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Optimized fuzzy logic model for predicting self-compacting concrete shrinkage

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1. Introduction

Concrete shrinkage is defined as the decrease in concrete volume with time. This volume decrease does not depend on external stress and it is not completely reversible. The shrinkage is associated with a series of factors, such as chemical reactions, gradient in temperature, and loss of water. Each one of these factors leads to different types of shrinkage, such as autogenous, plastic, drying, and thermal shrinkage [1, 2].

The occurrence of shrinkage leads to the development of internal tension stresses that can result in concrete cracking if the developed internal tension stresses surpass concrete tensile strength. Cracks in concrete create pathways for the easier access of aggressive agents that can contribute to the reduction in concrete's structure durability and service life. Moreover, the strain resulting from excessive shrinkage may reduce bounding tension and increase deflection in asymmetrically reinforced concrete structures [2].

For these reasons, a reliable prediction of concrete shrinkage strain is an important factor in the entire designing process. Predicting shrinkage, especially during the period of construction, allows early countermeasures to be taken, e.g., premature loading or prestressing to compensate for the negative shrinkage effect. As a result, accurate shrinkage prediction helps reduce maintenance costs and ensures that the designed structure will meet service life and durability requirements. An example that highlights the importance of modeling early age concrete time-dependent behavior is presented by Štemberk and Kalafutová [3].

Apart from external factors such as ambient temperature and humidity, concrete shrinkage is caused by hydration reaction in the cement paste. When considering self-compacting concrete (SCC) mixtures i.e. a high-performance concrete that can flow under its own weight and self-consolidate without any mechanical vibration [4], a high volume of cement paste is necessary in the composition to achieve excellent deformability. However, SCC is prone to higher shrinkage strains when compared to conventional concrete. Hence, measuring the shrinkage strain is especially important when working with SCC.

Nonetheless, the experimental measurement of shrinkage strain is laborious, time consuming, and expensive. These characteristics, added to short deadlines, tight budgets, and the industry's trend of accelerating the construction processes, sometimes make experimental measurements unfeasible. As a result, construction designers tend to use shrinkage prediction models.

Shrinkage prediction models aim to determine concrete shrinkage strain in a faster and less expensive way when compared to experimental measurements. Prediction models are based either on analytical or empirical approaches, although the later is used most frequently because of its simplicity. According to McDonald and Roper [5], complex prediction models do not necessarily lead to better prediction than simple ones.

One of several existing shrinkage prediction models that is frequently used is the EN1992 model, considered by the Eurocode. This model consists of a combination of CEB FIP 1990 and CEB MC90-99 prediction models and its equations are described in [6]. The EN1992 model is a standard and its prediction formulas are routinely used by the industry's experts for any concrete, including SCC which is not explicitly excluded in the Eurocode. Indeed, the European guidelines for SCC [7], state that the values and formulas given in the Eurocode for normal concrete are still valid in the case of SCC.

Although prediction models are regularly used, the shrinkage curve obtained from the models does not necessarily match experimental measurements. To verify that, experimental data taken from different authors [8-10], were compared with those predicted by the EN1992 model.

The error was computed through mean squared error (MSE). The obtained results are presented in Table 1. The MSE equations are:

$$f_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n} d_j^2} \; ; \tag{1}$$

$$f_{all} = \sqrt{\frac{1}{N}\sum_{j=1}^{n} f_j^2} \; , \tag{2}$$

where N and n relate to the number of data sets and data points considered in the analysis, respectively; d_j is the percent difference between predicted and measured strain for the data point i; f_j is the MSE for the data set j; and f_{all} is the overall MSE.

Table 1

MSE for EN-1992 prediction model for SCC

Input data: Author, [Ref.]		N	f_{model}, %	f_{all}, %
Guneyisi,	[8]	8	50.1	62.5
Bouzoubaa,	[9]	8	72.4	
Lemann,	[10]	3	63.1	

The overall MSE, f_{all} = 62.5% (Table 1), indicates that the EN1992 model did not lead to satisfactory results for the analyzed data. The scatter plot of the experimentally measured and predicted strain values for the analyzed data is illustrated in Fig. 1.

From Fig. 1 a considerable scatter can be seen, therefore showing the relative error as well as an underestimation trend of EN1992 in predicting shrinkage strains. Hence, it can be stated that the reliability of EN1992 model is open to discussion and improvements appear to be required.

