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Algorithmic mix design for 3D printing materials

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Abstract: Additive manufacturing technology aims to revolutionize the construction sector. Researchers are looking for the optimum materials to use in mix design to control the fresh and final properties of the mix. Those properties are contradictory to each other and finding the optimal mix design has always been a challenge. Developing an optimization tool that considers trade-offs among a variety of competing objectives can improve the mix design process. In this study, the mortars contained combinations of multiple factors, including the cement type, sand type, water content, and admixtures. Three properties investigated are flowability, buildability, and compressive strength. The buildability was assessed by measuring the shear stress with the direct shear apparatus based on the ASTM D3080. The workability was acquired by measuring the flow spread of the mortar mixes following the ASTM C1437, and the compressive strength following the ASTM C109. A multiobjective Pareto-optimization method is used to improve the properties simultaneously. Feedforward neural networks were used to predict the properties of new mixes. The genetic algorithm was used to optimize the network parameters. This approach yields promising capability to improve the competing objectives of the mortar mixes by considerably reducing the time and the number of experiments.

Keywords: 3D printing, cement, admixtures, mix design, optimization algorithms.

1 INTRODUCTION

Developing cement-based materials for three-dimensional (3D) printing applications is a complicated process with many conflicting goals (Marchon, Kawashima, Bessaies-Bey, Mantellato, & Ng, 2018). The necessity of recycling and reusing building materials adds to the complexity (Zou, Xiao, Ding, Duan, & Zhang, 2021). A mix design can be made by following a variety of techniques, such as modifying one factor at a time, or following a full-factorial design (Bos, Wolfs, Ahmed, & Salet, 2016; Buswell, Leal de Silva, Jones, & Dirrenberger, 2018; Charrier & Ouellet-Plamondon, 2022; Ding, Xiao, Zou, & Wang, 2020; Malo Charrier, 2022). As the number of factors or their levels rise, the number of experiments can become an onerous task to fulfill (Cavazzuti, 2013; Lawson, 2015). This study helps advance the development of a high-performance cement-based material for 3D printing applications. The proposed methodology gathers information on numerous factors in the mix design while using optimization algorithms and artificial intelligence. Many studies in civil engineering have used artificial intelligence (Ateş, Şahin, Kuvvetli, Küren, & Uysal, 2021; Pan & Zhang, 2021; Paul, Panda, Zhu, & Garg, 2019). While the final properties are always vital (Ghafor, Mahmood, Qadir, & Mohammed, 2020), the early age structural build-up throughout the dormant period and the flowability are equally important for 3D concrete printing (Jayathilakage, Sanjayan,

& Rajeev, 2019; Rahul, Santhanam, Meena, & Ghani, 2019; Shakor, Renneberg, Nejadi, & Paul, 2017; Tay, Qian, & Tan, 2019; Wolfs, Bos, & Salet, 2018, 2019). The printed region and buildability of the mixtures are defined using slump and flow tests (Tay et al., 2019). A smooth surface and great buildability are achieved, with mixtures having a slump flow value of 50% to 90% (Tay et al., 2019).

2 MATERIALS, TESTING METHODS AND METHODOLOGY

2.1 Materials

Three types of cement, three types of sand, and five admixtures, including superplasticizers, were chosen in total (V. Sergis & C. M. Ouellet-Plamondon, 2022a, 2022c). The two admixtures were the biopolymer polysaccharide viscosity modifying agent (B) and the calcium silicate hydrate admixture (CSH-C). Two out of the three selected superplasticizers are based on synthetic organic polymers (PCE 1 & 2), whereas the third is sulfonated naphthalene polymer based (SNP). For cement, the three types are general use Portland cement, binary cement with silica fumes (GUbSF) and Portland cement with a high early strength (HE). All three sand types were fine aggregates with particle sizes below 2.5 mm including one being recycled sand. The three sands used in this study are shown in Fig. 1, and their particle distribution in table 1. The mix design presented in table 2 was based on a design of experiments approach and more details are available in (V. Sergis & C. M. Ouellet-Plamondon, 2022b).

