OPTIMIZATION OF AGGREGATE TESTING USING POLYNOMIAL REGRESSION

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ABSTRACT

Recycled Aggregate (RA) has only been used as sub-grade applications, roadwork and unbound materials because it is believed that RA has lower strength and poorer quality than normal aggregate. This paper assesses RA quality by proposing a new testing procedure. The new procedure is developed by using correlation information among the standard twenty three tests commonly employed in the construction industry. Samples of RA from ten demolition sites were obtained with service life ranging from ten to forty years. One additional set of samples was specifically collected from the Tuen Mun Area 38 Recycling Plant, Hong Kong for testing. The characteristics of these eleven sets of samples were then compared with normal aggregate samples. A Vandermonde matrix for interpolation polynomials coefficient estimation is employed to yield detailed mathematical relationships between results of two particular tests, from that redundant tests can be identified. Different orders of interpolation polynomials are used for comparison, hence the best-fit equations with lowest fitting errors from different orders of polynomials can be found. This paper shows that four out of twenty three tests are required in the new testing procedure.

KEYWORDS

Recycled aggregate, concrete, correlation, property, porosity, strength, construction.

INTRODUCTION

Until recently almost all demolished concrete was thrown away and there is a shortage of landfill areas. Concrete is such an essential, mass-produced material in the construction industry, much effort has been made to recycle and conserve resources. Completed and repeated recycling can be suitable for concrete, as is the case for steel and aluminum (Noguchi and Tamura, 2001). Since concrete composes only of cementitious materials, and the powders generated during the RA production can be reused as cement resources, this permits repeated recycling. This also enables concrete to be recycled in a fully closed system, thus enhancing the benefit to the environment. Concrete recycling can be accomplished by converting them into secondary raw materials for filling, road bases and sub bases, or aggregate for the production of new concrete (Howard Humphreys and Partners, 1994, Torring, 2000).

Aggregate occupies the major part of concrete volume which thus significantly affects concrete properties (Mindess *et al.*, 2003, Troxell and Davis, 1968). Three general requirements should be considered when choosing aggregate: concrete economy, concrete strength, and concrete durability (Troxell and Davis, 1968). As RA has a high porosity, it is more subject to deformation and mechanically less resistant than the cement matrix coating after sufficient hardening time (Maso, 1996). A review on several studies (Cheung, 2003, Hassan *et al.*, 2000, Mehta and Monteiro, 1993, Poon *et al.*, 2003, Reusser, 1994) indicated that compared with concrete containing natural aggregate, recycled aggregate concrete could have at least two thirds of the compressive strength and modulus of elasticity, hence meeting workability and durability standards. A major obstacle in the way of using demolished concrete waste as aggregate for concrete is the cost of crushing, grading, dust controlling and separation of undesirable constituents. Crushed recycled concrete or waste concrete can be an economical aggregate source which is difficult to find, and is also important when waste disposal is increasingly becoming more costly (Mehta and Monteiro, 1993).

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RESEARCH OBJECTIVES

This paper aims to achieve the following objectives:

1. Investigating aggregate properties using twenty three standard tests. Eleven RA samples collected from demolished sites and natural aggregate are used in this study;
2. Using ten different polynomial orders to interpolate RA test results. The effectiveness of the interpolation method is determined by estimating their fitting errors;
3. Proposing a new testing procedure for RA.

AGGREGATE TESTING

Aggregate quality is assessed by using twenty three standard tests.

Test 1: Sieve analysis (10mm)

Test 2: Sieve analysis (20mm)

Test 3: Oven-dried basis of particle density (10mm)

Test 4: Oven-dried basis of particle density (20mm)

Test 5: Saturated and surface dried basis of particle density (10mm)

Test 6: Saturated and surface dried basis of particle density (20mm)

Test 7: Apparent particle density (10mm)

Test 8: Apparent particle density (20mm)

Test 9: Water absorption (10mm)

Test 10: Saturated time (10mm)

Test 11: Water absorption (20mm)

Test 12: Saturated time (20mm)

Test 13: Moisture content (10mm)

Test 14: Moisture content (20mm)

Test 15: Flakiness index (10mm)

Test 16: Flakiness index (20mm)

Test 17: Elongation index (10mm)

Test 18: Elongation index (20mm)

Test 19: Ten percent fine value (TFV)

Test 20: Aggregate impact value (AIV)

Test 21: Chloride content (10mm)

Test 22: Chloride content (20mm)

Test 23: Sulphate content

British standards are used for testing these aggregate properties (BS 812: Part 2, 1995, BS 812: Part 105.1, 1989, BS 812: Part 105.2, 1989, BS 812: Part 109, 1990, BS 812: Part 111, 1990, BS 812: Part 112, 1990, BS 812: Part 117, 1988, BS 882, 1992).

