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Automatic categorization of chloride migration into concrete modified with CFBC ash

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Abstract. The objective of this investigation was to develop rules for automatic categorization of concrete quality using selected artificial intelligence methods based on machine learning. The range of tested materials included concrete containing a new waste material - solid residue from coal combustion in fluidized bed boilers (CFBC fly ash) used as additive. The rapid chloride permeability test - Nordtest Method BUILD 492 method was used for determining chloride ions penetration in concrete. Performed experimental tests on obtained chloride migration provided data for learning and testing of rules discovered by machine learning techniques. It has been found that machine learning is a tool which can be applied to determine concrete durability. The rules generated by computer programs AQ21 and WEKA using J48 algorithm provided means for adequate categorization of plain concrete and concrete modified with CFBC fly ash as materials of good and acceptable resistance to chloride penetration.

Keywords: concrete durability; chloride ions migration; circulated fluidized bed combustion fly ash (cfbc fly ash); machine learning; classification rules; database.

1. Introduction

Increasing the use of fly ash in cement and concrete industry can considerably enhance the environmental friendliness of concrete production. Current practice for using fly ash as type II concrete additive according to EN 206-1 standard, does not cover the use of solid by-products resulting from advanced coal burning technologies, like Circulating Fluidized Bed Combustion (CFBC). This ‘clean coal technology’ for power production is used in several countries, e.g. Czech Republic, Estonia, France, Germany, Japan, Poland, USA, (Nowak 2003), China (Fu *et al.* 2008). The solid residue from coal combustion in fluidized bed boilers contains noncombustible mineral matter, sorbent material and unburned carbon (Giergiczny 2006). Mainly because of high sulfur content, high free lime content, high loss on ignition LOI and the lack of glassy phase CFBC ash does not meet the requirements defined by European standard EN 450-1 or in ASTM C618-03 in order to be used for cement or concrete production. The potential for using CFBC fly ash in concrete was recently investigated and the adequate strength and frost durability was revealed for selected kinds of CFBC fly ash used to replace 20% of cement mass in the binder (Glinicki and Zielinski 2009). Moreover, the efficient methods for selection of adequate CFBC fly ash to provide the long term durability of concrete are still required and possibility of 30-40% replacement is looked for.

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Modern computation methods that belong to the group of artificial intelligence soft methods could aid in searching for relationships between the composition of concrete modified with CFBC ash, its microstructure and technical properties, including durability in aggressive environments. Artificial intelligence methods are successfully used in many civil engineering problems (Melhem and Cheng 2003, Alterman and Kasperkiewicz 2006, Kasperkiewicz and Alterman 2007). Kasperkiewicz and Alterman concentrate on three basic concept: artificial neural networks, machine learning and genetic algorithms. In all these approaches the user is not obliged to bother about the model of the process or phenomenon, because the system itself gains adequate knowledge from the examined examples. It can generate thereupon answers in the form of unknown values of the attributes, classification of new examples of the same format or formulation of rules (hypotheses, generalisations) concerning the process under consideration. More details are given in relation to the applied solutions of Fuzzy ARTMAP and ML program AQ19.

The objective of current research was to develop rules for automatic categorization of concrete quality using machine learning techniques. The undertaken research was focused on the resistance of concrete with fluidized bed fly ash to chloride ions aggression. Performed experimental tests on chloride migration provided data for learning and testing of rules discovered by machine learning techniques.

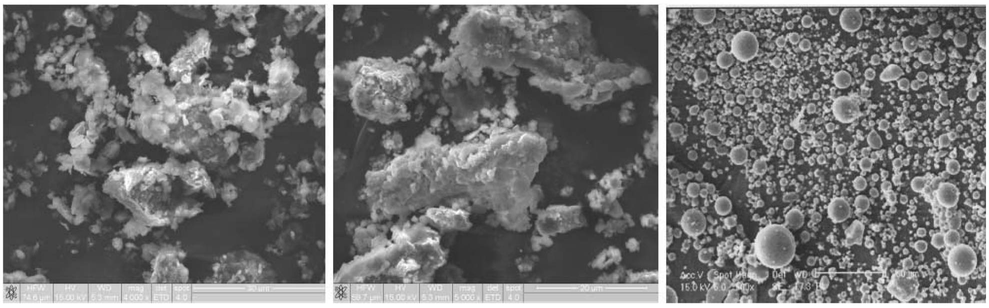
2. Laboratory tests

2.1 Materials and mixture proportions

The chloride migration coefficient in concrete specimens with different content of fluidized bed fly ash was measured (Jóźwiak-Niedźwiedzka 2009). Ordinary Portland cement CEM I 32.5 R from

