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Earthwork optimization system for sustainable highway construction

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Abstract. In highway construction, earthworks refer to the tasks of excavation, transportation, spreading and compaction of geomaterial (e.g. soil, rockfill and soil-rockfill mixture). Whereas relying heavily on machinery and repetitive processes, these tasks are highly susceptible to optimization. In this context Artificial Intelligent techniques, such as Data Mining and modern optimization can be applied for earthworks. A survey of these applications shows that they focus on the optimization of specific objectives and/or construction phases being possible to identify the capabilities and limitations of the analyzed techniques. Thus, according to the pinpointed drawbacks of these techniques, this paper describes a novel intelligent earthwork optimization system, capable of integrating DM, modern optimization and GIS technologies in order to optimize the earthwork processes throughout all phases of design and construction work. This integration system allows significant savings in time, cost and gas emissions contributing for a more sustainable construction.

Keywords. Earthworks, optimization, data mining, metaheuristics, sustainable

1. Introduction

Earthworks involve sequential tasks such as excavation, transportation, spreading, treatment, moisture conditioning and compactions that are strongly based on heavy mechanical equipment and repetitive processes (Figure 1). These tasks become as economically (and energy) demanding as they are time-consuming [1]. Given the percentage balance of costs and duration of earthworks in transport infrastructure construction projects (30 to 50%), the optimal usage of every resource in these tasks is paramount [1], [2] mainly in the reutilization of geomaterials (soil, rockfill, soil-rockfill mixture). These aspects embrace the sustainability principles [1], [3]. Figure 2 illustrates the various factors contributing for a sustainability approach [3].

The characteristics of earthworks construction can be viewed as a production line process based on resources (mechanical equipment) and a series of sequential, but interdependent, tasks; the process thus has the potential to be optimized [1], [2], [4], [5].

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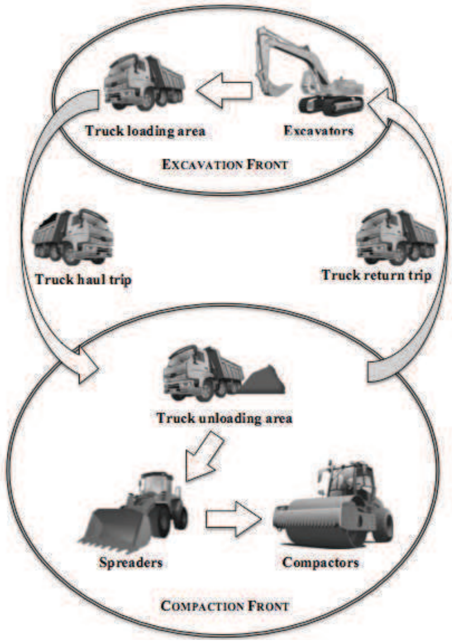

Figure 1. Earthwork resources and workflow [6]

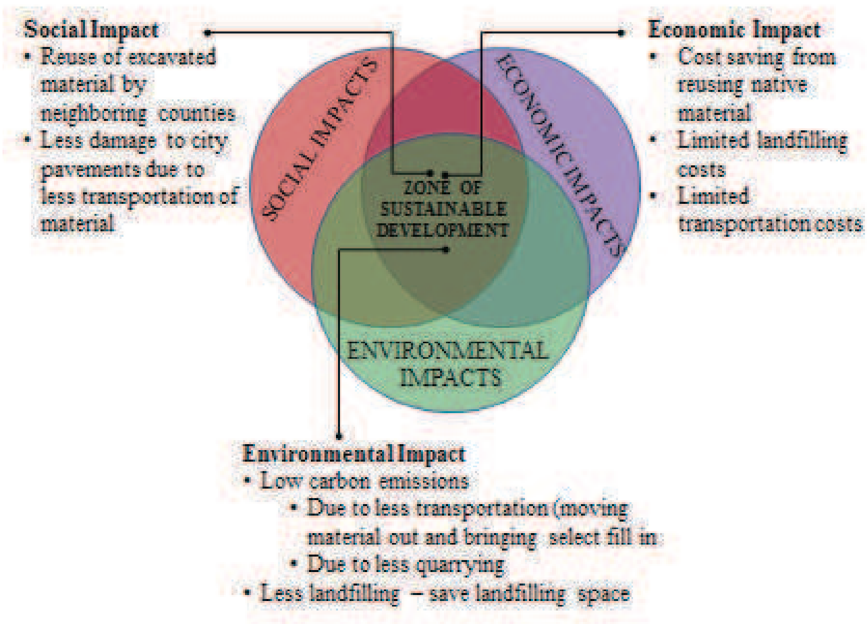

Figure 2. Soil reuse effects on various sustainability factors [3]

It should be mentioned that with the advances in automation and data collection technology in Civil Engineering construction, large databases of construction records gradually become available, including data related to project design and construction, such as the cost and/or duration of construction materials, processes and techniques. In highway construction context, this data is especially associated with the knowledge of the construction layout and the volumes of excavated and transported geomaterial (e.g. soil, rockfill and soil-rockfill mixture), as well as the volume of that material used in embankments.