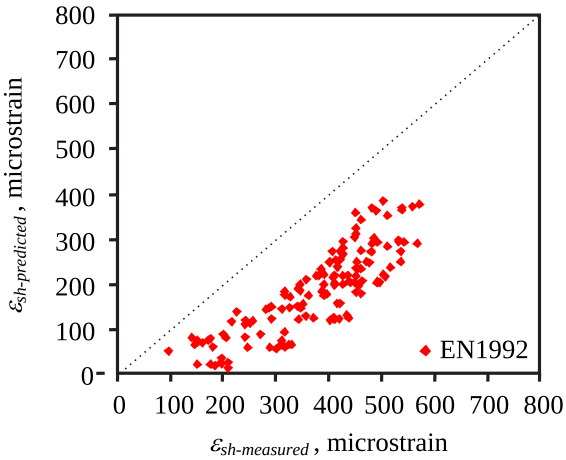

Fig. 1 Comparison of measured and predicted shrinkage strain for SCC using the EN1992 model

In light of this, this work aims to propose an experimental-based prediction model for SCC shrinkage. The model is developed based on an independent methodology that combines fuzzy logic and genetic algorithm. The hybridization of these techniques is advantageous once they complement each other as further discussed in section 2.

The proposed model aims to predict the behavior of concrete for a period of up to 90 days. This corresponds to a reasonable construction time during which countermeasures can be taken. Moreover, the model focuses on general applications of SCC when no experimental data is available. The final results obtained from the proposed model were compared not only to other published data, but also to EN1992 as it is the regularly used standard.

2. Fuzzy logic and evolutionary computing

Fuzzy theory, first introduced by Zadeh [11] corresponds to a natural way of thinking where verbally expressed rules are applied to deal with vagueness. The ability to deal with uncertainties makes fuzzy logic reasoning a robust and flexible tool that can be used in material modeling. For example, Štemberk and Rainová [12] used fuzzy logic for simulating hydration heat liberation of concrete.

Fuzzy logic systems comprise three basic steps: fuzzification, decision-making and defuzzification. The fuzzification consists of converting the crisp input values into degrees of membership through membership functions. This step is followed by the decision-making, which involves assigning a degree of membership to the output depending on the rule base of the system. Finally, the defuzzification is performed to convert the output fuzzy set into a single value.

The key factors to achieve an acceptable performance in a fuzzy logic system are connected to the proper determination of the number and shape of the fuzzy sets. Commonly, there are m^k fuzzy rules, where m and k are the number of fuzzy sets and input variables, respectively. In the classical fuzzy logic approach, the number of fuzzy rules can be reduced by the user's experience, and to simplify calculations the shape of the fuzzy sets is usually linear. However, when this approach is implemented to model the behavior of non-linear materials, the final result is a rather rough shaped piecewise curve. Using the classical approach is also feasible for material modeling; however, a larger number of linear fuzzy sets is required to obtain smoothed curves. This leads to a longer data collection time and high computational cost. Thus, to improve the modeling process a modified approach that includes an evolutionary computing method is proposed.

Evolutionary computing involves robust optimization methods that can be generally applied without recourse to domain-specific heuristics. These methods operate on a population of potential solutions and apply the principle of survival of the fittest to produce successively better approximations for a solution [13].

Among several evolutionary computing methods, genetic algorithms (GA) have been successfully applied in numerical optimization in civil engineering, e.g. [14]. They consist of adaptive heuristic search algorithms based on the principles of Darwin's theory of natural selection. They represent an intelligent exploitation of a random search that uses historical information to guide the search into the region of better performance, within a defined search space. The basic form of a GA involves three operators to achieve evolution: selection (or reproduction), crossover, and mutation [13].

The advantage of combining fuzzy logic and genetic algorithms is that they complement each other. Fuzzy logic is not capable of adaption or parallel computation, which are features found in GA. On the other hand, GA lacks knowledge representation and human interaction, which are the kernel of fuzzy systems [15].

3. Proposed methodology for optimization of fuzzy decision-making

The proposed approach combines fuzzy logics and genetic algorithms to optimize fuzzy decision-making, which is achieved by optimizing the shape of the membership functions. The proposed methodology is described as follows and summarized in Fig. 2.

