Artificial intelligence applied to compaction rules and management

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Large abstract

1. Introduction

In the last decades, there has been a trend to foster interdisciplinary research, where often one field provides the tools (e.g. methods), while the other poses interesting problems and data (the raw material). Following this trend, we present the possibilities of cooperation between the areas of Artificial Intelligence (AI) and Geotechnique.

In the past, simple conventional tools (e.g. linear regression, blind search optimization) were used to address real-world problems. Yet, real-world problems are complex, often nonlinear. Under such domains, traditional techniques become obsolete, leading to poor results. An alternative, is to use modern AI tools, often inspired in natural processes (e.g. human nervous system – neural networks; natural selection – evolutionary algorithms). Data Mining (DM) is the overall process of extracting high-level knowledge from raw data. Neural networks and support vector machines are flexible DM models (i.e. no *apriori* restriction is required) that are capable of complex, nonlinear mappings between a given set of inputs (independent variables) and an output (the dependent variable). On the other hand, evolutionary algorithms (e.g. genetic algorithms) are innate candidates for numerical optimization, particularly for large search space domains, performing a global search that quickly locates areas of high quality.

Most of the problems associated with the Structural Engineering involve some complexity, and even more when the materials have heterogeneous and anisotropics properties, such as those used in geoworks. For this reason, and as alternative to traditional techniques of mechanical modeling, analysis and design, several AI methods can be used. However, the potential of these methods are not yet sufficiently divulged among the geotechnical community. Hence, this communication will try to change this situation, by presenting the advantage of popular AI methods (e.g. neural networks and genetic algorithms) and demonstrating the efficiency of these techniques through the presentation of a case study: the compaction of geomaterials.

2. Artificial Intelligence in Geothecnics

In the past, several researchers have applied AI to management of geoworks, from roads to site investigation. As an example, Figure 1 shows the number of studies per geotechnical field using two AI techniques: Knowledge Based Systems (KBS) and Neural Networks.

In particular, within the domain of the compaction, there have also been some AI applications. Essentially, these studies were used to determine prediction models for parameters considered by the traditional control of "finished product". However, the experience from other countries shows benefits using the control by procedure. The French guide for road earthworks (Guide Terrassements Routiers), GTR (SETRA & LCPC 1992) is an example of this control philosophy.

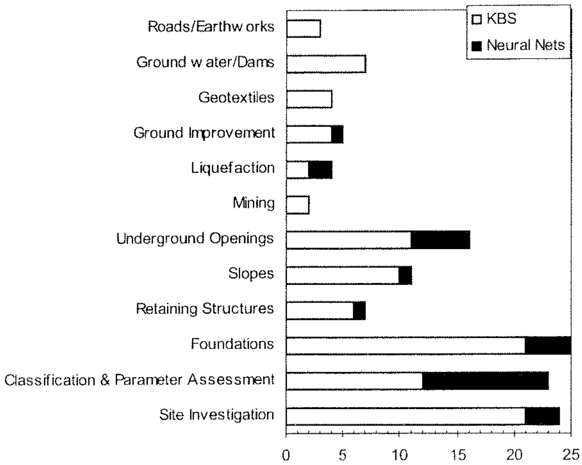


Figure 1. Artificial Intelligence (AI) studies on geoworks until 1996 (Tool 1996).

3. Knowledge Discovery on Compaction

The Knowledge Discovery from Databases (KDD) process can be viewed as a branch of the AI, where the goal is to extract high-level knowledge from raw data (fig. 2). In rigor, the Data Mining (DM) step is just a part of this process, aiming at pattern recognition from clean, preprocessed data. Often, the KDD and DM terms are used as synonyms and in this work we will adopt the latter one, since it is more widely adopted.

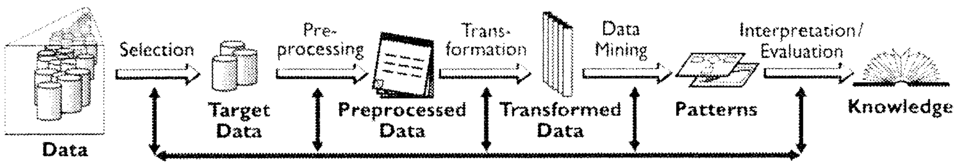


Figure 2. Overview of the steps constituting the KDD process (Fayyad et al. 1996).

Under this perspective, the collection of the "Compaction Tables" (see example in Table 1) on the GTR guide can be seen as a database, for which it is possible to apply a DM process. The data includes qualitative variables (material, compactor type and energy level) and quantitative variables (Q/S (compacted volume/surface covered by the compactor) parameter, layer thickness (e) and speed (V), number of load applications (N) and theoretical compaction capacity (Q/L) of the compactor).

Table 1. Compaction conditions to material A1 - C1A1 in embankments (SETRA & LCPC 1992).

