

Grab optimization

ME54035 Graduation project

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by

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Preface

This report documents the graduation project in obtaining my Master degree in Mechanical Engineering at the Delft University of Technology at the section of Transport Engineering and Logistics. The goal of the project was to develop a systematic design optimization framework for grabs handling cohesive and compressible bulk materials. This report will present and discuss the outcomes of the findings.

I want to thank the people who helped me during the process of my graduation project. Especially my daily supervisor, Javad Mohajeri, who gave me excellent support and provided me with useful criticism during the regular meetings we had at the university. He was always willing to make time to discuss the results and supporting me in making design decision for the following steps. I want to thank him for his efforts in reading my writings and giving me feedback on the thesis. I want to thank dr. ir. Dingena Schott for her constructive feedback during the progress meetings.

Also, I would like to express my gratitude towards Nomag, the company who initiated this research together with the university for allowing me to graduate on this subject. In particular, I would like to thank ir. Wilbert de Kluiver for his guidance and support and ir. Michel Corbeau for asking the right questions which kept me focused on the overall goal instead of getting lost in the details.

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*A.J. van den Bergh
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Summary

Grab unloaders are handling a variety of materials such as ores, coal, agriculture goods, biomass and scrap. The interaction of grabs with the bulk material is a complex process influenced by a variety of variables; grab, operational and bulk material variables. Cohesive bulk materials such as iron ore fines are complex bulk materials to handle; their bulk behaviour does not only depend on the mineral properties but also on the processing state such as consolidation effort and moisture content. Which makes design of such grabs complex and grab performance is hard to predict. To support the design process, a fast and effective model-based design in combination with a systematic optimization will be supportive.

The influence of cohesive and compressible bulk material on the grabbing process is researched. By a coupled DEM-MBD simulation, the grab interacting with bulk materials is analyzed. The contact parameters of the DEM model are varied by an experimental plan to investigate the influence of the DEM contact parameters (cohesion and plasticity) on the grabbing process. The influence of cohesion proved to be negligible, where the influence of compressibility (or plasticity) is significant. Increasing the plasticity of the bulk materials will increase the penetration resistance and thus influence the grabbing performance. Secondly, the bulk material consolidation state is investigated. When iron ores are stored in the hold of a bulk carrier the storage height will reach up to 12-15 meters, causing consolidation of the bulk material. Experiments at different consolidation pressures up to 300 KPa demonstrated that the effect of consolidation is significant in the grabbing process. These experiments showed a significant influence of the bulk variability on the grabbing process. Therefore, an generic optimization framework is developed to incorporate bulk material variability into the optimization process. The developed optimization framework consists of the following steps:

1. Initialization of optimization problem
2. Select incorporated bulk materials
3. Select design variables
4. Design experimental plan; Number of design points and creation of LHD.
5. Prepare and execute simulations
6. Fit surrogate model on simulation output
7. Define weight factors for bulk materials
8. Run optimizer
9. Validate results

The novelty of the optimization framework is that it is capable of handling the controlled and uncontrolled variables simultaneously. For cohesive iron ores, the bulk material behaviour is uncontrolled due to the dependency on moisture content and consolidation state. By incorporating various bulk materials at different consolidation states, the grab design could be optimized for a set of bulk materials. Which minimize the effect of the uncontrolled bulk variability on the grabbing process. To reach this goal the next objectives are set:

- Maximize mass performance indicator (payload)
- Minimize the standard deviation of the mass performance indicator

Where the first objective maximizes the payload for the crane capacity, the mass performance indicator is given by the ratio between payload en grab mass. The second objective minimizes the effect of bulk variability, when the standard deviation is zero the payload of the grab in each bulk material is equal, resulting in that the bulk material type or state does not influence the grab performance.

A design optimization of a NemaX iron ore grab is executed by following the optimization framework. Five grab design variables are explored to find the optimal solution. Three DEM bulk material models are incorporated to minimize the effect of bulk variability of the 'optimal' result. The bulk materials and corresponding weight factors are presented in Table 1.

Table 1: Bulk materials optimization framework

	Name:	Weight factor:
Bulk 01	Iron ore Pellets non-consolidated	0.1
Bulk 02	Artificial Fines low-consolidated	0.4
Bulk 03	Carajas Sinterfeed high-consolidated	0.5

In total 24 designs evaluated by LHD DoE method to explore the design space and create data points on which a surrogate model is fitted. By a genetic algorithm the optimal solutions for the two objectives are determined. Figure 1 shows the Pareto front and the design points for the weighted mass indicator and standard deviation of the mass indicator. Where the objective is to reach the right-bottom corner as far as possible.

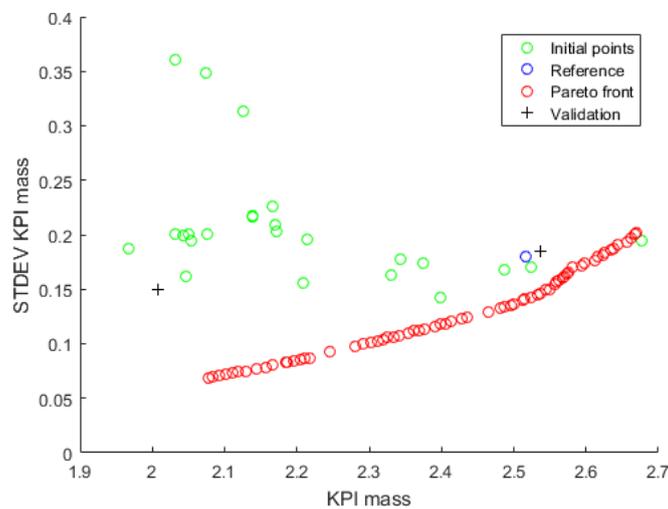


Figure 1: Pareto front

Support Vector Regression modeling with Polynomial Kernel functions proved to be the most accurate surrogate model, in order of prediction errors (<10%) and obtaining the optimal design.

The optimization framework proved to be effective to incorporate the bulk material uncertainties in the optimization process. By the framework, an iron ore grab is optimized by varying five grab variables and incorporating three bulk materials. Based on the optimization results for iron ores, the following design rules apply for iron ore grabs:

- Knife angle of around 5 degrees proved to be optimal in combination with a openings angle of 65 degrees.
- To maximize the payload regardless of the bulk variability, a short-wide grab is preferred.
- To minimize the influence of bulk variability, a long-small grab is preferred.
- The closing arm length must be as long as possible to maximize the strength of the closing mechanism. A stronger closing mechanism results in a better digging performance of the grab; the grab digs deeper into the bulk material.

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