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GENETIC PROGRAMMING FOR BRICK'S CHEMICAL ANALYSIS MODELLING

H. Marouf^{1*}, A. Semcha², N. Mahmoudi³, N. Bouhamou¹

¹Département de Génie Civil, Faculté des Sciences et de Technologie, Université de Mostaganem, Algérie

 ²Département de Génie Civil, Faculté des Sciences, Université de Adrar, Algerie
 ³Département de Génie Mécanique, Institue des Sciences et de Technologie, Centre Universitaire de Relizane, Algérie

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ABSTRACT

This study is part of the search for a sediment management methodology and the basic material that is designed for the manufacture of fired brick, in which we tackle the problem of choosing the mud samples from dredging the Algerian dams in particular (Bouhanifia dam western Algeria) and the choice of clay that comes from different deposits. We propose an approach for sampling using a computer optimization model that allows solving and optimizing a characterization to retain the best adapted sample (chemically) using the genetic algorithm.

Keywords: Sludge- Dredging- Sample- Chemical Characterization- Brick-Optimization Methods- Genetic Algorithm.

Author Correspondence, e-mail: hafidamaarouf@yahoo.fr

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1. CONTEXT AND PROBLEMATIC

The problem of siltation of dam reservoirs still has to be borne by the managers. At the same time, previous research conducted in the context of managing the fallout from dredging



operations has given promising prospects [1-14].

Procedures of study are summarized in characterization of the material, manufacture and at the end of the durability tests. Each researcher opted for a study that allowed him some satisfaction with the results obtained.

In this context, our study targets the Bou Hanifia dam, which is of great economic importance for the region of Mascara (Western Algeria), and which has a high rate of siltation. A reflection for a rational use of these sediments has been conducted in building materials and in particular in fired brick. During the chemical characterization of the sample taken, the sample must meet the recommended thresholds for the basic material used in the manufacture of the brick. While relying on an optimization method which is the genetic algorithm which consists in exploring domains with very many solutions. This model allows us to identify the best sample taken with percentages of oxides that meet the recommended thresholds and constraints.

1.1. The Principle of the Genetic Algorithm

Genetic algorithms have the distinction of being inspired by the evolution of species in their natural setting. Species adapt to their living environment that can evolve, individuals of each species reproduce, creating new individuals, some undergo modifications of their DNA, some disappear....

A genetic algorithm will reproduce this model of evolution in order to find solutions for a given problem [15]. The genetic algorithm of our example is as follows:

• A population will be a set of dredged silt samples

- An individual will be a solution to a given problem
- A gene will be part of a solution, so an individual
- A generation is an iteration of our algorithm

Figure 1 illustrates the operation of the genetic algorithm.

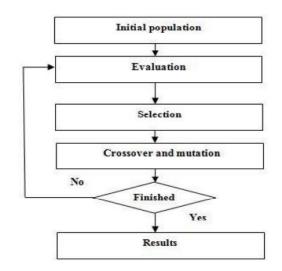


Fig.1. The Steps of the Genetic Algorithm [16-17]

2. PARAMETERS OF THE GENETIC ALGORITHM

2.1. Fitness

Fitness in genetic sense measures the quality of the individual expressed as a number or a vector. Plus a value i is close to the solution plus she is the best.

In our work we have to propose two methods to calculate fitness.

$$Fitness1 = \sum_{1}^{n} (Value \ oxides \ x \ weight) \ See \ table \ 1.$$

The different values of the oxides given in table 1 are extracted from the recommended thresholds of clay designed for the manufacture of a fired brick.

Oxides	Val Min (%)	Val Max(%)	Weight
SiO ₂	35	85	0.45
Al_2O_3	9	25	0.2
Fe_2O_3	3	9	0.1
CaO	0	25	0.11
MgO	0	5	0.01
SO_3	0	3	0.002
K ₂ O+Na ₂ O	1	5	0.03
TiO ₂	0.3	2	0.01
Fire loss	0	13	0.088

Table1.	The recommended thresholds of clay
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With respect to the weights given for each oxide, the latter reflects the importance of each oxide value in the chemical characterization of clay.