Simultaneously, an increase in productivity, efficiency and safety has been largely demanded in the earthwork construction environment, resulting in the need to optimize every task related to this process. To achieve this, the optimization of available resources is essential, taking into account site conditions and equipment specifications, which leads to a maximization of productivity and minimize costs, while ensuring the completion of the work within time and cost estimates, following the sustainable principles. Thus, effective planning in these constructions is essential, including the optimization of available resources or selection of the best equipment fleet for the work at hand. So far, there has been reasonable developed regarding the optimization of earthwork constructions, mainly in the form of equipment and operation modeling systems in order to simulate site conditions and work sequence. Among these, most authors focus on planning and optimization during a project design phase [7]–[13], whereas few look to optimize the earthwork tasks themselves throughout construction phase [14], [15]. These types of systems are generally based on acquisition and data processing tools and/or some Artificial Intelligence (AI) modern optimization methods such as Genetic Algorithms (GA), thus being considered intelligent earthwork systems.

In spite of that, during design phase of earthwork construction, the information regarding key factors with a direct influence on cost and duration (e.g. equipment productivity) of the planned tasks is more often very scarce or even inexistent. Although a limited number of these systems have the ability to calculate the real equipment productivity during the construction work itself and update or re-optimize the system, the lack of accuracy of this information during design phase can seriously hinder its ability to carry out accurate time/cost predictions, which may lead to considerably losses. As such, bearing in mind the availability of construction data, it becomes possible to use AI tools, as those based on Machine Learning algorithms, to predict those factors during design phase. These algorithms can, for instance, be used to adjust models which “learn” from past data, becoming able to predict how a particular set of features will behave in similar or future situation. In this sense, some applications [16], [17] with relevance for earthwork optimization have come to light, although these do not have the capability of optimizing an earthwork system by themselves. Nonetheless, the possibility of integrating both technologies has obvious advantages, especially considering how Machine Learning algorithms can compensate for the design phase limitations of the existent optimization systems by enhancing the predictive potential of the system.

In this paper, a survey regarding integration of such AI techniques in earthwork design and construction phases is presented. The analysis of the existent systems features leads to the identification of their capabilities and limitations, which, in turn, are the basis for the proposal of a novel intelligent earthwork optimization system. This novel system is able to optimize all tasks throughout both design and construction phases, including real-time data acquisition and re-optimization capabilities for dynamic construction environments. The application to a case study shows significant savings in construction cost and duration, which represents a major step towards sustainable construction.

2. AI and optimization in earthwork construction

2.1. Data-driven systems

Data Mining (DM) is usually considered part of a larger process known as knowledge discovery in databases (KDD), which corresponds to the process of analyzing large databases for patterns and trends in data in order to infer rules for them (Figure 3). The development of new automatic processing and artificial intelligence technologies enhances this process with the ability to analyze and interpret large volumes of data in a short time, transforming them into knowledge [18]. Having been successfully applied to several different areas [19]–[21], it is also often framed in the context of a methodology, such as CRISP-DM (Cross Industry Standard Process for Data Mining) [22], becoming easier to implement and analyze.

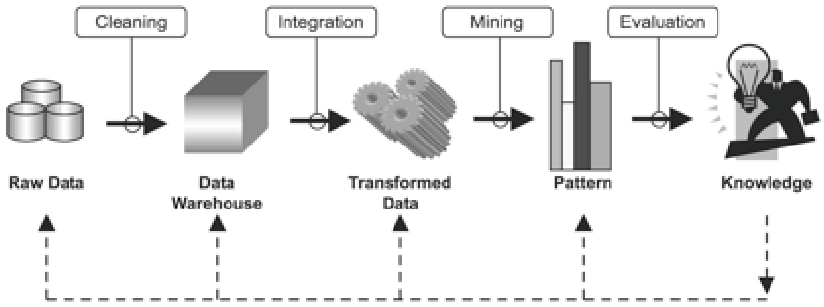

Figure 3. The KDD process [23].

In the context of earthwork construction, the most relevant goals consist of classification, which aim to distribute a given set of attributes into predefined classes, and regression, comprising the adjustment of a function to the current data with the capability of predicting one or more unknown values for variables. These goals may imply the application of Artificial Intelligence techniques by means of Machine Learning algorithms, such as Artificial Neural Networks (ANN) [24] or Support Vector Machines (SVM) [25].

Successful DM applications have targeted different areas of earthwork construction. Emphasis is given to some previously developed work [2], [26], [27], a support system for the compaction process in highway constructions involving earthwork tasks. In this system, the authors refer to the Road Earthworks Guide GTR [28] to determine the productivity of the equipment under evaluation. The GTR compaction tables were the support for the DM process in order to search for patterns and tendencies in the data. This allows the creation of a database for the determination of compaction parameters such as optimum number of passes and layer thicknesses for each class of geomaterial, type of compaction equipment and compaction energy. The most relevant components of the system can be divided into two parts.

The first part comprises a conventional expert system, which aims to classify compaction materials and equipment using logic rules. It follows the GTR classification extensively and as closely as possible, using the same procedure as a human expert. In the case of geomaterials, user inputs regarding the parameters obtained in the standard field and/or laboratory tests are required, as exemplified in Figure 4.

Considering that, especially in the case of geomaterial classification, a large number of laboratory tests are required; it is inferable that the system is demanding in terms of the number of user inputs. In fact, the user must provide information regarding the available geomaterials, which is different for soil, rocks and soil-rockfill mixtures, as well as concerning the available compaction equipment. These inputs are summarized in Table 1, conveying a global idea of the necessary information for achieving the GTR classification of compaction materials and equipment. In cases that include soil-rockfill mixtures, the characteristics combine both, depending mainly of the percentage of fines. In fact, whenever a significant percentage of fines is present in the rock-soil mixture, moisture control becomes essential for construction purposes.

