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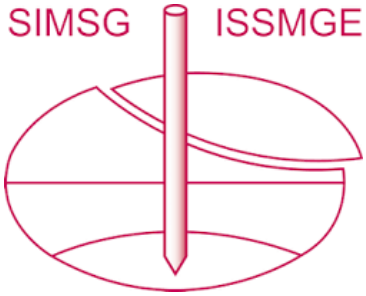

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Intelligent Earthworks Optimization System

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1 Introduction

Earthworks are often regarded as one of the most costly and time-consuming components of linear infrastructure constructions (e.g., road, railway and airports). Since actual construction requirements originate higher demands for productivity and safety in earthwork constructions, the optimal usage of every resource in these tasks is paramount. The management of resources in an earthwork construction site is, in great part, a function of the allocation of the available equipment, for which there are a vast number of possible equipment allocation combinations. Simultaneously, while there is often high competitiveness, where the pressure is to provide the least possible costs and durations, contractors and project designers often settle for an allocation solution that is mostly based on their own intuition and accumulated experience. This guarantees neither optimal resource usage, nor a solution associated with minimal cost and duration.

The optimal allocation of equipment in earthwork tasks is a complex problem that requires the study of several different aspects, as well as the knowledge of a large number of factors. In fact, earthworks are comprised by a combination of repetitive, sequential, and interdependent activities based on heavy mechanical equipment (i.e., resources), such as excavators, dumper trucks, bulldozers and compactors. In order to optimally allocate the available resources, knowledge regarding their specifications (e.g., capacity, weight, horsepower) and the work conditions to which they will be subjected (e.g., material types, required and available volumes in embankment and excavation fronts, respectively) is essential. This knowledge can be translated into the productivity (i.e., work rate) of each piece of equipment when working under a specific set of conditions. Moreover, since earthwork tasks are inherently sequential and interdependent, the interaction between the allocated equipment must be taken into account. A typical example of this is the need for matching the work rate of an excavator plant with the capacity of a truck plant to haul the excavated material to the embankment fronts.

Given the non-trivial characteristics of the earthwork allocation problem, conventional Operation Research (e.g., linear programming) and blind search methods are infeasible. As such, a potential solution is to adopt metaheuristics – modern optimization methods capable of searching large space regions under a reasonable use of computational resources. While this may address the issue of optimizing such a complex problem, the lack of knowledge regarding optimization parameters under different work conditions, such as equipment productivity, calls for a different approach. Bearing in mind the availability of large databases, including in the earthworks area, that have been gathered in recent years by construction companies, technologies like data mining (DM) come forward as ideal tools for solving this problem. Indeed, the learning capabilities of DM algorithms can be applied to databases embodying the productivity of several equipment types when subjected to different work conditions. The extracted knowledge can then be used to estimate the productivity of the available equipment under similar work conditions.

This work explores the integration of different technologies in order to allow for an optimization of the earthworks process. This is translated in the form of an evolutionary multi-criteria optimization system, capable of searching for the best allocation of the available equipment that minimizes a set of goals (e.g., cost, duration, environmental impact). The results stemming from the application of the system to a case study in a Portuguese earthwork construction site are presented. These comprise the assessment of the system performance, including a comparison between different optimization methods. Furthermore, an analysis regarding the improvement of workflow in the construction site after the implementation of the system is discussed, in the context of several comparisons between original (i.e., obtained by manual design) and optimized allocation solutions. Ultimately, these results illustrate the potential and importance of using this kind of technologies in the management and optimization of earthworks.

2 Tools and previous earthwork applications

As mentioned, since conventional and Operations Research optimization methodologies (e.g. linear programming) are not suitable to deal with the highly complex earthworks allocation problem, metaheuristics comprise some of the most successful and well-adjusted applications (Kataria, Samdani, & Singh, 2005; Moselhi & Alshibani, 2007; Parente et al., 2015a; Xu, Wang, & Xia, 2011; Zhang, 2008). These modern optimization methods are capable of searching large search space regions under a reasonable use of computational resources. Genetic algorithms (GA) are one of such techniques, consisting of stochastic algorithms whose search methods model natural phenomena, such as genetic evolution and the concept of Darwinian natural selection (Holland, 1975). In fact, GA come

forward as some of the most effective optimization tools, on account of their efficiency when dealing with extensive search spaces within reasonable computational effort, as well as their ease of interpretation and implementation. Based on artificial intelligence and natural selection processes, GA start by generating random solutions for a problem, which are iteratively improved, tending towards optimal or near-optimal solutions. With this in mind, by interpreting the problem as a series of production lines, it becomes possible to focus the GA's allocation of resources to the compaction task (last task of the production lines), which sets the work rate target value for each production line.