POLYNOMIAL REGRESSION

Interpolation using polynomial fitting or polynomial regression is a technique which uses polynomials of order up to 20 to fit a given set of data. This technique is well known because it is much better than the linear regression method of simply assigning the "line of best fit" to the data. Given a dataset in the form of $x(1)$, $x(2)$,..., $x(N)$, with values of $y(1)$, $y(2)$,..., $y(N)$, where N is the data length. The coefficients c_1, c_2, ..., c_N of the interpolating polynomial which can be used to "best fit" the data relate the input x to the output y via the Vandermonde matrix of the form (Press *et al.*, 1994).

$$\begin{bmatrix} 1 & x_0 & x_0^2 & \dots & x_0^{N-1} \\ 1 & x_1 & x_1^2 & \dots & x_1^{N-1} \\ \dots & \dots & \dots & \dots & \dots \\ 1 & x_N & x_N^2 & \dots & x_N^{N-1} \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ \dots \\ c_N \end{bmatrix} = \begin{bmatrix} y_0 \\ y_1 \\ \dots \\ y_N \end{bmatrix} \quad (1)$$

where the c matrix consists of polynomial coefficients. It should be stressed that the c matrix does not always exist; prompting that extra care must be taken when using the technique to interpolate different datasets. This also means that polynomial regression does not always work for a given dataset which shows the important role of the data nature. In this case, even though there are some abrupt changes in the dataset, it will be shown that polynomial regression yields positive outcomes.

Having obtained the c matrix, the interpolating polynomial is thus given by:

$$y_{\text{interpolate}} = c_N x^N + c_{N-1} x^{N-1} + \dots + c_1 x + c_0, \quad (2)$$

which can be used to mathematically model the given data. It should also be noted that $y_{\text{interpolate}}$ generally resembles the shape of the fitted data. However, sometimes, it is difficult to find all the coefficients for a particular data set. Thus, if the method is applicable to a set of data, then the process of studying and simulating the data becomes much easier and less time consuming as $y_{\text{interpolate}}$ can now be validly used. How-

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ever, no numerical methods can completely simulate a given dataset, thus, there exists some marginal curve-fitting errors which generally do not significantly alter the results obtained by analysing $y_{\text{interpolate}}$. Even though interpolation has been widely used in the field of signal and image processing (Press *et al.*, 1994), they have not been widely used in the field of construction material and management to process data and to study their correlation. Thus, one of the main aims of this paper is to show that these techniques can be successfully employed to study RA and to simplify aggregate testing procedures.

In this paper, there are twenty three tests which can be used as outputs for the interpolation. However, the first two tests do not have numerical results, leaving only tests 3 to 23 applicable for polynomial regressions. Results of tests 3 to 23 are used as inputs with results of the other tests as outputs to obtain their mathematical relationships. For example, the first patch of interpolation uses the results of test 3 as the inputs, thus results of tests 4 to 23 are used as the outputs. Consequently, the relationships between results of test pairs 4 and 3, 5 and 3, 6 and 3 and so on until the last pair of tests 23 and 3 are obtained. In the second patch of interpolation, results of test 4 are used as the inputs and results of tests 5, 6, 7 until 23 as the outputs. The interpolation process continues until results of test 22 are taken as the inputs and results of test 23 as the outputs, in this case, there is only one pair of input and output in the polynomial regression patch. At the end of the whole polynomial regression process, using one order, there are 210 equations describing the mathematical relationships among all test results, i.e. results of every test are interpolated with those of every other test, and therefore it is not difficult to estimate the results of a particular test using one of the many equations obtained from the interpolation process. In this paper, ten different order polynomials are used to interpolate the data, yielding 2,100 equations relating all test results. The challenge in this case is to choose the best polynomials with the lowest fitting errors. For example, by using results of test 3 as the inputs and results of test 4 as the outputs, results of test 4 can be approximately estimated by using the results of test 3. Because there are ten different polynomial orders, there exist ten different mathematical equations which can be used to estimate the results of test 4. The same process is carried out for all tests using all polynomial orders, yielding a total of 210 equations of different orders which can be chosen as the best-fit polynomials because of their lowest fitting errors. It is clear that the more polynomials the interpolation process uses, the easier it is to simplify aggregate testing procedures as there is more than one equation relating results of particular inputs to particular outputs. The effectiveness of a polynomial is assessed based on its fitting error. It is thus clear that the smaller the error the better the estimation.