Table 1 Chemical composition and physical properties of Portland cement CEM I, conventional fly ash and fluidized bed fly ashes from combustion of hard and brown coal (Małolepszy and Kołodziej 2009)

Chemical compounds	PC type I	Conventional fly ash	CFBC fly ash	
			From hard coal *K*	From lignite *T*
SiO_2	21.4	50.8	47.18	36.47
Fe_2O_3	3.5	8.6	6.8	4.4
Al_2O_3	5.7	23.9	25.62	28.4
TiO_2	NA	1.11	1.08	3.84
CaO	64.1	4.0	5.84	15.95
MgO	2.1	2.8	0.15	1.65
SO_3	2.1	0.8	3.62	3.8
Na_2O	0.5	0.8	1.18	1.64
K_2O	0.92	2.9	2.36	0.62
Cl^-	0.029	0.02	0.1	0.03
CaO_{free}	0.9	0.6	0.3	1.4
Specific gravity [g/cm^3]	3.15	2.16	2.68	2.75
Loss on ignition, 1000°C/1h	1.1	2.9	3.4	2.73



(a) (b) (c)

Fig. 1 The shape of ash particles from fluidized bed combustion of lignite (a) - 5000x and hard coal (b) 5000x, and from conventional combustion of hard coal, 500x

Małogoszcz cement plant, gravel fractions 2÷8 mm and 8÷16 mm, and sand fraction 0÷2 mm, were used for composition of concrete specimens. Two kinds of fluidized fly ash were tested: from hard coal combustion in the thermal-electric power station Katowice K and from brown coal - lignite in the power plant Turów T. Chemical and physical properties of Portland cement type I and both CFBC fly ashes are shown in Table 1. Solid residues from coal combustion in circulated fluidized bed boilers are characterized by different mineral and phase compositions than conventional fly ash, by angular shape of grains Fig. 1 and by lack of glassy phase.

Three chemical admixtures: a plasticizer (magnesium lignosulfonates), a high range water reducer

Table 2 Composition of concrete mixes and compressive strength tested after 28 and 90 days

Concrete mix		Cement	Addition		Aggregate	Water	Plasticizer	HRWR	AEA	f_{c28}	f_{c90}
			T	*K*							
		Content [kg/m^3]								[MPa]	
Series B	B0	360	-	-	1859	162	3.2	4.3	-	55.0	70.0
	B15K	306	-	54	1854	162	3.2	3.2	-	56.2	64.3
	B30K	252	-	108	1847	162	3.2	3.2	-	51.6	61.0
	B15T	306	54	-	1850	162	3.2	4.7	-	60.3	70.4
	B30T	252	108	-	1841	162	3.2	5.6	-	58.7	72.0
Series C	C0	380	-	-	1822	171	3.4	2.7	0.4	46.3	49.8
	C15K	323	-	57	1813	171	3.4	2.5	0.6	47.2	48.4
	C30K	266	-	114	1803	171	3.4	3.4	0.6	46.8	56.4
	C15T	323	57	-	1810	171	3.4	3.8	0.6	45.3	50.1
	C30T	266	114	-	1800	171	3.4	4.8	0.6	46.3	47.7
Series D	D0	406	-	-	1586	175	-	0.0	3.2	22.7	26.3
	D20T	290	73	-	1431	151	-	2.0	2.9	21.0	23.3
	D40T	217	145	-	1423	150	-	4.0	5.8	26.1	25.3
	D20K	323	-	81	1593	167	-	2.2	3.2	38.3	41.8
	D40K	244	-	162	1606	157	-	4.5	6.5	43.0	43.4

HRWR- high range water reducer, AEA- air-entraining admixture
0-no addition, *T* - fluidized fly ash from lignite, *K* - fluidized fly ash from hard coal

(polycarboxylane ether) and an air-entraining admixture (synthetic surfactants) were used to achieve approximately the same workability and porosity of fresh mix. Three concrete mixes were designed: series B with water to binder ratio w/b = 0.45, air-entrained series C with w/b = 0.45 and series D with w/b = 0.42. In Table 2 the mixture proportions of tested concretes and the compressive strength of hardened concrete are shown.