However, optimization methods like GA alone are not enough to optimize earthworks throughout its initial design phase. In fact, during this phase, it is very challenging to estimate the actual productivity of equipment, since it varies with a high number of variables (e.g., material types, available equipment, work conditions, meteorological conditions). Other than the experience of the designer, which may not be enough in many cases, data-driven prediction models are some of the few methods that have stood out as capable of providing realistic estimates for this problem (Cortez, Marques, & Gomes Correia, 2008; Edwards & Griffiths, 2000; Hola & Schabowicz, 2010; Parente, Correia, & Cortez, 2014; Shi, 1999; Tam, Tong, & Tse, 2002). These are mostly based on data mining (DM) methods. DM represents the overall process of discovering useful knowledge from data. This process that involves several steps, such as selection, pre-processing and processing of data, application of DM algorithms, interpretation and processing of knowledge (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). DM is often framed in the context of a methodology, such as CRISP-DM (Cross Industry Standard Process for Data Mining) (Chapman et al., 2000), a highly-accepted tool-neutral methodology, becoming easier to understand, implement and analyze. In the context of earthworks, the application of DM algorithms is used to analyze large databases for patterns and trends in data in order to infer trends and rules among the variables, being able to handle large volumes of data in a short time and transforming them into knowledge. The extracted knowledge can then be used to estimate the productivity of the available equipment under similar work conditions.

Furthermore, as previously referred, since earthwork tasks include the material hauling from excavation to embankment fronts, it also becomes imperative to analyze and optimize the possible transportation networks. In this context, the use of geographic information systems (GIS) provides an easy method to study the possible trajectories for transportation equipment in a construction site, ultimately allowing for a choice of the best paths to improve the workflow. Besides this, GIS further feature the advantage of seamless and real-time integration with several field technologies, working as a bridge between these and the aforementioned optimization technologies.

3 Proposed solution

Although several previously mentioned studies have adopted metaheuristics, many of these applications focus on single tasks or partial processes that comprise earthworks, i.e., excavation and hauling (Kataria et al., 2005; Xu et al., 2011), in an attempt to deal with the high complexity of the problem. For this reason, these systems lack the advantages of a global optimization of execution durations and costs throughout all construction phases. In terms of optimization objectives, existent systems tend to be limited to single objective optimization, such as cost (Marzouk & Moselhi, 2002) or duration (Kataria et al., 2005), or attempt to consider multiple objectives via a weight-based optimization (Zhang, 2008). Yet, although these solutions are considered effective in terms of computational requirements, they overlook the advantages of multi-objective optimization.

However, as one can easily infer in nontrivial multi-criteria optimization problems, there is often not a single optimal trade-off solution, but rather a set of trade-offs with conflicting objectives. Thus, a much natural multi-criteria optimization approach is to optimize a Pareto front of solutions, where each solution is called non-dominated, or Pareto optimal, if none of the objectives can be improved in value without worsening the other. In the context of earthwork optimization, all Pareto-optimal solutions are considered equally good and the main choice criteria for selecting one solution over the other is often decided by the project designer based on the construction final deadline and/or budget. Additional criteria can be used to support the final decision, such as environmental aspects, which can be assessed by the determination of carbon dioxide emissions in each solution.

Bearing this in mind, the proposed system architecture consists of three integrated main modules (Equipment, Spatial, and Optimization Modules) with capabilities to acquire and manipulate data from each phase of an earthwork project. In general terms, the Equipment Module (Cortez *et al.*, 2008; Parente *et al.*, 2014) is responsible for receiving the user input for available equipment/plants, while calculating or retrieving equipment costs. Simultaneously, this module should have a close interaction with the data mining (DM) models for determining the productivity rates for available rollers. This model is built upon the data comprised in the Guide des Terrassements Routiers (GTR) compaction guide, such as material characteristics, roller specifications (i.e., weight per drum length and maximum amplitude, in the case of vibratory rollers) and construction specifications (i.e., required compaction energy or specific layer depth). Given this input, the model is then capable of classifying both the material and roller types, as well as retrieve information regarding number of compaction passes and maximum productivity. Moreover, given the availability of further construction data, the DM models in this module can be expanded to include the whole construction equipment, such as spreading, transportation and excavation equipment.