First, the user determines the number of representative intervals, N_{int}, of shrinkage strain, ε_{sh}, and the concrete age, t, of the experimental shrinkage strain curves of concrete mixtures with different volumes of cement paste, V_{cp}. The more complex the shape of the curve the higher the number of intervals needed to achieve optimal results.

After that, the user specifies the size of the population, S_{pop}, to be used in the genetic part of the algorithm. From this point on the optimization process is automatic. Based on the value set for N_{int}, the encoding of each individual, or chromosome, from the population is defined. It comprises a string of $n_{enc} = 2 \times N_{int}$ real numbers, which correspond to the exponent values, E_L and E_R, related to the membership function to be optimized (Fig. 3).

Next, an initial random population is generated and the fitness function, $f(x)$, is evaluated. The fitness function corresponds to the MSE shown in Eq. (2). Then, three genetic operators (selection, crossover, and mutation) are applied to generate a new population.

The selection operator chooses the chromosomes for reproduction. In this case, the tournament selection scheme was applied. It selects the best fitness from individuals chosen at random from the population.

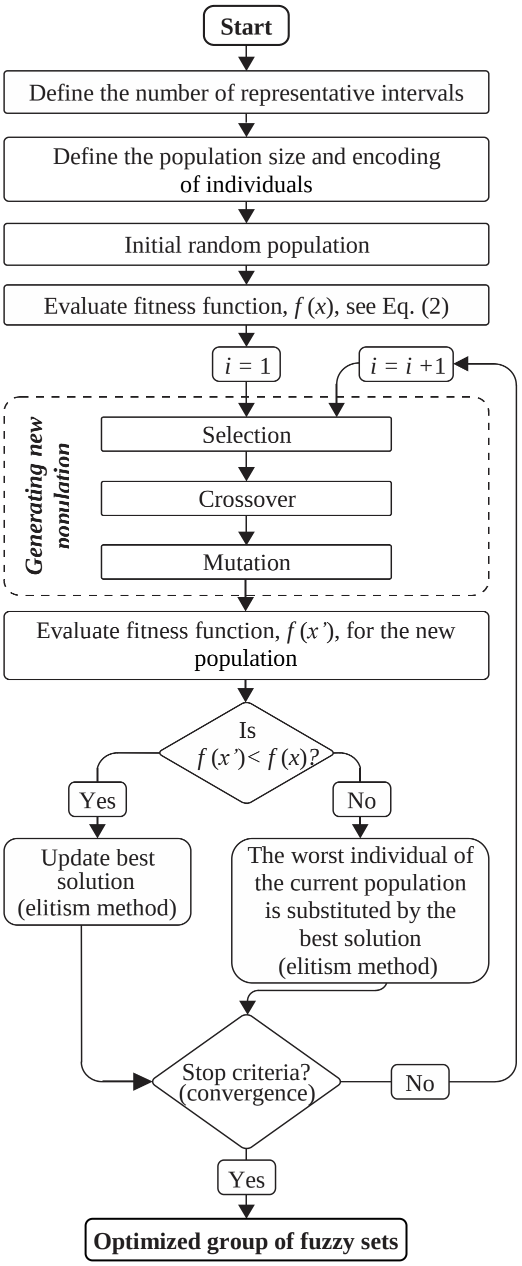

Fig. 2 Flowchart of the proposed methodology for optimization of fuzzy sets

The selected chromosomes, or parents, are then crossed over by one-point crossover scheme, with a probability, C_{prob}, set as 90.0%, to create a new individual to be included in the population. This scheme sets an independent randomized crossover point for couples of parents, whose data is swapped to create a new population.

Further, a mutation operator is applied to maintain genetic diversity. The mutation is performed by disturbance with a probability, M_{prob}, set as of 10.0%. This operator randomly flips some of the values in a chromosome to create a mutated version that will be incorporated in the population.

After a new population has been generated, the fitness function re-evaluates all individuals from the new population. The obtained results, i.e., $f(x')$, are then compared with those from previous populations, $f(x)$. Subsequently, elitism is applied, i.e., the best overall solution is stored. In case none of individuals from the new population shows better fitness than the stored solution, the individual with the worst solution from the new population is replaced by the best overall solution.