The composition of concrete mixes was based on the experimental method with replacement of cement mass by fluidized fly ash: 15% and 30% in series B and C, 20% and 40% in series D. The specimens were cast in cubical moulds 150 mm and in cylinder moulds ø100 mm × 200 mm. Fresh mixes were consolidated by vibration. After 48 hours the specimens were demoulded and cured in high humidity conditions RH > 90%, at temperature 18÷20ºC until the age of 28 days.

2.2 Testing procedure

The chloride penetration test for this study was based on the standard of Nordtest Build 492 - Non-Steady State Migration Test (NT Build 492 1999). The principle of the test is to subject the concrete to external electrical potential applied across a specimen and to force chloride ions to migrate into it (Antoni *et al.* 2005). After the specified period of time, depending of the initial current intensity, the specimen is split open and sprayed with silver nitrate solution, which reacts to give white insoluble silver chloride on contact with chloride ions. This provides a simple physical measurement of the depth Fig. 2 to which the sample has been penetrated.

The conformity criteria for concretes according to Non-Steady State Migration Test (NT Build 492 1999) are based on the voltage magnitude, temperature of anolite measured on the beginning and end of test and the depth of chloride ions penetration, are shown in Table 3 (Tang 1996). The non-steady-state migration coefficient, D_{nssm}, is calculated from equation derived from the second Fick's law:

$$D_{nssm} = \frac{0.0239(273+T)L}{(U-2)t}\left(x - 0.0238\sqrt{\frac{(273+T)Lx}{U-2}}\right) \tag{1}$$

here:

D_{nssm} – non-steady-state migration coefficient, $\times 10^{-12}$ [m^2/s],
U – absolute value of the applied voltage [V],
T – average value of the initial and final temperature in the anolyte solution [ºC],
L – thickness of the specimen [mm],
x – average value of the penetration depths [mm],
t – test duration [h].

Table 3 Estimation of the chloride resistance to chloride ions penetration

Non-steady-state migration coefficient	Resistance to chloride penetration
$< 2 \times 10^{-12}$ m^2/s	Very good
$2 - 8 \times 10^{-12}$ m^2/s	Good
$8 - 16 \times 10^{-12}$ m^2/s	Acceptable
$> 16 \times 10^{-12}$ m^2/s	Unacceptable

2.3 Test results of chloride migration coefficient

Tables 4 and 5 present the values of chloride migration coefficient determined after 28 and 90 days of maturity period for concretes series B, C and D.

The results show the same general trend in almost all concrete mixtures that values of D_{nssm}

Table 4 Results of tests of chloride ions penetration after 28 days, series B, C and D (mean values from 3 specimens)

Series	Depth of chloride penetration [mm]	D_{nssm} [$\times 10^{-12}$ m^2/s]	Resistance to chloride penetration
B0	27.2	15.25	Acceptable
B15K	20.3	8.68	Acceptable
B30K	15.2	4.98	Good
B15T	17.9	6.40	Good
B30T	12.2	3.02	Good
C0	26.3	13.83	Acceptable
C15K	19.0	7.53	Good
C30K	18.7	6.57	Good
C15T	23.1	9.35	Acceptable
C30T	28.2	10.08	Acceptable
D0	23.3	10.60	Acceptable
D20T	22.5	7.83	Good
D40T	21.7	5.69	Good
D20K	19.4	6.19	Good
D40K	14.1	1.58	Very good

Table 5 Results of tests of chloride ions penetration after 90 days, series B, C and D (mean values from 3 specimens)

Series	Depth of chloride penetration [mm]	D_{nssm} [$\times 10^{-12}$ m^2/s]	Resistance to chloride penetration
B0	20.5	9.29	Acceptable
B15K	18.0	6.29	Good
B30K	12.1	2.93	Good
B15T	14.0	4.81	Good
B30T	11.7	2.66	Good
C0	22.1	10.31	Acceptable
C15K	15.2	4.75	Good
C30K	15.1	4.19	Good
C15T	12.9	4.36	Good
C30T	18.7	4.67	Good
D0	26.6	10.3	Acceptable
D20T	22.7	5.68	Good
D40T	20.6	2.33	Good
D20K	18.9	4.58	Good
D40K	17.9	0.99	Very good