The weights are inspired by a synthesized reading of the various tested chemical analyzes. The sum of the different weights given equal to 1.

Fitness2 = SiO_2 /Al_2O_3 . (Silica and Alumina are the two main constructive components of clay).

2.2. Selection Rate

The selection rate indicates the rate of individuals selected from the initial population, if the selection rate is 100% then the entire population is selected, and if it is 0% the new generation is the exact copy of the individuals from the old population, in our example it is fixed at 0.8 because the optimal rate varies between 0.8 and 0.9 [17].

2.3. Crossing Rate

The crossing rate indicates the rate of participation in breeding, the proportion of the population that breeds by crossing. If the crossing rate is 100%, then the whole population participates in the crossing. On the other hand, if it is 0%, the new generation in full is the exact copy of the individuals of the old population, in our example it is fixed at 0.7 because the optimal rate varies between 0.25 and 0.7 [17].

For an efficient use of a material for the construction of vase-based brick, we use the model of genetic algorithm which is heuristic metas; which aims to solve an optimization problem as it can determine the different percentages of oxides during a chemical analysis). Our contribution is to propose a model for optimization.

2.4. Mutation Rate

The mutation rate indicates the rate that each gene of each individual a mutation during a reproductive phase. If the mutation rate is 0%, the individuals that are produced just after crossing do not change. On the other hand, if the probability of mutation is 100%, the whole chromosome of the individual is changed: In our example we set it to 0.1 because the rate varies between 0.01 and 0.1 to prevent the algorithm from converging to a local minimum.

2.5. Number of Iterations

It is a number that limits the number of evolutions of the population generated by the

algorithm. The search is thus stopped after a certain number of generations: In our example it is fixed at 100 iterations. Because the optimal number of iterations must be between 10 and 500 iterations.

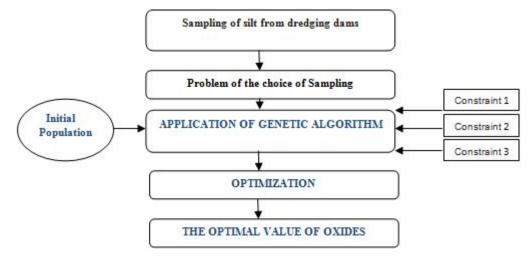


Fig.2. The Proposed Model

Following the steps of the genetic algorithm and optimizing the chemical analyzes of the samples, three constraints were posing:

- **First** is to give a minimum threshold for fitness 2 which is 2.7, (the classic value of bentonites [18-19] and a maximum value of 5 which is an approximate value.
- Second constraint is to minimize the Alumina content to 15%.
- Third constraint consists of applying the total sum of the oxides during the 100% chemical analysis with a tolerance interval of $\pm 2\%$.

The creation of the initial population see table 2.

Dam		Marine			nmended reshold)	Initial P	opulation	Fitness Evaluation		
N°	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	$K_{2O+}N_2O_3$	TiO ₂	LF	
4	45.92	16.271	6.88	17.128	2.983	1.229	2.668	0.4424	7.31	
7	47.774	15.127	7.713	9.784	2.874	0.336	2.281	1.255	12.12	
14	48.401	16.827	5.147	14.412	3.481	0.678	3.219	0.919	7.847	
17	55.895	16.409	8.327	2.411	3.801	1.064	1.665	1.136	10.226	
22	50.87	16.383	4.41	9.129	1.84	2.824	3.355	0.833	9.821	
26	57.616	15.656	3.018	9.799	0.892	1.273	3.374	1.786	6.858	
29	65.907	18.371	6.757	0.116	2.696	1.987	3.914	0.455	0.683	
31	52.544	15.62	6.417	14.174	3.862	2.471	1.425	1.661	2.683	
33	49.93	15.693	7.232	12.716	3.382	1.414	4.038	1.504	4.996	
34	59.518	15.057	6.647	1.399	1.112	2.508	3.051	1.531	10.176	
35	56.92	16.046	4.75	4.319	2.790	1.955	1.919	0.826	10.507	
40	47.044	16.413	3.292	14.803	4.96	1.263	3.029	1.766	6.655	

Table 2. The Generation of the Initial Population

In the table 3 we note the selection of initial population with the first fitness