The automatic process of generating a new population and evaluating the best fit is repeated until convergence occurs. In this case, convergence is considered as achieved when more than 200 consecutive runs do not lead to any improvements in the fitness function result.

The final result consists of a group of optimized fuzzy sets that will compose the fuzzy decision-making. Moreover, the decision-making is also composed by the rule base, R^n, defined in Eq. (3). Finally, the predicted shrinkage strain, $\varepsilon_{sh,output}$, is computed by means of Eq. (4).

$$R^n\text{: IF } V_{cp} \text{ is } V_{cp,n} \text{ THEN } \varepsilon_{sh} \text{ is } \varepsilon_{sh,n}; \quad (3)$$

$$\varepsilon_{sh,\,output} = \sum\nolimits_{n=1}^{n} \mu_n\, \varepsilon_{sh,n} \Big/ \sum\nolimits_{n=1}^{n} \mu_n \,, \quad (4)$$

where n is the number of rules; V_{cp} is the cement paste volume input value, in l/m^3; $V_{cp,n}$ and $\varepsilon_{sh,n}$ are the optimized group of fuzzy sets for cement paste volume and shrinkage strain, respectively; μ_n is the degree of membership assigned to each $\varepsilon_{sh,n}$ group from the rule R^n.

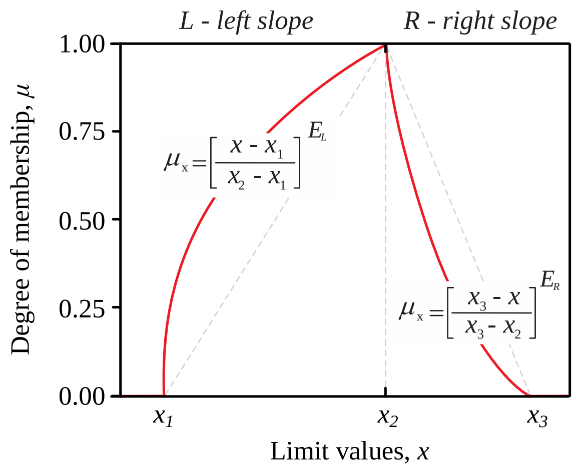

Fig. 3 General equation and shape of the membership functions to be optimized

The methodology illustrated in Fig. 2 was applied for the experimental data presented by Leemann et al., [10], and the results from Loser et al., [16], were used to verify the optimized model.

4. Results and discussion

In the present analysis the volume of cement paste, V_{cp}, was chosen as input parameter and two experimental curves, illustrated in Fig. 4, were considered as training data. These curves were taken from the experimental database presented by Leemann et al. [10],where further details concerning the materials properties and curing conditions can be verified.

The number of representative intervals was defined as N_{int} = 3. The population size was set as S_{pop} = 10. The proposed methodology, see Fig. 3, was then performed and convergence was achieved after around 500 runs.

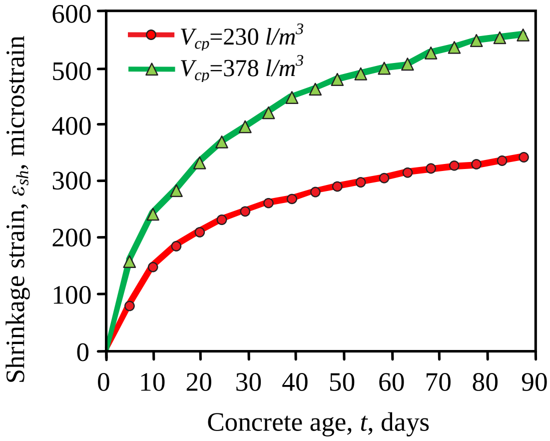

Fig. 4 Shrinkage strain curves of SCC, [11]

The representative intervals of the experimental curves and the exponent values, E_L and E_R, of the group of optimized fuzzy sets are listed in Table 2 and 3, respectively. Since only two curves were available for the optimization process, the fuzzy sets connected to V_{cp} were set as linear.