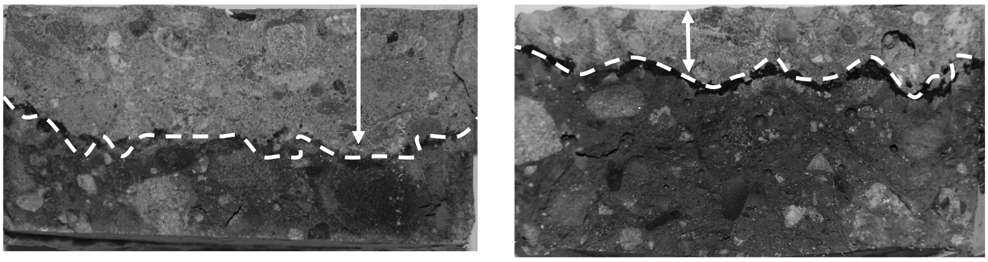


Fig. 2 Example of the depth of chloride ions penetration in concrete series B, without FBCFA and with 30% of FBCFA from lignite

decreased with increased FBCFA content because of the changes in concrete microstructure. The concretes without FBCFA were the ones that showed the highest values of D_{nssm} only acceptable resistance to chloride penetration according to criteria shown in Table 3. In all series of concrete specimens the chloride migration coefficient tested after 90 days showed relative stabilization.

The example of depth of chloride ions penetration in series B (B0 and B30T) tested after 28 days is showed in Fig. 2.

The comparable tests results based on eight concrete mixtures was obtained. The ordinary Portland cement replacement by ground fly ash varied from 0% to 70% in steps of 10%. For high volume fly ash concrete better chloride resistance than in ordinary concrete has been achieved (Sengul *et al.* 2005).

3. Machine learning methods

Data mining can be defined as the process of discovering patterns in a dataset. By a dataset we mean a *database* i.e., collection of logically related records. Each record can be called an *example* or *instance* and each one is characterized by the values of a set of predetermined *attributes*. A few different styles of learning appear in data mining applications but the most common is a *classification*. The aim of the classification process is to learn a way of classifying unseen examples based on the knowledge extracted from the provided set of classified examples. In order to extract the knowledge from the provided dataset the attribute set characterizing the example has to be divided into two groups: the *class* attribute or attributes and the *non-class* attributes. It is obvious that for an unseen examples only *non-class* attributes are known, therefore the aim of data mining algorithms is to build such a knowledge model that allows predicting the example class membership based only on non-class attributes. The knowledge model is dependent on the way how the classifier is constructed and it can be represented by decision trees (e.g. algorithm C4.5) or classification rules (the AQ algorithms family). Regardless of the representation both types of algorithms create hypotheses.

In order to evaluate the classifier i.e., to judge the hypotheses generated from the provided *training set* we have to verify the classifier performance on the independent dataset which is called *testing set*. Of course both sets of training data and test data should be representative samples of the considered problem. The classifier predicts the class of each instance from the test set; if it is correct, that is counted as a success; if not it is an error. In order to measure the overall performance of the classifier some quantitative analysis should be done.

The example of such a quantitative measure are a success rate usually called a *classification accuracy.* This is the number of correct classifications of the instances from the test set divided by the total number of these instances, its measure is expressed as a percentage.

In order to get a deeper understanding which types of errors are the most frequent the result obtained from a test set is often displayed as a two-dimensional *confusion matrix* with a row and a column for each class. Each matrix element shows the number of test examples for which the actual class is the row and the predicted class is the column. Good results correspond to large numbers down the main diagonal and small, ideally zero, off-diagonal elements. The sum of the numbers down the main diagonal divided by the the total number of test examples determine classification accuracy.