Table 1: Particle size distribution of the three types of sands.

Sieve size	Passing through (%)		
	Fine sand	Coarse sand	Recycled sand
2.5 mm	100	100	100
1.25 mm	90	96	83
630 µm	78	67	66
315 µm	57	24	34
160 µm	20	4	12
80 µm	3	3	5

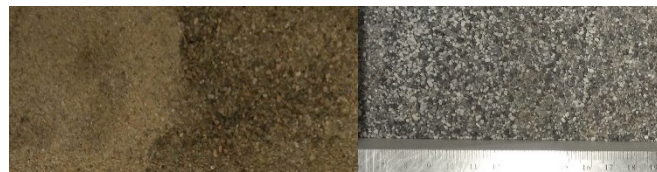


Fig. 1. Three sands used in the study; fine, coarse and recycled sand.

Table 2: Mix design based on design of experiments

Mixes	Cement	Sand	Water:binder	Sand:binder	Superplasticizer (Type A&F)	Type S admixtures
1	GU	Coarse	0.320	1.8	PCE-1	-
2	GU	Coarse	0.345	2.0	SNP	B
3	GU	Fine	0.320	2.3	SNP	CSH-C
4	HE	Fine	0.345	2.0	PCE-2	CSH-C
5	HE	Fine	0.370	2.3	PCE-1	-
6	HE	Recycled	0.345	1.8	PCE-1	B
7	GUbSF	Coarse	0.370	2.0	PCE-2	-
8	GUbSF	Recycled	0.320	1.8	PCE-2	CSH-C
9	GUbSF	Recycled	0.370	2.3	SNP	B
10	GU	Fine	0.370	1.8	PCE-2	B
11	GU	Recycled	0.345	2.3	PCE-2	-
12	GU	Recycled	0.370	2.0	PCE-1	CSH-C
13	HE	Coarse	0.320	2.3	PCE-2	B
14	HE	Coarse	0.370	1.8	SNP	CSH-C
15	HE	Recycled	0.320	2.0	SNP	-
16	GUbSF	Coarse	0.345	2.3	PCE-1	CSH-C
17	GUbSF	Fine	0.320	2.0	PCE-1	B
18	GUbSF	Fine	0.345	1.8	SNP	-

2.2 Testing methods

The proposed testing methods are the flow test, the direct shear test and the compressive strength. The results from those tests were correlated with the flowability and buildability of the mixes during the first few minutes, and their compressive strength. From the ASTM D3080 direct shear test, strength development can be observed during the dormant period. Following a similar methodology where the same test was performed (Wolfs et al., 2018, 2019), multiple direct shear tests were conducted within 90 minutes. The direct shear apparatus generally used in soil mechanics was modified instead of creating a new apparatus as in the reference study. The modified apparatus consisted of a shear box, a displacement sensor, a load sensor and a linear displacement motor. An illustration of the equipment is shown in Fig. 2a.



Fig. 2. The modified direct shear apparatus (a) and top view of the flow table (b).

The ASTM C1437 flow test was used to measure the spread of the mixes and to correlate the results with the pumpability of the mixes. The flow target was to achieve a spread of at least 60 % (Tay et al., 2019) 5 minutes after the mixing process. Multiple flow tests were conducted within 90 minutes after mixing, with a time interval of 15 min. Two cameras were placed, capturing a side and the top view, to inspect the behavior of each mixture over time (Fig. 2b). Lastly, The ASTM C109 compressive strength provided information about the compressive strength of the mixes. A semiautomatic concrete compression machine with a hydraulic piston was used to perform the test. Two inches or 50 mm test cubes were prepared and placed in a room where the temperature and humidity were controlled for up to 28 days. Tests were conducted after 1, 7 and 28 days.