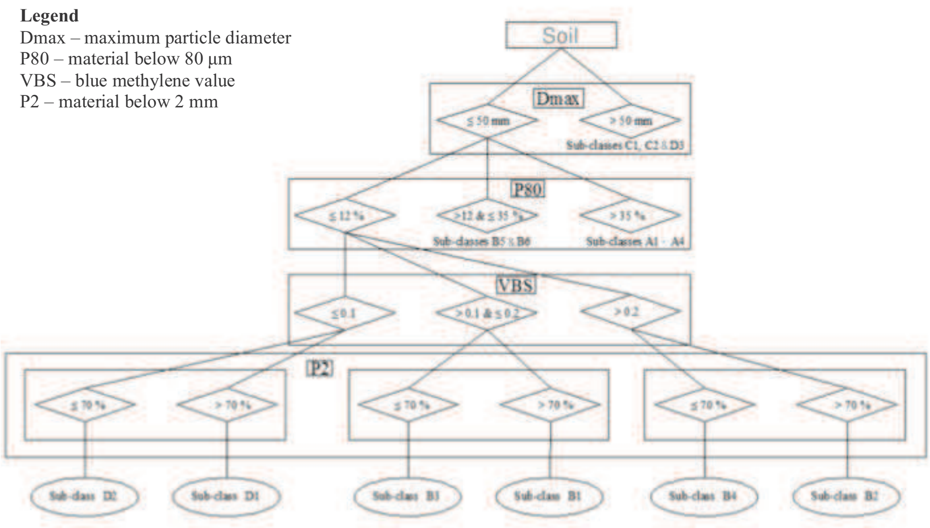

Figure 4. Material classification flowchart

Table 1. Required inputs for geomaterial (soil and rock) and compaction equipment classification

Soil	*Rock*	*Equipment*
- Maximum soil grain size (D_{max}, mm); - P80 and P2, referring to the % of material passing through the correspondent sieve; - Methylene blue absorption value measured on 0-50mm fraction (VBS, grams methyl blue per 100g soil); - Plasticity index (I_p, %); - Sand equivalent (ES, %); - Material texture; - Ratio of material fraction 0/50 mm (%); - Natural moisture content (W_n, %); - Standard Proctor optimum moisture content (W_{opn}, %); - Consistency index (I_c); Immediate bearing index (IPI, %); - Los Angeles coefficient measured on 10-14mm fraction or 6.3-10mm if unavailable (LA, %); - Micro-deval coefficient in water measured on 10-14mm fraction or 6.3-10mm if unavailable (MDE, %); - Sand friability coefficient (FS, %).	- Nature of rock; - Los Angeles coefficient measured on 10-14mm fraction or 6.3-10mm if unavailable (LA, %); - Fragmentation coefficient (FR, %); - Degradability coefficient (DG, %); - Immediate bearing index (IPI, %); - Micro-deval coefficient in water measured on 10-14mm fraction or 6.3-10mm if unavailable (MDE, %); - Bulk unit weight of dry rock sample (ρ_d); - Natural moisture content (W_n, %); - Soluble mineral content (%).	- Compactor family (Pneumatic tyred rollers, vibratory rollers, etc.); - Load per wheel (CR, kN); - Mass per unit length of the static or vibrating drum (M1/L; kg/cm); - Theoretical empty amplitude, A0 = 1000 me/M0, in which me is the eccentric moment in mkg and M0 is the mass in kg of the vibrating part excited by the eccentric (mm).

The second part of the system is responsible by its categorization as a data-driven system. Indeed, it is comprised of the application of ANN to the GTR data related to compaction productivity. In general terms, a series of neural networks are applied to data stemming from the GTR compaction tables, with the purpose of predicting several compaction parameters, as a function of the material to be compacted, the state conditions and energy of compaction. The information regarding material and equipment classification determined in the first part of the system is used as the reference for which the adjusted neural networks determine equipment productivity.

Figures 5 and 6 depicts the performance of the DM models regarding the prediction of two of these parameters (i.e. elementary thickness – a thickness of a given geomaterial that can be compacted in a roller application to obtain the desired density – Q/S, and an value of layer thickness times roller speed, e*V, respectively), showing an excellent level of adjustment and predictive capability [27]. Having gathered the knowledge of these parameters, it is easily to calculate the theoretical productivity (Q/L) value for each compactor-geomaterial pair.

$$Q/L = 1000 \times (Q/S) \times V \tag{1}$$

where: Q is the volume of compacted geomaterial during a given time (in m^3), S is the surface compacted under the same time (in m^2), L is the length of the roller (in m), and V is the velocity of the roller (in km/h).

This methodology is illustrated in the flowchart shown in Figure 7.

Using similar methodologies, other relevant applications were used to estimate equipment productivity using DM on earthwork construction databases, namely application of ANN for the estimation of excavation and transport equipment productivity rates [29] or execution time and cost in earthwork design [17].

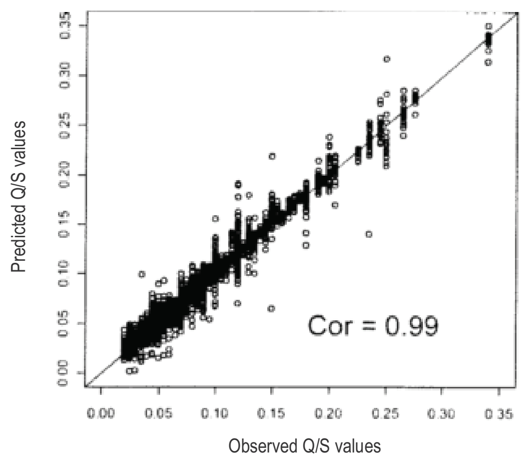

Figure 5. Predicted values vs. observed values for Q/S parameter [27].