Table 2

Representative intervals of the experimental curves

V_{cp}, l/m^3	t_1, days	ε_{sh1}, microstrain	t_2, days	ε_{sh2}, microstrain
230	0	0	15	175
	15	175	70	305
	70	305	90	325
328	0	0	20	315
	20	315	70	500
	70	500	90	530

Table 3

E_L and E_R values of the optimized fuzzy sets

Fuzzy set	MF	E_L	E_R
V_{cp}	V_{cp1}	-	1.000
	V_{cp2}	1.000	-
ε_{sh1}	ε_{sh11}	-	1.573
	ε_{sh12}	0.842	1.436
	ε_{sh13}	0.498	0.726
	ε_{sh14}	1.144	-
ε_{sh2}	ε_{sh21}	-	1.621
	ε_{sh22}	0.393	1.519
	ε_{sh23}	0.636	1.512
	ε_{sh24}	0.762	-

The fuzzy logic prediction model for SCC is then composed of the optimized fuzzy sets shown in Table 3, the rule base and the final output equation, presented in Eq. (3) and (4). The obtained prediction model, named the FL model, is suitable for predicting shrinkage strain up to 90 days of SCC with V_{cp} ranging from 230 to 378 l/m^3 and testing conditions designed by Leemann et al., [10].

To verify the quality of the FL model in predicting shrinkage strain, the experimental data published by Loser et al. [16] was used for comparison. This data comprises shrinkage curves of five SCC mixtures that were tested in conditions compatible with the limits of the developed model. The V_{cp} of each SCC mixture is listed in Table 4. The experimental and predicted shrinkage strains were compared and the MSE values, computed by Eq. (2), are presented in Table 5.

As a complementary analysis, the shrinkage strain curve of each SCC mixture from [16] was also compared to the strain curves predicted by the EN1992 model. For that, the input data listed in Table 4 was taken into account. The obtained results are presented in Table 5 together with those from FL model to ease the comparison of the models.

Table 4

Input data used to predict shrinkage strain - EN1992 and FL model, [16]

Input Parameters	SCC				
	1	2	3	4	5
Cement paste volume, V_{cp}, l/m^{3*}	329.0	349.0	316.0	342.0	332.0
Curing time, t_c , days	1				
Relative Humidity, RH, %	70.0%				
Cement type	CEM I 42.5				
Design compressive strength, f_c', MPa	53.3	63.1	51.0	49.4	66.0
Compressive strength at 28 days, f_{cm28} , MPa	61.3	71.1	59.0	57.4	74.0
Specimen size, mm	120 × 120 × 360				
Member shape	Infinite prism				

* V_{cp} was only considered by FL model;

Table 5

MSE values for different shrinkage prediction models

f_{model}, %	SCC					f_{all}, %
	1	2	3	4	5	
EN1992	56.8	51.1	57.1	55.9	49.7	54.2
FL model	6.9	19.1	4.4	16.2	14.1	13.4

From Table 5, it can be seen that the FL model presented lower MSE in all cases, indicating that the FL model is more reliable in predicting SCC shrinkage than EN1992 for the evaluated data.

The comparison of experimental shrinkage curve for SCC 1 and the correspondent predicted shrinkage strain curves obtained from EN1992 and FL models is illustrated in Fig. 5.

Although the MSE presented by FL model was lower than EN1992 in all cases, this value is still considered high, around 15.0%. The reason for this is probably that only two experimental curves were used as training data, which led to linear membership functions for the fuzzy sets connected to V_{cp}. If an intermediary curve was included as training data, the linear shape of the V_{cp} fuzzy set, see Table 3, would be optimized. Consequently, the lower MSE of FL model would be reached.

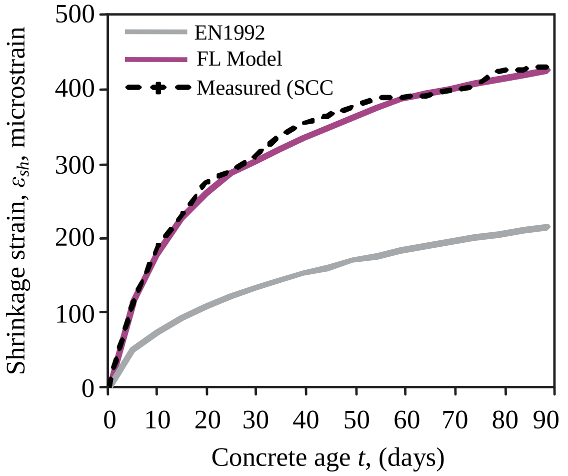

Fig. 5 Experimental and predicted curves from FL and EN1992 for SCC 1

To verify the assumption that additional training data would lead to a more reliable model, one of the experimental curves from Loser et al. [16] particularly SCC 4, was included as additional training data. The optimization process was performed again and the exponent values, E_R and E_L, obtained for the optimized fuzzy sets are indicated in Table 6.The experimental data from SCC 4 was only used as training data to optimize the shape of the V_{cp} fuzzy sets, therefore the optimized fuzzy sets ε_{sh1} and ε_{sh2}, see Table 3, remained unchanged. The obtained model was named the FL-2 model.