The Spatial Module (Parente *et al.*, 2016a; Parente *et al.*, 2016b) allows the user to input a functional model of the work site by user input using a geographic information system (GIS), namely including all the possible work fronts and potential equipment trajectories/paths. Simultaneously, the path finder algorithms integrated in most GIS software can be used to determine the best routes or trajectories for transportation equipment, by making use of both the created work site model and the equipment specifications from the equipment module. This results in the optimization of the workflow in the construction site. Furthermore, depending on the availability of global positioning system (GPS) equipment, by including GPS receivers in the active earthwork equipment during construction phase and associating these with the GIS software, it becomes possible to determine the actual equipment work rates. This allows the system to automatically update and optimally adjust itself in real-time as the construction process goes on. For instance, consider the possibility that the real rate of transport equipment (such as a dumper truck) is inferior to what was originally predicted in the modelling phase in terms of travels between excavations or borrow sites and work fronts per hour. By monitoring and re-evaluating the real rate of this equipment via GPS (i.e., number of trips per hour), the system would then be able to perform adjustments, such as relocating another piece of equipment, in order to keep the original work flow. Depending on the availability of GPS on site, this function is ideally susceptible to be extended to all the working equipment in the fleet.

Finally, the Optimization Module (Parente *et al.*, 2015a; Parente *et al.*, 2015b) works by means of an optimization algorithm (i.e., a GA), which attempts to find a near optimal solution for the problem of determining the best possible equipment fleet and its optimal distribution throughout the work area. The optimization is carried out bearing in mind both construction time and costs, which are often conflicting interests in earthwork tasks, defining the problem as multi-objective optimization with conflicting objectives. Additionally, considering that the optimum equipment locations are not static over time, since as the tasks in one work front are completed the equipment should be optimally reassigned to other work fronts, one could further define the problem as a dynamic multi-objective optimization with conflicting objectives. As such, both the Equipment Module and the Spatial Module feed the Optimization Module with the necessary data to carry out the search for the near optimal solutions for the problem. The latter is able to evaluate the performance of each solution by means of a fitness function regarding both costs and time. The simulation method is based on the simulation of the whole construction process for each potential solution, allowing for the determination of both costs and construction time in each equipment fleet configuration. After the best solutions have been considered and evaluated, the Optimization Module returns the best-found solutions to the user as output.

It is important to refer that, in what concerns the optimization and performance evaluation processes, the earthwork process can be regarded as a production line in which its global work rate corresponds to the productivity achieved in the last

process (in this case, compaction). In turn, considering that the latter depends on the rates of all precedent processes, then maximizing production in an earthwork production line means maximizing the productivity of compactors throughout the whole construction. In this context, the optimization of the earthwork process must take into account not only the optimal allocation of compaction equipment, but also the determination of a compatible production line preceding the compaction task. As such, the work rates of spreading, transportation and excavation equipment, as well as any intermediate tasks (i.e., soil treatment), must take into account the compactor rate in each work front so as to allow for the constant work flow in those areas. In other words, each work front has to be "fed" just enough material for the rollers to constantly work at their maximum rate, minimizing idle time, which demands the synchronization of all the equipment fleet, including transportation and excavation equipment.

4 Case study and results

In this application, a subset from a database devised from the earthworks of a Portuguese road construction site was used for that purpose. The original database includes the description of several years of earthworks construction, broke down into the daily activities of the available mechanical equipment. In this application, the data subset regards the activities of earthwork equipment throughout 6 months of construction phase, featuring around 1250 entries (after data preparation) with information on date, work hours, atmospheric conditions, number and distance of load trips and resource types, as depicted in Table 1.