Select	Selection		Crossing		Transfer		Best individual		Better Composition	
N°	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	$K_{2O+}N_2O_3$	TiO ₂	LF	Fitness
32	48.8378	15.889	7.451	16.524	4.547	1.238	1.071	1.467	2.261	0.0
27	55.895	16.409	8.327	2.411	3.801	1.064	1.665	1.136	10.226	0.0
80	49.93	16.3125	7.232	12.716	3.382	1.414	4.038	1.504	4.996	28.465
85	45.92	16.271	6.88	17.128	2.983	1.229	2.668	0.424	7.31	28.792
156	62.786	17.08	6.968	4.304	3.365	1.09	2.614	1.319	0.798	31.563
158	57.995	16.3176	4.61	6.738	3.862	1.586	2.852	1.751	3.621	31.697
22	52.544	15.62	6.417	14.147	3.862	2.471	1.425	1.661	2.683	0.0

2.6. Best Individual

The best people are a collection of the best people who have almost the same percentages of oxides (see table 4)

 Table 4. Best Individual

Select	Selection		Crossing		Transfer		Best individual		Better Composition		
N°	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	$K_{2O+}N_2O_3$	TiO ₂	LF	Fitness	
39	46.137	16.413	3.292	14.803	4.96	1.263	3.029	1.766	6.655	26.748	
57	46.101	16.848	3.292	14.803	4.96	1.263	3.029	1.766	6.655	26.819	
44	46.279	16.413	3.292	14.803	4.96	1.263	3.029	1.766	6.655	26.820	
34	44.979	16.271	6.88	17.128	2.983	1.229	2.668	0.424	7.31	26.827	
20	45.101	16.271	6.88	17.128	2.983	1.229	2.688	0.424	7.31	26.881	
94	45.142	16.271	6.88	17.128	2.983	1.229	2.688	0.424	7.31	26.900	

2.7. Better Composition

The better composition is the optimal solution. See table 5

Table 5. Better Composition

Crossing	ossing Transfer		Best ind	ividual	Better	Compositio	on		
SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	K ₂₀₊ N ₂ O	3 TiO ₂	LF	Fitness
46.137	16.413	3.292	14.803	4.96	1.263	3.029	1.766	6.655	26.748

The variation of the fitness in figure 3



Fig.3. variation of the first Fitness

Selection		Crossing		Transfer	Transfer		Best individual		Better Composition	
N°	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	$K_{2O+}N_2O_3$	TiO ₂	LF	Fitness
43	59.682	17.701	4.064	9.251	0.889	0.232	2.515	1.337	3.508	0.00
50	51.713	18.356	7.519	3.025	4.826	2.25	1.696	1.432	10.533	2.817
191	61.526	16.589	6.844	3.889	3.461	1.347	1.321	1.795	3.12	3.708
202	58.604	15.437	4.61	6.738	3.862	1.922	2.852	1.751	3.621	3.796
160	53.172	15.062	4.306	16.513	2.729	0.073	1.633	1.007	5.966	3.611
138	60.154	17.12	6.233	1.781	3.022	1.725	2.173	1.542	5.966	3.514
103	52.544	16.0328	6.417	14.174	3.862	2.471	1.425	0.427	2.597	3.158

Table7. Best Individual

Select	Selection		Crossing		Transfer		Best individual		Better Composition	
N°	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	$K_{2O+}N_2O_3$	TiO ₂	LF	Fitness
145	57.128	21.131	4.079	11.677	1.048	0.766	2.801	0.382	1.151	2.703
115	45.92	16.978	6.88	17.128	2.983	1.229	2.668	0.424	7.31	2.704
177	57.455	21.238	4.079	11.677	1.048	0.766	2.801	0.382	1.151	2.705
100	46.742	17.265	3.292	14.803	4.96	1.263	3.029	1.766	6.655	2.707
132	47.044	17.356	3.292	14.803	4.96	1.263	3.029	1.766	6.655	2.710
113	57.310	21.131	4.079	11.677	1.048	0.766	2.801	0.382	1.151	2.712