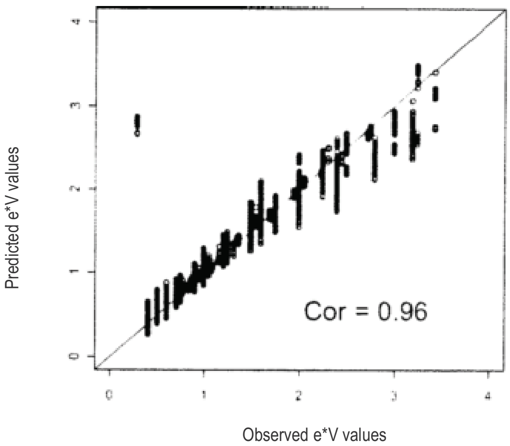

Figure 6. Predicted values vs. observed values for e*V value [27].

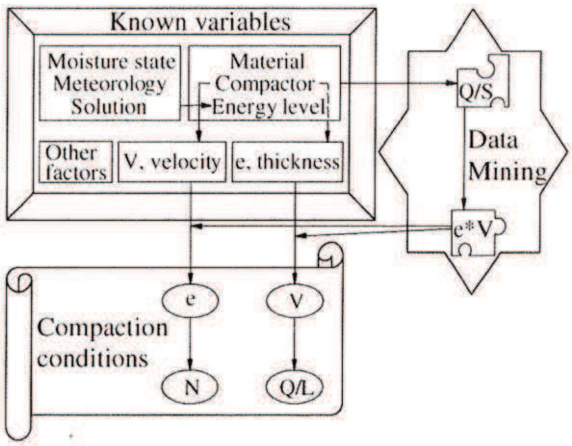

Figure 7. Flowchart for the determination of compaction conditions and productivity [21].

2.2. Simulation-optimization systems

The concept of Artificial Intelligence (AI) is far from limited to Machine Learning algorithms, since it includes several other applications, as is the case of modern optimization techniques. Modern optimization methods aim to deal with the large number of problems for which no algorithms are fast enough to achieve a solution in an acceptable time span. Even though in a relatively small solution space, the classical methods of exhaustive search for solutions may be enough, in many cases the solution space is considerably larger, demanding the need of different search methods [30].

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 [31]. Somewhat similar to GA, particle swarm optimization (PSO) [32] is inspired by social behaviour and movement dynamics of insects, bird flocks and fish schools. Finally, Petri nets [33] are mathematical models based on transitions (representing events), places (corresponding to conditions) and directed arcs (which signify the dependencies and relationships between places and transitions), being especially well suited for modelling the concurrent behaviour of systems.

Generally, simulation-optimization systems rely on an optimizer, which searches for potential solutions for a problem while overseeing a specific type of evaluation function, namely simulation, which, in turn, attempts to punctuate or otherwise differentiate between the found solutions (as exemplified in Figure 8). For each system, the optimization and evaluation methods can vary. In some cases, the optimizer can be a GA [8], [9] or a PSO algorithm [12] associated with object-oriented simulation. Other authors suggest hybrid GA optimization approaches connected to a well known commercial simulations engines such as CYCLONE [10]. Moselhi and Alshibani [14], [15] also proposed a GA associated with object-oriented simulation an GPS technology, which, unlike the previous similar architectures, focuses on optimizing resources during construction phase itself. Lastly, the framework suggested by F. Cheng et al. [34] illustrates the used of Petri nets to represent the dynamic constraint relationships among the various types of equipment and their functions, so as to describe the process and equipment workflow throughout excavating and hauling tasks.

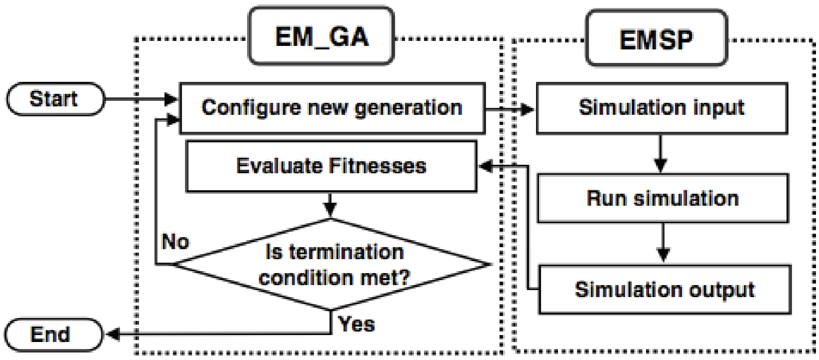

Figure 8. Typical architecture for a simulation-optimization system [9].

3. System architectures and applications

Early attempts of integrating both AI and optimization technologies were based on expert knowledge acquired from planning engineers and construction equipment specialists. However, as expert systems, they are limited to the structured rules with which they are developed. In this point of view, they do not take advantage of the full capabilities of the most recent AI techniques, such as DM.