Lets consider what can be done when the number of data for training and testing is limited. The simplest way is to reserve a certain number for testing and to use the remainder for training. Of course, the selection should be done randomly. In practical terms, it is common to hold out one-third of the data for testing and use the remaining two-thirds for training (Witten and Frank 2005). The main disadvantage of this simple method is that this random selection may be not representative. A more general way to mitigate any bias caused by the particular sample chosen for holdout is to repeat the whole process, training and testing, several times with different random samples. This process is called the *k-fold cross-validation.* In this technique a fixed number of folds – k is arbitrary described. Then the data set U is split into k approximately equal portions $(U = E_1 \cup \ldots \cup E_k)$ (Krawiec and Stefanowski 2003). In each iteration i the set E_i is used for testing and the remainder $U \setminus E_i$ is used for training.

Overall classification accuracy is calculated as an average from the classification accuracy for each iteration $\eta(E_i)$, i.e., is defined as

$$\overline{\eta} = \frac{1}{k}\sum_{i=1}^{k} \eta(E_i) \tag{2}$$

In order to generate rules describing the concrete resistance to chloride penetration several numerical experiments were performed using program AQ21 and algorithm J48 from the WEKA workbench. Algorithm AQ21, invented in the Machine Learning and Inference Laboratory of George Mason University (Wojtusiak 2004) is based on covering approach alike most of the rule-based data mining algorithms. Therefore, the AQ21 algorithm generates subsequent rules until all the examples (sometimes not all) are covered. The idea of adding a new rule or a new term to existing rule is to include as many instances of the desired class (*positive examples*) as possible and to exclude as many instances of other classes (*negative examples*) as possible.

The second considered algorithm, J48, is available as a part of WEKA workbench, which was developed at the University of Waikato in New Zealand (Witten and Frank 2005). Algorithm J48 is an implementation of the last publicly available version of an algorithm C4.5 devised by J. Ross Quinlan. Construction of decision trees is based on a simple divide and conquer approach, which is well known in computer science. The main problem is connected with a selection of tests (splits of attributes) which should be placed in the nodes. The test is good if it allows to shorten the way from the root to the leaves representing classes. Decision trees can be converted to classification rules with ease.

4. Seeking for the rules describing chloride ions penetration

4.1 Chloride ions penetration after 28 days

4.1.1 Results obtained from AQ21

As the results of the experiments carried on the specimens with different contents of fluidized fly ash, as shown in tables 2 and 4, the following database consisted of 15 records was introduced. This database was used to determine the rules describing the concrete resistance to chloride penetration after 28 days. The database with one nominal and 6 numerical attributes is presented in Table 6 (Marks *et al.* 2009).

where:
*C*1 – cement content, [kg/m^3],
pfT – fluidized fly ash from brown coal content (power plant Turów), [kg/m^3],
pfK – fluidized fly ash from hard coal content (power station Katowice), [kg/m^3],
W – water content, [kg/m^3],
A_fr – air content in fresh mix, [%],
*fc*28 – compressive strength tested after 28 days, [MPa],
Resistance – concrete resistance to chloride ions penetration (Acceptable, Good).

The last attribute – resistance - is a nominal one which takes on two possible values: Acceptable, Good. In the considered database to the class [Resistance=Acceptable] belongs 6 examples and to the class [Resistance=Good] belongs 9 examples.

The aim of an experiment is to generate the rules, which allow us to determine concrete resistance to chloride ions penetration. As an training set all the instances from the database were considered. The rules generated by an AQ21 algorithm are presented below

Table 6 The database

C1	*pfT*	*pfK*	*W*	*A_fr*	*fc*28	Resistance
360	0	0	162	2.1	55.0	Acceptable
306	0	54	162	1.8	56.2	Acceptable
252	0	108	162	1.3	51.6	Good
306	54	0	162	1.6	60.3	Good
252	108	0	162	1.6	58.7	Good
380	0	0	171	6.2	46.3	Acceptable
323	0	57	171	6.8	47.2	Good
266	0	114	171	5.8	46.8	Good
323	57	0	171	6.6	45.3	Acceptable
266	114	0	171	6.2	46.3	Acceptable
406	0	0	175	4.9	22.7	Acceptable
290	73	0	151	6.9	21.0	Good
217	145	0	150	7.8	26.1	Good
323	0	81	167	4.6	38.3	Good
244	0	162	157	4.6	43.0	Good

[Resistance=Good]
  # Rule 1
<-- [pfK>=55] : p=5, n=0, q=0.556

  # Rule 2
<-- [$C1$<=258] : p=4, n=0, q=0.444

  # Rule 3
<-- [pfT>=27] [W<=166] : p=4, n=0, q=0.444 (3)

[Resistance=Acceptable]
  # Rule 1
<-- [pfK<=55] [A_fr=1.7..6.75] : p=6, n=0, q=1

  # Rule 2
<-- [pfK<=55] [$fc28$=44.15..57.45] : p=5, n=0, q=0.833

where p denotes the number of positive examples covered by the rule, n denotes the number of negative examples covered by the rule (i.e., the number of records from the other classes satisfying the rule) and q denotes the quality of the rule.