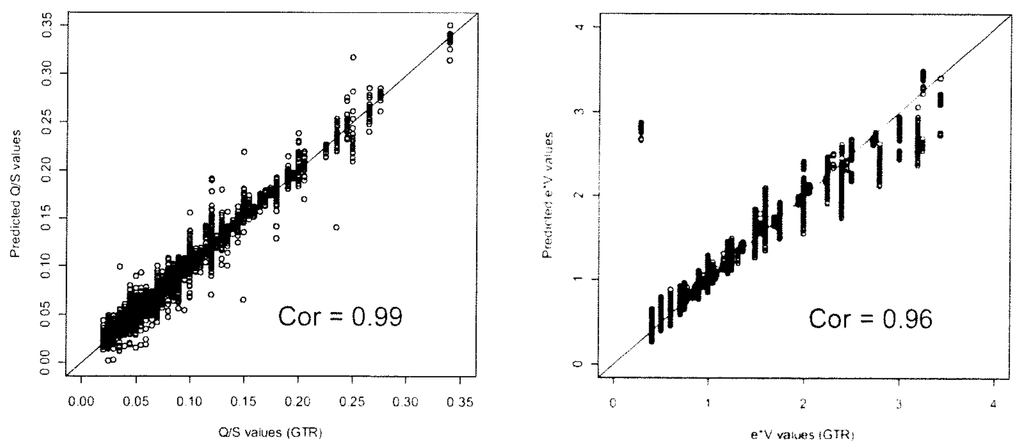
A1 C A1

Modalities \ Compactor		P1	P2	P3	V1	V2	V3		V4		V5		VP1	VP2	VP3	VP4	VP5	SP1	SP2	PQ3	PQ4
Low compaction energy	Q/S	0.08	0.12	0.18	0.055	0.085	0.125		0.165		0.205		0.055	0.085	0.165	0.205	0.265	0.07	0.1		0.065
	e	0.3	0.45	0.6	0.25	0.35	0.3	0.5	0.35	0.65	0.4	0.8	0.25	0.3	0.3	0.35	0.4	0.25	0.4		0.2
			(1)	(1)					(1)	(1)	(1)	(1)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	0	(1)
	V	5	5	5	2	2.5	4	2.5	5	2.5	5	2.5	2	3	4	5	5	8	8		1
Code 3	N	4	4	4	5	5	3	4	3	4	2	4	5	4	2	2	2	4	4		3
	Q/L	400	600	900	110	215	500	315	825	415	1025	515	110	255	660	1025	1325	560	800		65
Medium compaction energy	Q/S	0.045	0.065	0.095		0.04	0.065		0.085		0.1			0.04	0.085	0.1	0.13	0.04	0.07		
	e	0.25	0.35	0.45		0.25	0.3	0.4	0.3	0.5	0.3	0.6		0.25	0.3	0.3	0.3	0.2	0.3		
					0								0	(2)	(2)	(2)	(2)	(2)	(2)	0	0
	V	5	5	5		2	2.5	2	3.5	2	4	2		2	2.5	3.5	4	8	8		
Code 2	N	6	6	5		7	5	7	4	6	3	6		7	4	3	3	5	5		
	Q/L	225	325	475		80	165	130	300	170	400	200		80	215	350	520	320	560		
High compaction energy	Q/S		0.035	0.05		0.025	0.04		0.05		0.065			0.025	0.05	0.065	0.085		0.04		
	e		0.2	0.3		0.2		0.3	0.3	0.4	0.3	0.45		0.2	0.3	0.3	0.3		0.25		
		0			0								0					0		0	0
	V		5	5		2		2	2.5	2	3	2		2	2	2.5	3		8		
Code 1	N		6	6		8		8	6	8	5	7		8	6	5	4		8		
	Q/L		175	250		50		80	125	100	195	130		50	100	165	255		280		

Q/S	(m)
e	(m)
V	(km/h)
N	-
Q/L	(m^3/h.m)
0	compactor not adequate

In a previous study (Marques et al. 2008), we tested different DM techniques for model adjustment, including the traditional technique of multiple regression, non-parametric methods of decision trees and k-nearest neighbors, and nonlinear and more flexible techniques based on neural networks and support vector machines. In that work, the evaluation scheme was based on 20 executions (runs) of a 10-fold cross-validation.

The best models obtained in the DM process, which are valid for the case of embankment layers, were the *Q/S* prediction in function of the material, compactor type and energy level, and the $e*V$ prediction in function of the material, compactor type, energy level and *Q/S* parameter. The models show high correlation coefficients (Cor), particularly the neural network to predict *Q/S* (fig. 3a) and the support vector machine to predict $e*V$ (fig. 3b).



a) b)

Figure 3. Predicted values versus real values: a) *Q/S* and b) $e*V$.