Table8. Better Composition

Crossing	;	Transfer	ransfer		Best individual			ompositic	n	
SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	K ₂	$_{O+}N_{2}O_{3}$	TiO ₂	LF	Fitness
57.128	21.131	4.079	11.677	1.048	0.766	2.8	801	0.382	1.151	2.703

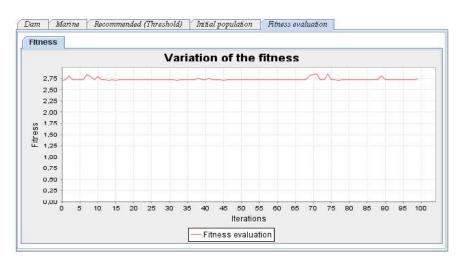


Fig.4. Variation of second Fitness

3. **DISCUSSION**

Along the iterations the first fitness varies timidly but unstable, against the second fitness appears with more sensitive wave variation and tends to stabilize.

The wave stability allows us to define an optimal approach, so the second function or the fitness 2 is more accurate than the fitness1

3.1. Comparison with Clays used in Neighborhood Brickworks

Table9.	The C	Generation	of the	Initial	Pop	ulation	Brickw	orks i	in the	West o	f Algeria

Selection		Crossing		Transfer		Best ind	ividual	Better Composition	
N°	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	$K_{2O+}N_2$ $O_3+P_2O_5$	TiO ₂	LF
1	54.09	12.24	4.94	9.93	2.56	0.11	2.62	0.66	12.86
2	48.12	15.5	5.49	9.97	3.01	0.52	3.23	0.75	13.41
3	47.86	12.67	5.34	12.26	3.15	0.37	2.73	0.68	14.96
4	48.17	14.46	5.78	10.49	3.01	0.03	3.21	0.71	14.31
5	47.83	16.83	6.1	9.04	2.68	0.07	3.38	0.79	13.19
6	47.71	15.81	5.91	9.94	2.88	0.46	3.09	0.78	13.41
7	47.91	14.4	5.94	10.4	2.73	0.4	3.00	0.78	14.44
8	62.33	11.04	5.58	7.32	1.51	0.01	1.70	0.58	9.93
9	53.88	10.75	5.39	11.94	1.79	0.02	1.92	0.57	13.74
10	52	9.99	4.96	13.49	2.02	0.06	1.97	0.53	14.97

Crossing		Transfer		Best individual			Better C	ompositic	n	
SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	K ₂	$_{0+}N_{2}O_{3}$	TiO ₂	LF	Fitness
47.71	15.81	5.91	9.94	2.88	0.46	3.0	9	0.78	13.41	26.501

Table10. Better Composition with the first Fitness

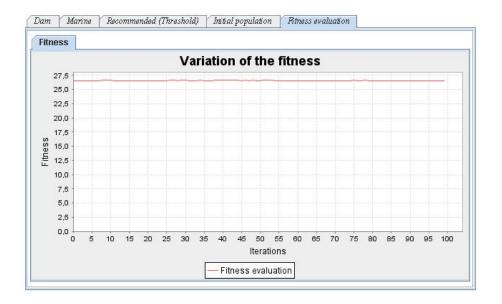


Fig.5. Variation of first Fitness of Brickworks

Table11. Better Composition with the second Fitness

Crossing		Transfer		Best indi	vidual	Better Composition			
SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	K _{2O+} N ₂ O ₃ +P ₂ O ₅	TiO ₂	LF	Fitness
47.83	16.83	6.1	9.04	2.68	0.07	3.38	0.79	13.19	2.841

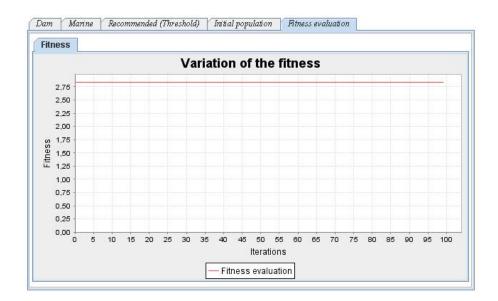


Fig.6. Variation of second Fitness of Brickworks

3.2. Comparison with the chemical composition of the Bouhanifia sludge In table 12

Crossing		Transfer		Best individual			Better Con	nposition			
SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	$K_{2O+}N_2O_3 + P_2O_5$		TiO ₂	LF	Fitness	
47.83	16.83	6.1	9.04	2.68	0.07	3.38		0.79	13.19	2.841	
Chemical Composition of Dam's Sludge											
49.36	12.26	5.13	10.03	2.34	1.77	3.3	33	0.63	15.15	4.02	