2.3 Optimization Methodology

Optimization methods were used starting from the mix design. The D-optimal design was used to generate the optimum initial set of mixes, reducing the required number from ($3^6=$) 729 to 18 mixes (V. Sergis & C. M. Ouellet-Plamondon, 2022a). After the initial set, a multiobjective Pareto optimization algorithm guided the procedure. The objective functions were artificial neural networks that were trained using data from lab experiments. These networks were then used to predict the properties of the new mixtures proposed during Pareto optimization (V. Sergis & C. Ouellet-Plamondon, 2022). The best mixes were created and tested in the lab to acquire the real fresh and final properties of the mixes. The objectives were to increase simultaneously the buildability and the mechanical properties of the mixes, while acquiring an acceptable flowability.

3 RESULTS

Twenty-one new mixes were introduced after five iterations of the Pareto optimization process. In total, 39 mixes were formed, including the initial set of mixes from the D-optimal design. The algorithm was able to determine which materials performed better and what was the optimum dosage for each one despite the high complexity of the mix design. The best materials were the HE and GUbSF cement types, the admixtures B, CSH-C and PCE-2 superplasticizer. Part of the results obtained are shown in Figures 3 until 6. The results are grouped based on cement and sand type combinations. The initial mixes are represented with hollow markers whereas the mixes proposed during the optimization process are shown with filled markers.

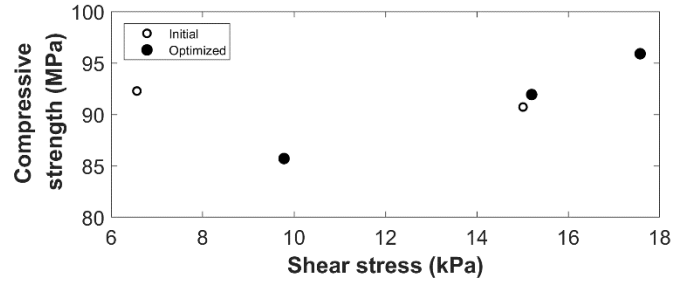


Fig. 3. Measured properties of mixes containing GUbSF cement and coarse sand proposed during the D-optimal design and the optimization process.

In Fig. 3, the x-axis is the shear stress at 90 minutes after the mixing process, and the y-axis is the compressive strength at 28 days. Aiming to improve both properties, the best mixes are located in the top right corner of the figure. All mixes in Fig. 3 include the GUbSF cement and the coarse sand. As it can be noticed, two mixes in the initial set were formed with this cement/sand combination and three more were generated from the optimization algorithm. The best mix of the initial set and the optimization set are compared in Fig. 4 and their mix proportions are presented in table 3.

Table 3: Mix proportions of the initial and optimized mix containing GUbSF cement and coarse sand.

Mixes	Cement	Sand	Water:binder	Sand:binder	Superplasticizer (Type A&F)	SP (%w/w)	B (%w/w)	CSH-C (%w/w)
Initial	GUbSF	Coarse	0.345	2.3	PCE-1	0.26	-	0.3
Optimized	GUbSF	Coarse	0.3	1.8	PCE-2	0.26	0.018	-

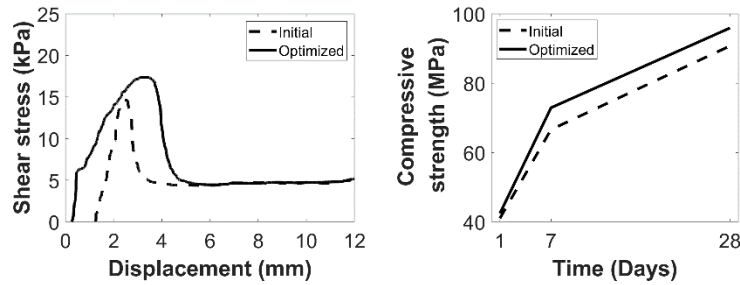


Fig. 4. Comparison between the best initial and optimized mix containing GUbSF cement and coarse sand. The measured shear-displacement graph in 90 minutes after mixing (a) and the compressive strength after 28 days (b).