Moreover, a sensitivity analysis procedure was applied to these models, which measured the impact of each independent (input) variable when predicting the output target (dependent variable). It was assumed in a first moment that the *Q/S* parameter would be dependent, in the case of embankment layers, mainly of three attributes: material, compactor type and energy level. For this scenario, the sensitivity analysis showed greater dependence of *Q/S* from the energy variable, revealing the other attributes smaller importance. On the other hand, the sensitivity analysis on the model obtained for the prediction of the $e*V$ product shows a strong relation of this variable with the *Q/S* parameter and a low importance of the material and energy level variables. The importance of the energy level is implicit in the *Q/S* value.

It should be also mentioned that the high performance achieved with the techniques based on neural networks and support vector machines demonstrates the non-linearity characteristics of this domain. In effect, the models obtained with these techniques show a high predictive potential, and in particular enable a faithful reproduction of the data contained in the GTR Tables of Compaction.

4. Management of compactors

The management of compactors can be seen as an optimization problem of the compaction cost that results from multiplying the compaction time by the cost of the compactors set per time. The selection of equipment for the compaction task can be a dilemma if the areas or volumes of the geomaterial to compact are large, and particularly if the embankment is composed by different materials. This problem can be viewed as a numerical optimization task. When the size of the compactors set is high, the huge of all combinations is computationally intensive and more sophisticated optimization techniques should be used.

In effect, the AI field has led to modern optimization methods that were inspired in the natural evolution of biological systems, such as genetic algorithms and evolutionary strategies. These methods are innate candidates for parameter estimation, since they implement a global multi-point search, quickly locating areas of high quality. In this work, we applied genetic algorithms to the optimization of compactor sets. The algorithm manages high quality solutions using few computational resources. Thus, it is possible to select a compactors set that allows compact with quality at the lowest cost.

The optimization is made assessing successive combinations of compactors with respect to a *fitness* function basically dependent of the compaction capacity of the compactors set extended to the different materials and of the cost of each combination (fig. 4). The fitness function also implies a restriction on the term of the compaction work. In the right of Figure 4 is shown the evolution of the fitness function (Time x cost/UT) allowed by the genetic algorithm along 100 generations.

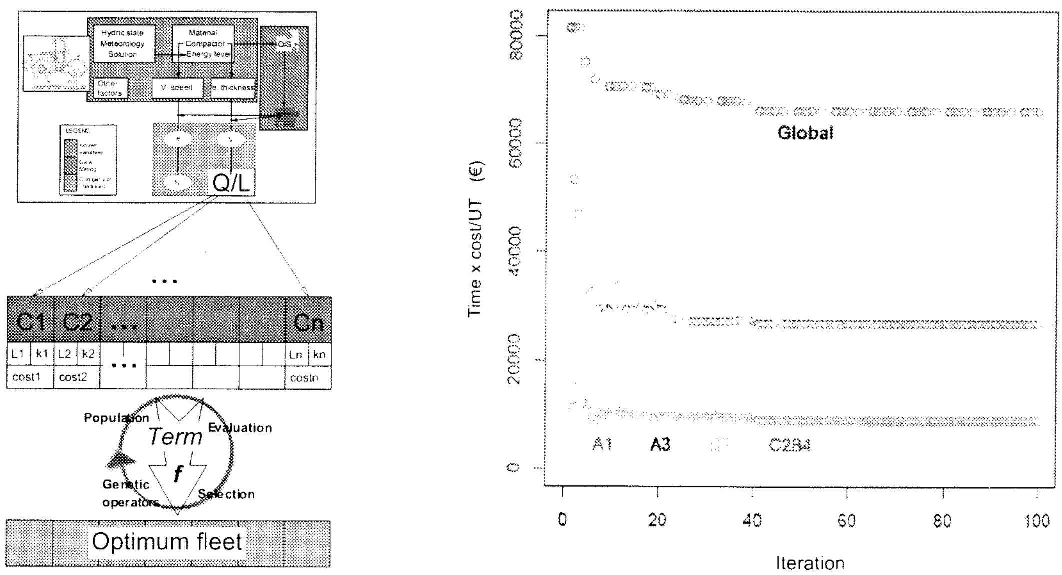


Figure 4. Optimization process of compactors by a genetic algorithm.

5. Conclusions

In this work we show the application of Artificial Intelligence (AI) tools to the compaction of geomaterials domain. In particular, the Data Mining (DM) process allows the extraction of knowledge from raw data, while Evolutionary Algorithms (EAs) are global optimization problems that can be applied to distinct domains, gaining good results with a low computational cost. Regarding the former, several DM methods were applied to model the GTR Tables of Compaction. The Q/S and e^*V dependent output variables were successfully modelled by neural networks and support vector machines, outperforming other techniques and demonstrating the nonlinear interrelationship.

The dilemma of selection of equipment for the compaction task can be solved using optimization processes based on biological processes, such as EAs, allowing a compaction combining quality and low cost. In the future, we hope such examples can increase the application of AI tools in the Geotechnique domains, in particular in the railway fields.

Acknowledgements

This study was supported by "Fundação para a Ciência e a Tecnologia" in Portugal, under the Project POCI/ECM/61114/2004 "Interaction soil-railway track for high speed trains".

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