Generally, DM applications in earthwork constructions are based on the learning capabilities of AI algorithms. In fact, the feature of learning from past data and predicting the behaviour of the same data in different or future situations has great potential for engineering applications, especially considering that it essentially simulates the process of gaining experience by an engineer, which is then used as a basis in new construction projects. Thus, DM earthwork systems rely on the existence of databases to which the learning algorithms are applied, while their outcome is limited to the type of present data and the experience gained. However, they are susceptible of being integrated into more complex systems. This idea has already been explored, even if only theoretically, in the form of a framework for a DM system in which a “prediction module” combined with an optimization method is capable of performing data extraction and analysis in order to determine and select the best solutions for a certain problem [16]. The proposed architecture integrates the ability to be fed new data and immediately adapt and “learn” from it in real time. This fact inherently grants the system with the aptitude for working in dynamic, every-changing environments. Even though no direct applications have been developed in the context of Civil Engineering, the idea of coupling DM with optimization is discussed further on.

Simulation-optimization systems are different from DM systems taking into account that the use of artificial intelligence is not in the form of machine learning algorithms, but rather modern optimization algorithms. In the earthwork construction context, simulation is the most common evaluation method for its capabilities and ease of interpretation on expressing real construction processes in dynamic environments. Earthwork simulation-optimization applications can be divided into global resource allocation systems and task-specific optimization systems, depending on their optimization objectives. On the one hand, resource allocation systems [8]–[10], [12] mostly focus on the optimization of all available earthwork equipment and machinery during design phase by using an optimization method to search for possible distributions of equipment throughout the construction site at each construction phase. The optimizer is linked to a simulation module, which evaluates each solution in function of predefined optimization objectives (e.g. time/cost minimization). A noteworthy exception for these possibilities is the system proposed by Moselhi and Alshibani [14], [15] which focuses on the optimization of available resources mostly during construction phase, incorporating the use of GPS to help estimate the real productivity of each available equipment and automatically re-allocating resources if these productivity rates suffer any alteration. On the other hand, task-specific optimization systems [13] generally focus on improving the processes that form specific earthwork tasks themselves, overlooking the advantages of global optimization. These systems also fall under the same architecture of associating optimizers with simulation as an evaluation function. However, the fundamental difference between these and the previous systems lies not only on the objective of the optimization, but also on the type of simulation used for evaluating solutions. In fact, since these systems usually require a much more detailed simulation of internal processes and constraints within a specific earthwork task, the most used simulation methods are based on queuing theory and dependency relations between processes.

In order to structure the information regarding the discussed types of earthwork optimization systems, Figure 9 depicts a concept map, in which the most relevant system architectures are classified into groups (examples) and related to both the technologies that support them and their intended application areas.

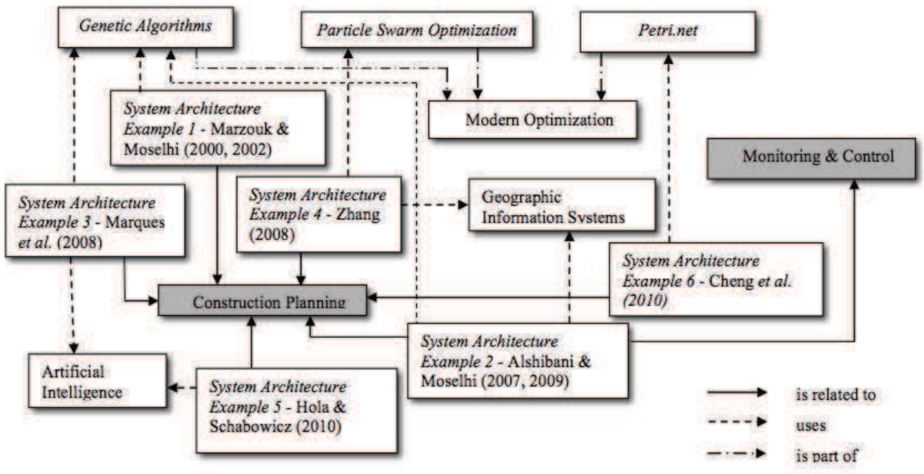

Figure 9. Concept map.

Considering the different capabilities of each technology, an ideal system for earthwork control and optimization should be able to integrate all modules in order to work throughout the whole design and construction process. Nevertheless, the systems developed so far for earthwork construction applications are predominantly kept within to only one of these areas. As described in Table 2, most simulation-optimization systems focus on optimization during design phase, with the exception of the one developed by Moselhi and Alshibani [14], [15], which centres its capabilities on construction phase. In fact, the inability of these systems to adapt to the frequent unforeseen events associated with in-situ construction can be seen as a significant limitation, since most of these events are impossible to predict during early planning. Concurrently, AI based systems based focus on data acquisition and analysis methodologies, which are mostly applied to design phase as a resort for estimating unknown material and equipment characteristics or parameters.

Accordingly, the next logical step should be related to the integration of all these technologies into a single intelligent earthwork optimization system, in order to develop a reliable system capable of optimization and automatic re-optimization throughout all phases of a construction work, including earthwork construction phase. In Section 4, the framework for an intelligent earthwork optimization system is presented, based on presently available technology and with the potential to integrate all the mentioned areas. It include knowledge extraction from databases as a means to support a simulation-optimization system capable of not only planning and optimizing earthwork construction tasks, but also monitor in real-time the actual productivity of construction equipment during construction phase, re-optimizing the system should efficiency fall short of what was estimated during design.