The interpolating polynomials can be implemented in MATLAB via the command polyfit. The order of the polynomials is considered to be an important parameter as the higher the polynomial order, the more difficult it is to avoid over-fitting as noted earlier. However, high-order polynomial fitting can be more effective for datasets with abrupt changes than the lower orders. Thus, in this initial study, low and high polynomial orders from 1 to 10 are employed to detect all salient features in the data. For this particular dataset, polynomial orders of one to ten are used to thoroughly study the effectiveness of polynomial regression.

ANALYSIS

Ten series of RA samples (Samples 1 to 10) were obtained from ten demolition sites with service life ranging from ten to forty years. Sample 11 was specifically collected from the Tuen Mun Area 38 Recycling Plant which is located at the boundary between Mainland China and Hong Kong. Tuen Mun Area 38 recycling plant is situated next to a landfill which makes it easier to access all types of construction and demolition waste (Tam and Le, 2007a; 2007b). Samples 1 to 11 are compared with normal aggregate which is Sample 12. The results of 23 tests for Samples 1 to 12 are summarized in Table 1.

Since the strength of fully compacted concrete with a given water to cement ratio is independent of aggregate grading, sieve analysis (Tests 1 and 2) is important only if it affects fresh concrete workability (Neville, 1995). From Table 1, Samples 1 to 12 have met the sieve analysis requirement of being 10mm and 20mm aggregate.

Aggregate particle density (Tests 3 to 8) is the ratio of the mass of a given volume of material to the mass

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TABLE 1. Results from Samples 1 to 12

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7	Sample 8	Sample 9	Sample 10	Sample 11	Sample 12
Test 1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
Test 2	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
Test 3	2.16	2.22	2.20	2.20	2.15	2.25	2.11	2.10	2.21	2.20	2.46	2.59
Test 4	2.20	2.14	2.18	2.20	2.19	2.27	2.13	2.12	2.24	2.23	2.53	2.62
Test 5	2.33	2.38	2.36	2.37	2.32	2.41	2.31	2.30	2.37	2.36	2.53	2.62
Test 6	2.36	2.32	2.35	2.36	2.34	2.42	2.31	2.31	2.39	2.36	2.58	2.64
Test 7	2.60	2.64	2.62	2.65	2.59	2.66	2.61	2.62	2.64	2.60	2.65	2.67
Test 8	2.61	2.61	2.63	2.63	2.59	2.67	2.60	2.61	2.63	2.57	2.66	2.66
Test 9	5.83	6.36	7.50	6.93	7.31	5.20	8.74	8.58	6.94	6.85	2.63	0.77
Test 10	96	85	115	120	124	117	120	119	127	100	24	24
Test 11	6.89	6.40	7.35	7.25	6.82	5.77	7.30	7.99	6.11	5.95	1.65	0.57
Test 12	91	82	122	120	108	116	122	102	118	77	24	24
Test 13	1.01	1.05	1.35	1.25	1.25	0.98	1.02	1.63	1.24	1.26	0.49	0.15
Test 14	1.24	1.21	1.35	1.35	1.25	0.97	0.95	1.35	0.84	1.42	0.33	0.15
Test 15	11.13	10.44	15.17	15.42	17.82	11.96	12.86	15.12	13.78	16.47	25.97	28.27
Test 16	9.68	10.08	8.61	7.91	12.96	9.93	5.70	9.78	12.17	9.92	29.52	22.52
Test 17	29.00	24.18	20.99	27.29	36.13	26.43	21.56	27.41	21.92	30.46	34.62	28.20
Test 18	16.19	25.15	22.78	24.05	23.86	21.91	22.18	28.26	18.25	21.09	33.76	26.01
Test 19	93.89	61.36	107.42	112.82	92.09	155.53	110.18	83.48	92.87	89.91	102.97	189.38
Test 20	33	36	31	23	32	25	30	34	36	28	33	21
Test 21	0.0078	0.0108	0.0013	0.0019	0.0054	0.0008	0.0976	0.0013	0.0459	0.0494	0.0021	0.0012
Test 22	0.0089	0.0091	0.0019	0.0019	0.0061	0.0025	0.0902	0.0014	0.0352	0.0430	0.0070	0.0016
Test 23	0.031	0.017	0.005	0.005	0.006	0.0006	0.013	0.005	0.024	0.018	0.008	0.003

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of same volume of water (BS 812: Part 2, 1995). Aggregate particle density usually is an essential property for concrete mix design and also for calculating the concrete volume produced from a certain mass of materials (Hewlett, 1998). Density of cement mortar of around 1.0-1.6 Mg/m^3 is less than that of stone particles of about 2.60 Mg/m^3 (Oklahoma State University, 2006), the smaller the particle density, the higher the cement mortar content adhering to the RA. From Table 1, Samples 7 and 8 have the lowest values of particle density, inferring the highest amount of cement mortar adhering to RA, while Sample 12 (normal aggregate) has the highest particle density. Furthermore, particle densities of 20mm aggregate are larger than those of 10mm aggregate, inferring a higher amount of cement mortar attached to the 10mm aggregate. This also implies that the larger the aggregate size, the smaller the amount of cement mortar attached to its surface, yielding better aggregate quality.