Table 6

Exponents values, E_L and E_R, of the optimized group of fuzzy sets for FL-2 model

Fuzzy set	MF	E_L	E_R
V_{cp}	V_{cp1}	-	0.251
	V_{cp2}	2.099	-
ε_{sh1}	ε_{sh11}	-	1.573
	ε_{sh12}	0.842	1.436
	ε_{sh13}	0.498	0.726
	ε_{sh14}	1.144	-
ε_{sh2}	ε_{sh21}	-	1.621
	ε_{sh22}	0.393	1.519
	ε_{sh23}	0.636	1.512
	ε_{sh24}	0.762	-

The predicted shrinkage strain from FL-2 model was compared to the data from Loser et al. [16] and the MSE was computed. The obtained results are listed in Table 7 together with those from EN1992 and FL model.

From Table 7, it can be seen that the overall MSE for FL-2 model were considerably reduced when compared with the first version of the model. This confirms the assumption that the inclusion of additional training data would lead to a prediction model with lower overall error.

Table 7

Individual and overall MSE values for EN1992, FL, and FL-2 shrinkage prediction models

f_{model}, %	SCC 1	SCC 2	SCC 3	SCC 4	SCC 5	f_{all}, %
EN1992	56.8	51.1	57.1	55.9	49.7	54.2
FL model	6.9	19.1	4.4	16.2	14.1	13.4
FL-2 model	8.9	3.8	11.2	–**	3.9	7.6

** used as training data to develop the FL-2 model.

Moreover, it also indicates that the proposed methodology is able to adjust according to the training data. For instance, this allows for including long-term shrinkage experimental measurements, e.g., up to 365 days, to build a model for different applications than the one presented in this work.

Finally, the lower MSE values from FL and FL-2 models against EN1992 confirm their quality in simulating the materials behaviour, and also the success in combining fuzzy logics and GA to develop optimized materials models.

5. Conclusions

By developing a shrinkage strain prediction model for SCC the objective of this paper has been achieved. The proposed methodology for optimization of fuzzy decision-making has shown satisfactory results.

In addition, the optimized fuzzy sets led to a proper prediction of the shrinkage with a reduced number of rules, making the modeling process more effective.

The statistical analysis pointed to an overall MSE around 50.0% for EN1992, against ~15.0% for FL model, indicating that the FL model better represents the materials behaviour and can be used to predict SCC shrinkage within the limits of the model.

The further inclusion of additional training data in the optimization methodology contributed to reduce the overall error of the FL model from ~15.0% to ~7.0%, demonstrating the flexibility of the model in self-adjusting according to the training data. Such flexibility is a great advantage of the FL model when compared to models based on defined equations and its constants.

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References

1. **Brook, J.** 2003. Elasticity, Shrinkage, Creep and Thermal Movement. In: Newman, J.; Choo, B.S. Advanced Concrete Technology – Testing and Quality. Elsevier, London, Vol. 1, 320 p. http://dx.doi.org/10.1016/B978-075065686-3/50254-8.
2. **Mehta, P.K.; Monteiro, P.J.M.** 2006. Concrete: Microstructure, Properties and Materials, 3rd Ed. McGrawHill, New York, 660p.