Tab. 1: Values extracted from the available earthwork construction database

Date	Work Hrs.	Atm. Cond.	Nr. of Loads	Excav. #	Load Zone	Unload Zone	Resource Type	Transp. Volume
9/2/11	7	Rain			7+850	8+625	Excavator50T	
9/2/11	3	Rain			7+850	8+625	Roller15T	
9/5/11	9	Sun	37	20/871	13+750	12+250	Dumper40T	481
9/5/11	9	Sun	39	20/871	13+750	12+250	Dumper50T	634
9/5/11	9	Sun			13+750	12+250	Tractor40T	

The used database subset is related with 4 excavation fronts supplying two types of soil (a soil and a soil-rockfill mixture) to 5 embankment fronts. The total volume of transported material is approximately 89,356 m3. The distances from excavation to embankment fronts vary between 100 m to nearly 4,000 m, stressing the need for proper resource management. The available equipment of the construction company for these operations included 12 excavators (with sizes ranging from 25 to 75 tons), 22 trucks (either 30 or 40 ton dumper trucks), 8 spreaders (between 20 and 50 ton) and 5 vibrating soil compactors. Both the materials and the compaction equipment were classified according to the aforementioned GTR guide. As such, the materials were classified as A1 and C2A1 for the soil and the soil-rockfill mixture, respectively. Accordingly, 4 out of 5 of the vibrating soil compactors

were classified as V3, while the remaining one as a V4. The originally designed resource distribution, considering the construction deadlines and budget of the project, resulted in approximately 127 hours of work, spread through 21 days of work (about 1 month). All the available equipment was put to use, with an average value of daily work hours per day approximately equals to 9.9h. Taking this setup into account, the final cost obtained in the process was around 135,200 €.

The proposed system results were compared against the original manual allocation obtained by conventional design, as shown in Figure 1. In the figure, the left graph shows the average (over all 30 runs) optimized Pareto front, while the right graph compares these results (black line) with the original solution obtained by manual allocation (white point). When analysing Figure 1, it is clear that the algorithm (NSGA-II) performs a substantial improvement (both in terms of cost and duration) when compared with the manual equipment allocation. The system output indicated several potential setups ranging from approximately 38 to 73 hours of construction duration, associated with approximate costs of 40,000 € to 43,000 €, respectively. This corresponds to a reduction of around 55% in duration and 70% in cost, when compared to the original duration and cost that was obtained in the original allocation. The original conventional manual allocation solution is far from optimal, which can be explained by the lack of an efficient optimization, and also by unforeseen delays that are not taken into consideration by the system.

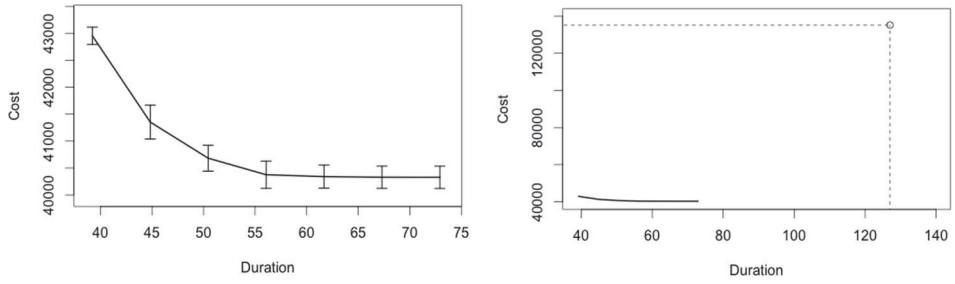

Fig. 1: Optimization results: left - vertically averaged Pareto front; and right - comparison between Pareto front (black curve) and original allocation (circle point) (x-axis is in hours and y-axis in €) (Parente et al., 2015a)

Regarding the lack of efficient allocation, a closer analysis of individual cases reveals that the original setup displays bottlenecks in several of the production lines in one of the tasks preceding compaction, resulting in several occurrences of idle equipment. To illustrate this, two distinct production lines are further analysed in Table 2. It is easy to infer that, for both production lines the work rates in each task of the original distribution setup are not homogeneous, as opposed to the work rates of the optimized solution. In these cases, the whole production line is limited by the work rate of excavators in the original setup, which means that the other tasks have to wait for material to be excavated in order to allow for its transport, spreading and finally compaction. This incurs in equipment idle time while waiting for material to be ready for handling, which represents wastes in terms of resources