The rules showed in Eq. (3) can be interpreted as follows but it should be underlined that the presented rules concern concretes with the overall mass of cement and additions equal 360, 380 or 406 [kg/m^3] (Table 2).

[Resistance is **Good**]
IF
[pfK >= 55]
OR
[$C1$ <= 258]
OR
[pfT >= 27] and [W <=166]

[Resistance is **Acceptable**]
IF
[pfK <= 55] and [A_fr = 1.7..6.75]
OR
[pfK <= 55] and [$fc28$ = 44.15..57.45]

In order to evaluate the classifier, i.e., to judge the hypotheses (classification rules, decision trees) generated from the provided training set, we have to verify the classifier performance on the independent testing set. When we have only one database consisting of a very small number of records, the estimation of classification accuracy (measure of the overall performance of the classifier) can be done using the n-fold cross validation, where n is the number of examples in the database (Witten and Frank 2005). In this method each example in turn is left out, and the learning method is trained on all the remaining examples. It is judged by its correctness on the remaining example – one or zero for success or failure, respectively. The results from n judgments, one for each member of the database, are averaged, and that average represents the classification accuracy (Witten and Frank 2005). This method, named *leave-one-out* cross validation, is useful to the database of a very small number of records. It seems to offer a chance of squeezing the maximum out of a small dataset and obtaining as accurate an estimate as possible.

The results from n judgments may be displayed as a two-dimensional confusion matrix with a row and a column for each class. Each confusion matrix element shows the number of test examples for which the actual class is the row and the predicted class is the column. The numbers of examples down main diagonal are predicted correctly. The classification accuracy is the sum of numbers down the main diagonal divided by the total number of data set examples.

Applying the n-fold cross validation for n = 15 (number of examples in Table 6) we obtain a confusion matrix in the following form:

	Acceptable	Good	Other
Acceptable	4	2	0
Good	4	4	1

The value of classification accuracy is equal to 53.3%.

4.1.2 Results obtained from J48

In order to generate the rules, which allow us to determine the concrete resistance against chloride ion penetration the J48 algorithm was also used. As the training set all the instances from the database (Table 6) were considered. The decision tree generated by the J48 algorithm is presented in Fig. 3.
where the first number in brackets denotes the number of examples from the training set covered by a selected leaf, and the second number – just after the sign "/" – indicates the number of incorrectly classified instances (negative examples). When there is only one number in brackets, then it indicates the number of examples correctly classified (positive examples).

The obtained decision tree (Fig. 3) can be easily transformed into the following rules:

[Resistance=Good]
Rule1 [$C1$ <= 323] and [pfK <= 54] and [W <= 162]
Rule2 [$C1$ <= 323] and [pfK > 54] (4)

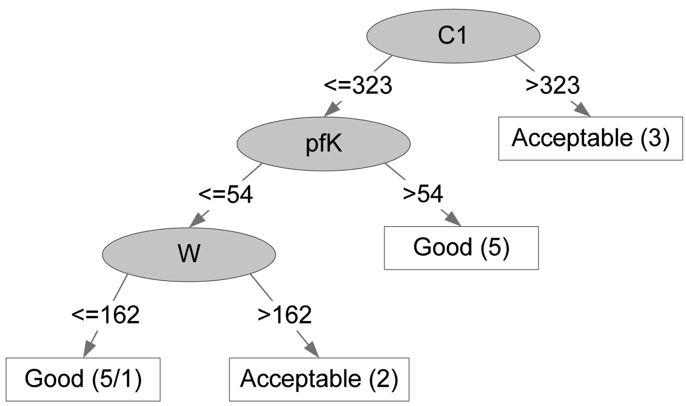


Fig. 3 The decision tree generated by the J48 algorithm for chloride penetration after 28 days

[Resistance=Acceptable]
Rule1 [*C*1 <= 323] and [*pfK* <= 54] and [*W* > 162]
Rule2 [*C*1 > 323]

Using the *n*-fold cross validation for J48 algorithm we obtain the confusion matrix in the following form:

	Acceptable	Good
Acceptable	2	4
Good	2	7

and the classification accuracy equal 60%.