3. **Štemberk, P.; Kalafutová, P.** 2008. Modeling very early early age concrete under uniaxial short-time and sustained loading, Mechanika, 2(70): 16-21.
4. **Skarendahl, A.** 2005. Changing Concrete Construction Through Use of Self-Compacting Concrete. In: PRO 42 1st International Symposium on Design, Performance and Use of Self-Consolidating Concrete – SCC'2005, RILEM Publications, 17-24. http://dx.doi.org/10.1617/2912143624.002.
5. **Mcdonald, D.B.; Roper, H.** 1993. Accuracy of prediction models for shrinkage of concrete, ACI Materials Journal 90(3): 265-271.
6. **EN1992-1-1:2004**. 2004 EuroCode 2**:** Design of concrete structures - Part 1-1: General Rules and Rules for Buildings, European Committee for Standardization, Brussels.
7. **The European Project Group.** 2005. The European guidelines for Self-compacting concrete. 63p.
8. **Guneyisi, E.; Gesoglu, M.; Ozbay, E.** 2010. Strength and drying shrinkage properties of self-compacting concretes incorporating multi-system blended mineral admixtures, Construction and Building Materials 24(10): 1878-1887. http://dx.doi.org/10.1016/j.conbuildmat.2010.04.015.
9. **Bouzoubaa, N.; Lachemi, M.** 2001. Self-compacting concrete incorporating high volumes of class F fly ash: Preliminary results, Cement and Concrete Research 31(3): 413-420. http://dx.doi.org/10.1016/S0008-8846(00)00504-4.
10. **Leemann, A.; Lura, P.; Loser, R.** 2011. Shrinkage and creep of SCC – The influence of paste volume and binder composition, Construction and Building Materials 25(5): 2283-2289. http://dx.doi.org/10.1016/j.conbuildmat.2010.11.019
11. **Zadeh, L.A.** 1965. Fuzzy sets, Information and Control 8: 38-53. http://dx.doi.org/10.1016/S0019-9958(65)90241-X.
12. **Štemberk, P.; Rainová, A.** 2011. Simulation of hydration and cracking propagation with temperature effect based on fuzzy logic theory, Mechanika, 17(4): 358-362.
13. **Coley, D.A.** 1999. An Introduction to Genetic Algorithms for Scientists and Engineers, World Scientific, Singapore, 244 p.
14. **Rokonuzzaman, Md.; Sakai, T.** 2010. Calibration of the parameters for a hardening-softening constitutive model using genetic algorithms, Computers and Geotechnics 37(4): 573-579. http://dx.doi.org/10.1016/j.compgeo.2010.02.007.
15. **Cordon, O.; Herrera, F.; Hoffman, F.; Magdalena, L.;** 2002. Genetic Fuzzy Systems: Evolutionary Tuning and Learning of Fuzzy Knowledge Bases, In: Zadeh, L.A. Advances in fuzzy systems: applications and theory. World Scientific, London, Vol.19, 448 p.
16. **Loser, R.; Leemann, A.** 2009. Shrinkage and restrained shrinkage cracking of self-compacting concrete compared to conventionally vibrated concrete, Materials and Structures 42: 71-82. http://dx.doi.org/10.1617/s11527-008-9367-9.

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OPTIMIZUOTAS NERAIŠKIOSIOS LOGIKOS MODELIS VIENODAI PASISKIRSČIUSIO BETONO SUSITRAUKIMUI NUSTATYTI

R e z i u m ė

Straipsnio tikslas – sukurti eksperimentinį modelį vienodai pasiskirsčiusio betono susitraukimui įvertinti. Modelis skirtas nustatyti betono elgsenai 90 dienų periodu, atitinkančiu statybos trukmę, per kurią galimi atsakomieji veiksmai. Modelis sukurtas taikant nepriklausomą metodologiją, jungiančią neraiškiąją (fuzzy) logiką ir genetinį algoritmą. Ši metodologija pritaikyta eksperimento duomenims, o naudojantis šiuo modeliu gauti rezultatai palyginti su kitais publikuotais rezultatais. Statistinė analizė patvirtino pasiūlytojo modelio, vertinamo Eurokodu, patikimumą.

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OPTIMIZED FUZZY LOGIC MODEL FOR PREDICTING SELF-COMPACTING CONCRETE SHRINKAGE

S u m m a r y

This paper aims to develop a shrinkage prediction model for self-compacting concrete based on experimental data. The model focuses on predicting the behavior of concrete up to a period of 90 days, which corresponds to a construction time during which countermeasures can be taken. The model was designed based on an independent methodology that combines fuzzy logic and genetic algorithm. This methodology was applied for an experimental data set, and the obtained model was compared to other published data and the prediction model considered by the Eurocode. The results were verified by statistical analysis that confirmed the reliability of the proposed model.

Keywords: Self-compacting concrete, shrinkage, fuzzy logic, genetic algorithm, material modeling.

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