Table 2. Application areas of existent earthwork optimization systems

System Type	Data acquisition & application	Planning & Design phase	Monitoring & Control phase
AI based systems	Marques et al. (2008)		
		Hola and Schabowicz (2008, 2010)	
Simulation optimization systems		Marzouk and Moselhi (2002)	
		T. Cheng et al. (2005)	
			Moselhi and Alshibani (2007, 2009)
		Zhang (2008)	
		F. Cheng et al. (2010)	

4. Proposal and application of a novel intelligent earthwork optimization system

4.1. Novel system architecture

The implemented system architecture is inspired in the work of [2] and assumes the integration of 3 main modules (Equipment module, Spatial module and Optimization module) with capabilities to acquire and manipulate data from each phase of an earthwork project.

In general terms, the Equipment Module is responsible for receiving the user input for available equipment/plants, while calculating or retrieving equipment costs. Simultaneously, this module should include Data Mining models, used for the determination of the productivity rates for available equipment. These models are based on previously developed work [26], which is described in Section 2.2, requiring easily available information, 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 [4].

The Spatial Module allows for the creation of a functional model of the work area by user input using a GIS, namely including all the possible work fronts and potential equipment trajectories/paths. The GIS Path Finder algorithm determines the best routes or trajectories for transportation equipment regarding the location of work fronts and borrowing sites and potential equipment paths, with the purpose of optimizing the workflow inside the work site (Figure 10). 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 modeling 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 number of GPS equipment present on the site, this function is ideally susceptible to be extended to all the working equipment in the fleet.

Finally, the Optimization Module receives information from both previous modules and integrates an evolutionary optimization algorithm, more specifically a genetic algorithm, 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 objectives in earthworks construction, defining the problem as multi-objective optimization with conflicting objectives. Additionally, considering that the optimum equipment locations are not static over time, since equipment from one work front should be reassigned to others as their initial tasks are completed, the problem is defined as 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 (Table 3). 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 may be, for instance, based on object-oriented 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 presents the user with the best-found solutions through the User Interface as the output for the system. Figure 11 depicts the system, as well as the flow of information throughout its modules.

Figure 10. Optimization of truck routes

Table 3. Data from each model imported into the optimization module

Equipment module	Spatial module
- Material volumes required in embankment fronts and available in excavation fronts - Material type in each excavation front - Type and number of available equipment associated with each task (excavation, transportation, spreading and compaction) - Equipment direct and indirect costs and work rate (when not estimated by DM models)	- Optimal travel distance/time from each excavation front to each embankment front (OD cost matrix)

Although the optimization output regards cost and time as the main optimization objectives, its design was carried out also bearing in mind the sustainability concept, particularly integrating the environmental aspects of earthwork construction. Indeed, the minimization of carbon emissions is achieved by both the increase in efficiency associated with the optimization module (i.e., optimizing resource usage to its maximum potential), and the minimization of transportation distances and time, ultimately contribution towards a more sustainable construction. Furthermore, these aspects can easily be used directly as minimization objectives.

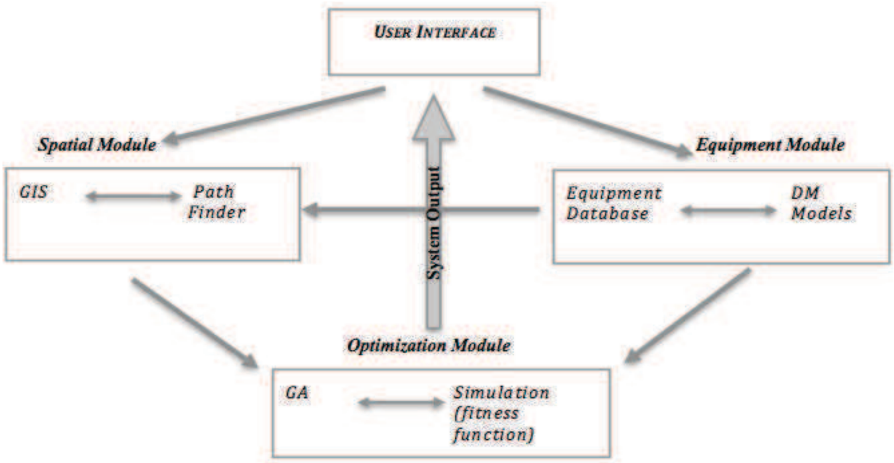

Figure 11. Proposed system architecture (adapted from [2])

4.2. Application in a case-study

This novel system was applied to a database created from the earthworks of a Portuguese highway construction site. 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 for each piece of mechanical equipment used in the construction process.

As previously referred, the purpose of the optimization system is to determine the solution that minimizes both cost and time for the whole earthwork construction process. However, in practical terms, an ideal distribution solution must take into account the interaction between the different types of equipment that encompass the earthwork process. In other words, the productivity of the equipment allocated to a task is always conditioned by the productivity of the equipment allocated to the previous tasks. Indeed, while adding more equipment to a specific task may increase its productivity, its maximum work rate cannot exceed that of the task that precedes it. This means that it is essential to synchronize the productivity of the equipment teams that are allocated to each task, so as to allow for a constant flow of material from excavation to embankment fronts, thus using the allocated equipment to its full efficiency, and reducing equipment idle time. Such details are very challenging to take into account in conventional design.

This is clearly depicted in Figure 12, where it is easy to infer that the work rates in each task of the original distribution setup are not homogeneous, as opposed to the work rates of the optimized solution. As such, in this case, the productivity of the excavator team represents a bottleneck in the original solution. In fact, the whole production line is limited by the work rate of excavators, 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. In contrast, the work rates obtained in the proposed optimized solutions for each task that comprises the earthwork process are as homogeneous as possible, given the available equipment. For instance, the conventional manual allocation solution features a clear excess of work capacity regarding transportation equipment that is not contributing for its progress, as it is limited by the work rate of the excavation plant. In order to counter this, the optimization system allocated smaller trucks (lower capacity, lower fuel consumption and, thus, lower operation costs) to fulfill this role instead, while investing its resources on the excavation, spreading and compaction equipment allocation. As such, a constant flow of material throughout tasks can be achieved, using the allocated resources to their full potential. As a result, it is easy to infer that, besides influencing construction cost and duration, this also represents a significant step towards sustainable construction.