In Fig. 4, the mix from the initial set is shown with dashed line whereas the mixed proposed from the algorithm in solid line. Both properties were improved, where the shear stress was increased from 15 to 17.6 kPa and the compressive strength from 91 to 96 MPa. As in Fig. 3, the x-axis and the y-axis of Fig. 5 are the shear stress at 90 minutes after the mixing process and the compressive strength at 28 days, respectively. The best mixes are located in the top right corner of the figure. The mixes in Fig. 5 include the HE cement and the recycled sand. As it can be noticed, one mix in the initial set was formed with this cement/sand combination and four more were proposed by the optimization algorithm. All of the proposed mixes performed better than the mix in the initial set. The mix from the initial set and the mix with the best performance from the optimization set are compared in Fig. 6 and their mix proportions are presented in table 4.

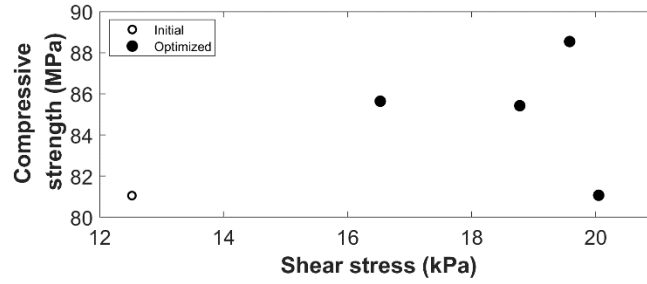


Fig. 5. Measured properties of mixes containing HE cement and recycled sand proposed during the D-optimal design and the optimization process.

Fig. 6 presents the mix proposed from the algorithm in solid line whereas the mix from the initial set is shown with dashed lines. Both properties were improved, where the compressive strength was increased from 81 to 88.5 MPa and the shear stress had a major increase from 12.5 to 19.6 kPa.

Table 4: Mix proportions of the initial and optimized mix containing HE cement and recycled sand.

Mixes	Cement	Sand	Water:binder	Sand:binder	Superplasticizer (Type A&F)	SP (%w/w)	B (%w/w)	CSH-C (%w/w)
Initial	HE	Recycled	0.345	1.8	PCE-1	0.26	0.013	-
Optimized	HE	Recycled	0.3	1.7	PCE-2	0.28	0.013	0.11

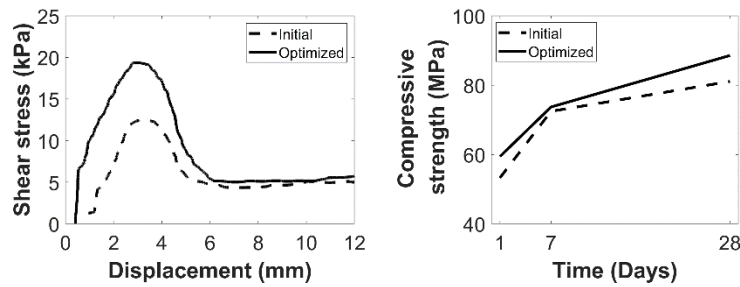


Fig. 6. Comparison between the best initial and optimized mix containing HE cement and recycled sand. The measured shear-displacement graph in 90 minutes after mixing (a) and the compressive strength after 28 days (b).

4 CONCLUSION

The proposed methodology allowed for improving the properties of the mixes following a trend towards a multiobjective optimization. The Pareto algorithm narrowed down the factors and their levels after identifying the important factors. It also determined the preferred dosages to improve the conflicting objectives. On the other hand, the neural networks helped to visualize the effect of each material. This approach yields promising capability to improve the competing objectives of the mortar mixes by considerably reducing the time and the number of experiments required.

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