able to converge in less than half of NSGA-II generations.

References

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