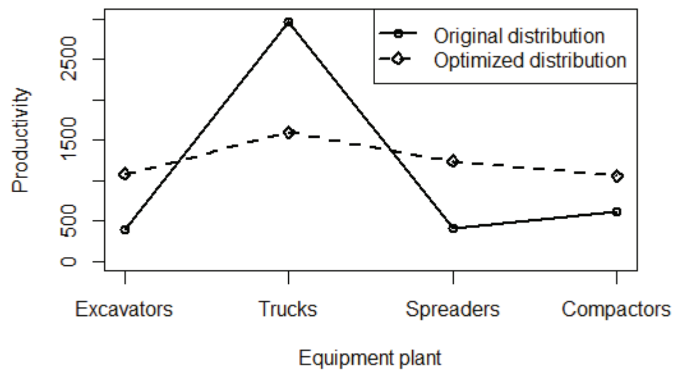

Figure 12. Comparison between equipment productivity (in m^3/h) in each task for the original equipment distribution determined manually by conventional design and the optimized equipment distribution solution

By using this methodology, the system was able to achieve a high impact in both construction cost and duration for this case-study. Figure 13 illustrates the output of the system in the form of a Pareto front. In this figure, each point represents a feasible and optimal equipment distribution solution for the earthworks project, evaluated in terms of its associated duration (in hours) and cost (in euro). The system output presents several solutions ranging from approximately 32 to 42 hours of construction duration, associated with approximate costs of 40,000 € to 47,000 €, respectively. This corresponds to a reduction of around 50% to 70% in cost and duration, when compared to the duration of 127 h and cost of 135,200 € that was obtained in the original allocation. Additionally, this type of output is flexible enough to allow the designer to select the solution that best fits the current project restrictions (i.e., budget and deadlines), which represents another advantage when compared with conventional design.

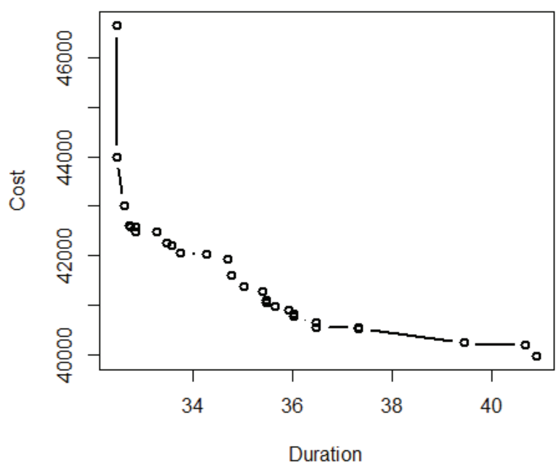

Figure 13. Output associated with one run of the optimization system for the case-study (*x*-axis is in hours, and *y*-axis in €)

5. Conclusions

The development of an earthwork construction project includes different tasks, ranging from excavation to embankment construction, comprised in design and construction phases. Even though integrating all tasks throughout all phases should be essential in optimizing processes strongly based in dependency relations, such as those in earthwork construction, existing optimization systems generally focus on the application of specific technologies in order to improve certain tasks or aspects in one of those phases.

As such, the framework for a novel integrated intelligent earthwork optimization system was implemented which, by coupling AI techniques such as DM and modern optimization with GIS technology, is able to optimize all tasks throughout both design and construction phases, including real-time data acquisition and re-optimization capabilities for dynamic construction environments.

The results of an application of the proposed system in a case study using real-world data from a Portuguese construction site were also analyzed, showing that the system is quite competitive when compared with conventional design. In fact, for this case study, a high impact would be achieved by the implementation of this system, as results indicate a reduction of 50% to 70% 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), which outputs a new set of optimal allocation solutions. As such, these results bring forth the potential of the system, highlighting the importance of optimization in earthwork construction, not only in terms of cost and duration, but also as a tool that supports a more sustainable construction process.

References

[1] A. Gomes Correia, "Geotechnical engineering for sustainable transportation infrastructure," in *Keynote lecture in Geotechnical Engineering for Infrastructure and Development*, 2015, (accepted for publication).

[2] A. Gomes Correia and J.-P. Magnan, "Trends and challenges in earthworks for transportation infrastructures," in *Advances in Transportation Geotechnics 2*, Taylor & Francis Group, 2012, pp. 1–12.

[3] B. S. Chitoori, A. J. Puppala, R. K. Reddy, and D. Marshall, "Sustainable reutilization of excavated trench material," in *ASCE GeoCongress*, 2012, pp. 4280–4289.

[4] M. Parente, A. Gomes Correia, and P. Cortez, "Artificial Neural Networks Applied to an Earthwork Construction Database," in *Second International Conference on Information Technology in Geo-Engineering*, 2014, pp. 200–205.

[5] M. Parente, A. Gomes Correia, and P. Cortez, "Modern optimization in earthwork construction," in *Geotechnical Engineering for Infrastructure and Development: Volume 2: Infra-structure*, 2015, (accepted for publication).