The overall aggregate porosity or absorption either depends on a consistent degree of particle porosity or represents an average value for a mixture of variously high and low absorption materials (Hewlett, 1998). In this study, Tests 9 to 14 are used to assess the level of porosity and absorption of the samples. The RA water absorption and moisture content (Samples 1 to 11) are generally higher than that of normal aggregate (Sample 12) (see Table 1). 10mm aggregate of Sample 7 exhibits the highest water absorption rate and moisture content of about 9.06 and 1.70 respectively, and 20mm aggregate from Sample 12 has the lowest water absorption rate and moisture content of about 0.53 and 0.15 respectively. One of the most obvious attributes between RA and normal aggregate is the higher water absorption rate and moisture content of RA, which are affected by the amount of cement paste sticking on the aggregate surface. Cement mortar describes the soundness of aggregate since its porosity is higher than that of aggregate, i.e. RA with higher absorption rate tends to be worsened in strength and resistance under freezing and thawing conditions [18-20] than aggregate with a lower absorption rate. In most samples, the water absorption rate of 20mm aggregate is less than that of 10mm aggregate, inferring that larger size aggregate may have less cement mortar adhered to its surface, leading to a lower water absorption rate as explained in the last section.

Aggregate particle shape (Tests 15 to 18) can affect concrete strength and workability (Hewlett, 1998). The shape can be described in using two main principal parameters: 'sphericity' and 'roundness'. Aggregate particles are classified as flaky when they have a thickness (smaller dimension) of less than 0.6 of their mean sieve size. Aggregate particles are classified as elongated when they have a length (greatest dimension) of more than 1.8 of their mean sieve size (BS 812: Part 105.2, 1989). BS 882 (BS 882, 1992) limits the flakiness index determined in accordance with BS 812: Part 105:1 (BS 812: Part 105.1, 1989) to about 50 percent for uncrushed gravel and 40 percent for crushed rock or crushed gravel, with a warning that lower values may have to be specified for special circumstances such as pavement wearing surfaces. All the twelve samples in this study have a flakiness index lower than 40%.

In most cases, inherent aggregate strength is dependent upon aggregate 'toughness', a property broadly analogous to 'impact strength'. Tests 19 and 20 are used to determine the strength and toughness of the twelve samples. The TFV measures the aggregate resistance to crushing which is applicable to both weak and strong aggregate (BS 812: Part 111, 1990), the larger the TFV value, the more resistant the aggregate to crushing (Hewlett, 1998). The AIV relatively measures the aggregate resistance to sudden shock or impact, which in some aggregate is different from its resistance to a slowly applied compressive load (BS 812: Part 112, 1990). The smaller the AIV value, the tougher the aggregate or more impact resistant than higher strength concrete aggregate (Hewlett, 1998). Out of the twelve samples, Sample 12 (ordinary aggregate) has the highest value of TFV and the lowest value of AIV at about 189kN and 21% respectively; while Sample 2 achieves the lowest value of TFV and the highest value of AIV at about 61kN and 36% respectively (see Table 1). The obvious reason is that the cement paste attached to the RA directly affecting the aggregate strength.

RA chloride and sulphate contents (Tests 21 to 23) are critical. Chloride contamination of RA mainly derived from marine structures or similarly exposed structural element is of concern which can lead to corrosion of steel reinforcement. However, for most RA (Samples 1 to 6 and 8 to 12), the chloride ion contents are low and within the limit of standards

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(under 0.05%). Nevertheless, Sample 7 falls beyond the limit with chloride contents of about 0.0976% and 0.0902% for 10mm and 20mm aggregate respectively (see Table 1). From further investigation of the RA of Sample 7, some shell (from fine marine aggregate) contents were found. The major reason may be the use of marine water or stream water for concrete mixing during periods of shortage of fresh water supply in the 1960s, which has been banned since 1970s. This could have increased the chloride composition in the sample. In general, RA has higher sulphate content than natural aggregate. The occurrence of sulphate-based products such as plaster as contaminants in demolition waste is common. Consideration must be given to the use of sulphate resisting cement in situation where plaster contamination is suspected (Crentsil and Brown, 1998). However, gypsum plaster is rarely used in Hong Kong where lime plaster is more common. In fact, the highest recorded sulphate content is about 0.0308% for Sample 1, which is still within the standard of 1% (see Table 1). Therefore, contamination of sulphate content is not a major problem for RA.