Table12. Comparison between Dam Sludge and Brickworks Clay

4. CONCLUSIONS AND PERSPECTIVES

In conclusion, this paper presented the steps of an optimization approach to a set of samples that meet the recommended thresholds for the chemical analysis of clay used for the manufacture of a fired brick. The model used is the genetic algorithm that gave us the optimal chemical analysis of a sample suitable for the design of a fired brick. The intended experimental goal through the choice of this model is the comparison between different samples analyzed and to correct the typical chemical composition. To answer the need of our research, we propose to continue the development of the algorithm used in complex function algorithm. We plan to include as functions the mechanical and physical parameters that characterize the baked brick.

REFERENCES

[1] Cappuyns et al, 2015 "Dredged sediments as a resource for brick production: Possibilities and barriers from a consumers' perspective" Waste Management 38 (2015) 372–380.

[2] Yang Xu et al , 2014 "The use of urban river sediments as a primary raw material in the production of highly insulating brick" Ceramics International40(2014)8833–8840.

[3] Lafhaj Z., Construction and Building Materials 22 (2008) 755–762.

[4] Andrea Mezencevova et al, 2012 « Utilization of Savannah Harbor river sediment as the primary raw material in production of fired brick" Journal of Environmental Management 113 (2012) 128-136

[5] Kung-Yuh Chiang et al, 2008 « Study on the characteristics of building bricks produced from reservoir sediment" Journal of Hazardous Materials 159 (2008) 499–504

[6] Mazen Samara et al, 2009 « Valorization of stabilized river sediments in fired clay bricks:Factory scale experiment" Journal of Hazardous Materials 163 (2009) 701–710

[7] Faycal El Fgaier et al,2013 « Use of clay bricks incorporating treated river sediments in a demonstrative building: Case study" Construction and Building Materials 48 (2013) 160–165

[8] Y.M. Zhang et al, 2016 « Fabrication, microstructure and properties of bricks fired from lake sediment, cinder and sewage sludge" Construction and Building Materials 121 (2016)
154–160

[9] F. Messina et al,2017 « Synergistic recycling of calcined clayey sediments and water potabilization sludge as geopolymer precursors: Upscaling from binders to precast paving cement-free bricks" Construction and Building Materials 133 (2017) 14–26

[10]Imen Said et al,2015 « Reuse of Tunisian marine sediments in paving blocks: factory scale experiment » Journal of Cleaner Production 102 (2015) 66e77

[11]Fayçal El Fgaier et al, 2016 « Effect of sorption capacity on thermomechanical properties of unfired claybricks" Journal of Building Engineering 6(2016) 86–92

[12] REMINI B. Larhyss Journal 05 (2006) 75-89.

[13] Labiod Z., Remini B., Belaredj M. (2004). *Traitement de la vase du barrage de Bouhanifia en vue de sa valorisation*. Larhyss Journal 03(2004) 7-12.

[14] Martinez G., J. Envir. Manag 95 (2012) S343-S348

[15] Schwartz, P. (2005) Les algorithmes génétiques. Developpez.com. Available from:

http://khayyam.developpez.com/articles/algo/genetic/

[16]Dipama, J. (2010) Optimisation multi objectif des systèmes énergétiques, Thèse de doctorat,

Université de Montréal, Canada.

[17] Khadidja Yachba, Shahin Gelareh, Karim Bouamrane, Transport and Telecommunication Vol. 17, no. 4, 2016

[18] A. Qlihaa, S. Dhimni, F. Melrhaka, N. Hajjaji, A. Srhiri J. Mater. Environ. Sci. 7 (5)

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[19] M. Gourouza, A. Zanguina, I. Natatou, A. Boos, Rev. CAMES – Sciences Struct. Mat. Vol. 1, Déc. 2013

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