[6] M. Parente, P. Cortez, and A. Gomes Correia, "An evolutionary multi-objective optimization system for earthworks," *Expert Syst. Appl.*, vol. 42, no. 11, pp. 6674–6685, 2015.

[7] S. M. AbouRizk and D. Hajjar, "A framework for applying simulation in construction," *Can. J. Civ. Eng.*, vol. 25, no. 3, pp. 604–617, 1998.

[8] M. Marzouk and O. Moselhi, "Optimizing earthmoving operations using computer simulation," in *Proceedings of the 2000 Winter Simulation Conference*, 2000, pp. 1932–1936.
[9] M. Marzouk and O. Moselhi, "Selecting Earthmoving Equipment Fleets Using Genetic Algorithms," in *Proceedings of the 2002 Winter Simulation Conference*, 2002, pp. 1789–1796.
[10] T. Cheng, C. Feng, and Y. Chen, "A hybrid mechanism for optimizing construction simulation models," *Autom. Constr.*, vol. 14, no. 1, pp. 85–98, 2005.
[11] H. Zhang and H. Li, "Simulation-based optimization for dynamic resource allocation," *Autom. Constr.*, vol. 13, no. 3, pp. 409–420, May 2004.
[12] H. Zhang, "Multi-objective simulation-optimization for earthmoving operations," *Autom. Constr.*, vol. 18, no. 1, pp. 79–86, 2008.
[13] F. Cheng, Y. Wang, and X. Ling, "Multi-Objective Dynamic Simulation-Optimization for Equipment Allocation of Earthmoving Operations," *Construction Research Congress*, Jan-2010.
[14] O. Moselhi and A. Alshibani, "Crew optimization in planning and control of earthmoving operations using spatial technologies," *J. Inf. Technol. Constr.*, vol. 12, pp. 1–17, Feb. 2007.
[15] O. Moselhi and A. Alshibani, "Optimization of earthmoving operations in heavy civil engineering projects," *J. Constr. Eng. Manag.*, vol. 135, no. 10, pp. 948–954, Jan. 2009.
[16] Z. Michalewicz, M. Schmidt, M. Michalewicz, and C. Chiriac, *Adaptive Business Intelligence*. Springer-Verlag, 2007.
[17] B. Hola and K. Schabowicz, "Estimation of earthworks execution time cost by means of artificial neural networks," *Autom. Constr.*, vol. 19, no. 5, pp. 570–579, Aug. 2010.
[18] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, "From Data Mining to Knowledge Discovery in Databases," *Am. Assoc. Artif. Intell.*, vol. 17, no. 3, pp. 1–18, Sep. 1996.
[19] D. G. Toll, "Artificial intelligence applications in geotechnical engineering," *Electron. J. Geotech. Eng.*, vol. 1, pp. 1–11, 1996.
[20] S. Liao, P.-H. Chu, and P.-Y. Hsiao, "Data mining techniques and applications – A decade review from 2000 to 2011," *Expert Syst. Appl.*, vol. 39, no. 12, pp. 11303–11311, 2012.
[21] A. Gomes Correia, P. Cortez, J. Tinoco, and R. Marques, "Artificial Intelligence Applications in Transportation Geotechnics," *Geotech. Geol. Eng.*, vol. 31, no. 3, pp. 861–879, 2013.
[22] P. Chapman, J. Clinton, R. Kerber, T. Khabaza, T. Reinartz, C. Shearer, and R. Wirth, "CRISP-DM 1.0 Step-by-step data mining guide," 2000.
[23] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, "The KDD process for extracting useful knowledge from volumes of data," *Commun. ACM*, vol. 39, no. 11, pp. 27–34, Nov. 1996.
[24] S. Haykin, *Neural Networks – A Compreensive Foundation*, 2nd Editio. Prentice Hall, 1999.
[25] M. A. Hearst, "Support vector machines," *IEEE Intell. Syst.*, vol. 13, no. 4, pp. 18–28, 1998.
[26] R. Marques, A. Gomes Correia, and P. Cortez, "Data Mining Applied to Compaction of Geomaterials," in *Eight International Conference on the Bearing Capacity of Roads, Railways and Airfields*, 2008.
[27] P. Cortez, R. Marques, and A. Gomes Correia, "Artificial intelligence applied to compaction rules and management," in *International Seminar on Interaction Soil-Rail Track for High Speed Railways*, 2008.
[28] SETRA and LCPC, "Guide des Terrassements Routiers – Réalisation des remblais e des couches de forme." Laboratoire Central des Ponts et Chaussees, Paris, France, 1992.
[29] K. Schabowicz and B. Hoła, "Application of artificial neural networks in predicting earthmoving machinery effectiveness ratios," *Arch. Civ. Mech. Eng.*, vol. 8, no. 4, pp. 73–84, Jan. 2008.
[30] Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs*, 3rd Editio. Springer, 1999.
[31] J. H. Holland, *Adaptation in Natural and Artificial Systems*. Ann Arbor, Michigan: University of Michigan Press, 1975.
[32] J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization," in *Proceedings of IEEE International Conference on Neural Networks*, 1995, pp. 1942–1948.
[33] C. A. Petri, "Fundamentals on the description of discrete processes," in *3rd Colloquium on Automata Theory*, 1966.
[34] F. Cheng, Y. Wang, and X. Ling, "Multi-Objective Dynamic Simulation-Optimization for Equipment Allocation of Earthmoving Operations," *Constr. Res. Congr.*, pp. 328–338, Jan. 2010.