(since these do not work at full efficiency) and fuel (contributing to unnecessary costs), as well as an increase on unnecessary carbon emissions. Consequently, the total work rate of these production lines cannot be considered superior to that of the minimum work rate obtained in the production line tasks, in this case excavation (394 m3/h in production line 1 and 540 m3/h in production line 2). In contrast, the work rates obtained in the proposed optimized solutions for each task that comprises the production line are as homogeneous as possible, given the available equipment. As such, a constant flow of material throughout tasks can be achieved, using the allocated resources to their full potential. It is noteworthy to emphasize that, besides optimizing the whole allocation in terms of costs and durations, the developed system is expected to always keep the allocated equipment working at full efficiency. It achieves this by focusing on the minimization of equipment idle time, which will also indirectly result in minimization of unnecessary carbon emissions. This last aspect is very challenging to accomplish by conventional design methods.

Tab. 2: Comparison between original and optimized setups for both cases

Original setup 1		**Original setup 2**	
Average geomaterial transport distance:: 175 m		Average geomaterial transport distance: 500 m	
Hauled material volume: 29,753 m^3		Hauled material volume: 10,647 m^3	
Equipment distribution and work rate		*Equipment distribution and work rate*	
1 Excavator (50T):	394 m^3/h	1 Excavator (75T):	540 m^3/h
2 Dumper trucks (30T, 40T):	2,960 m^3/h	3 Dumper trucks (40T):	1,280 m^3/h
1 Spreader (20T):	413 m^3/h	1 Spreader (40T):	675 m^3/h
1 Vibratory roller (15T):	614 m^3/h	1 Vibratory roller (19T):	683 m^3/h
Minimal production line work rate: 394 m^3/h (excavation)		Minimal production line work rate: 540 m3/h (excavation)	
Duration: 75.5 h		Duration: 19.7 h	
Cost: 24,462 €		Cost: 7,996 €	
Optimized setup 1		**Optimized setup 2**	
Average geomaterial transport distance: 175 m		Average geomaterial transport distance: 500 m	
Hauled material volume: 29753 m^3		Hauled material volume: 10647 m^3	
Equipment distribution and work rate		*Equipment distribution and work rate*	
2 Excavator (75T):	1,080 m^3/h	2 Excavators (25T, 75T):	743 m^3/h
2 Tipper trucks:	1,600 m^3/h	2 Dumper trucks (30T):	880 m^3/h
2 Spreaders (20T, 50T):	1,239 m^3/h	1 Spreader (50T):	820 m^3/h
1 Vibratory roller (19T):	1,055 m^3/h	1 Vibratory roller (19T):	683 m^3/h
Minimal production line work rate: 1,080 m3/h (compaction)		Minimal production line work rate: 683 m3/h (compaction)	
Duration: 28.2 h		Duration: 15.6 h	
Cost: 12,718 €		Cost: 5,740 €	

5 Final remarks

The novel system proposed in this work was applied in a case study using real-world data from a Portuguese construction site, showing that it is quite competitive when compared with conventional design, and that it can be easily adapted to dynamic changes that are inherent to earthworks constructions. In fact, for this case study, a high impact on would be achieved by the implementation of this system, as results indicate a reduction of approximately 50% in construction cost and duration when compared with the originally adopted solution (achieved via conventional manual design). Naturally, these results do not take into account the possible delays and costs associated with unpredictable events and obstacles that occur during construction (e.g., equipment malfunction). However, the system features the flexibility to deal with these issues, since it allows for the user to easily rerun the optimization procedure with an updated set of conditions and constraints (e.g., less available equipment).

The computational experiments not only bring forth the potential of the system, but also identify some significant of the limitations of conventional manual earthworks design, in particular where the production line equipment is either significantly above the required work rate requirements (incurring in unnecessary costs) or below it (resulting in idle times and low efficiency ratios). Moreover, it was possible to verify the capability of the proposed system to distribute equipment in a relatively homogeneous way (when compared to conventional design), while minimizing costs and durations, which was one of the goals of this research. Ultimately, the obtained results highlight the potential of the application of this type of optimization technologies to earthwork design and construction.

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