4.2 Chloride ions penetration after 90 days

4.2.1 Results obtained from AQ21

In order to generate rules describing the concrete resistance to chloride penetration after 90 days a database was used, that was very similar to the database shown in Table 6. The first five numerical attributes are identical as in Table 6. The last numerical attribute *fc*90 determines compressive strength tested after 90 days, [MPa]. In the considered database three examples belong to the class [Resistance=Acceptable] and 12 examples belong to the class [Resistance=Good] (Table 7).

As a training set all the instances from the database were considered. The rules generated by an AQ21 algorithm are presented below:

[Resistance=Good]
  # Rule 1
<-- [*C*1<=341] : *p*=12, *n*=0, *q*=1

Table 7 The database

*C*1	*pfT*	*pfK*	*W*	*A_fr*	*fc*90	Resistance
360	0	0	162	2.1	70.0	Acceptable
306	0	54	162	1.8	64.3	Good
252	0	108	162	1.3	61.0	Good
306	54	0	162	1.6	70.4	Good
252	108	0	162	1.6	66.3	Good
380	0	0	171	6.2	49.8	Acceptable
323	0	57	171	6.8	48.4	Good
266	0	114	171	5.8	56.4	Good
323	57	0	171	6.6	50.1	Good
266	114	0	171	6.2	47.7	Good
406	0	0	175	4.9	26.3	Acceptable
290	73	0	151	6.9	23.3	Good
217	145	0	150	7.8	25.3	Good
323	0	81	167	4.6	41.8	Good
244	0	162	157	4.6	43.4	Good

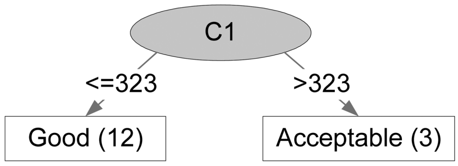


Fig. 4. The decision tree generated by the J48 algorithm for chloride penetration after 90 days

Rule 2
<-- [C1<=351] [fc90<=68.15] : p=11, n=0, q=0.987

[Resistance=Acceptable]
# Rule 1
<-- [C1>=342] : p=3, n=0, q=1

In order to estimate the classification accuracy the n-fold cross validation was used for n =15. The results of this method are described by the following confusion matrix:

	Acceptable	Good
Acceptable	3	0
Good	1	11

Here one example from Acceptable class is classified incorrectly to Good class, the remaining examples are classified correctly and the classification accuracy is equal 93.3%.

4.2.2 Results obtained from J48

In order to generate the rules, which allow us to determine concrete resistance against chloride ions penetration the J48 algorithm was used also. As the training set all the instances from the database (Table 7) were considered. The decision tree generated by an J48 algorithm is presented in Fig. 4.

When n-fold cross validation was used we obtain the following confusion matrix:

	Acceptable	Good
Acceptable	3	0
Good	0	12

and the classification accuracy was equal 100%.

5. Conclusions

The rules generated by computer programs AQ21 and WEKA using J48 algorithm have provided means for automatic categorization of plain concretes and concretes modified with CFBC fly ash as materials of good or acceptable resistance to chloride penetration. Due to a small number of tested specimens the rules are applicable only to concrete mix compositions with similar binder content and similar values of water to cement ratio.

The rules describing the concrete resistance to chloride penetration after 90 days, which were determined by AQ21 algorithm as well by J48 algorithm, are similar. According to generated rules, resistance was qualified as acceptable for tested concrete without fluidized fly ash, whereas resistance was good for the same concrete with replacement of cement mass from 15% to 40% by fluidized fly ash from hard coal or brown coal. Therefore, application of CFBC fly ash improved the resistance of concrete in respect to chloride penetration.

Application of AQ21 and WEKA programs provided similar estimation of the concrete resistance to chloride ion penetration. Further tests are needed in order to enlarge the experimental data basis and to cover larger variety of concrete compositions.

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