It is clear that the more tests being conducted, the more costly aggregate testing. Thus, one of the main aims of this paper is to reduce the number of tests which is currently 23, out of which 21 give numerical results, to improve aggregate testing efficiency. To achieve that, one possible way is to accurately relate the results of one or a number of tests to results of the other tests using polynomial regression. Polynomial fitting of test results (outputs) based on the results of a particular test (inputs) can be achieved by using an appropriate polynomial order. Generally, the higher the polynomial order, the better the fitting. However, it is not always the case if there are abrupt changes in the outputs because a very high-order polynomial is required, which is not practical if the order is larger than the upper limit of twenty given in MATLAB. Thus, care must be taken to choose the appropriate polynomial order, otherwise large errors can be generated. In this paper, polynomials of orders one to ten have been chosen to model the test results. As a result, two thousand and one hundred equations can be generated from the interpolation process. The fitting errors of all orders are given in Figure 1 to assess the effectiveness and validity of each polynomial order. Simulation results show that the errors for tests 3 to 20 are mostly acceptable with the maximum errors lower than the chosen error limit of 15%.

From the results obtained in this paper, the tests can be divided into two major groups: group 1 consists of tests 3 to 20, and group two consists of tests 21 to 23. It is clear that the tests in group one are strongly correlated. This means that the results of any test in this group can be successfully estimated by using the results of another test from the same group. The error percentage of the first test group is satisfactory. However, there are a small number of tests possessing errors of more than 15% with some particular tests, which do not affect the findings of this paper since there is more than one mathematical expression describing them.

It should also be noted that there are some satisfactory relationships among the three tests in the second test group (tests 21 to 23). However, most equations in this group have large fitting errors which suggest that they are poorly correlated.. Thus, the results of the first test group should not be used to estimate the results of the second test group. Thus, two tests out of tests 3 to 23 are required instead of 21 tests being routinely conducted in the industry. In addition to tests 1 and 2, in total, there are four tests which are required to be conducted. It should be noted that tests 1 and 2 are not applicable to the interpolation process as they do not have numerical results. It should also be noted that out of tests 3 to 23, the results of one of these tests are required which provide the flexibility in conducting the test depending on the conditions and

FIGURE 1. Normalised average error matrix of all tests with orders 1 to 10.

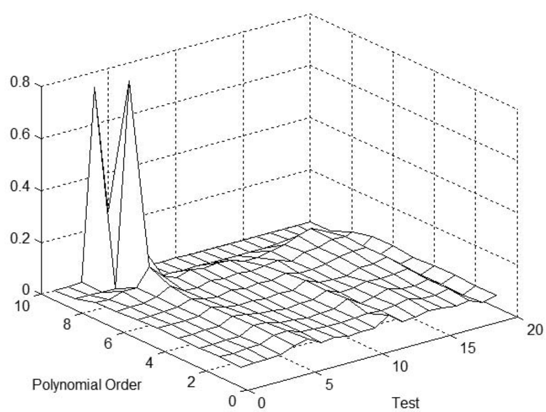

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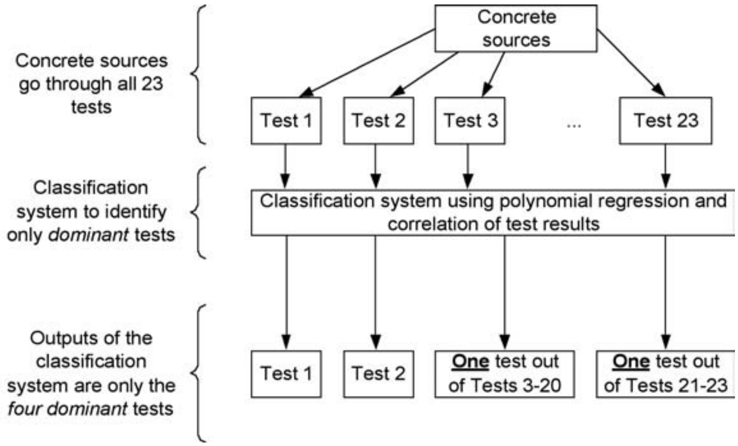
FIGURE 2. New procedure for testing RA.



available equipment. Thus, the findings in this paper offer flexibility and significant efficiency improvement in aggregate testing. As construction sites in Hong Kong are limited in size, eliminating redundant tests significantly lowers cost and shortens aggregate testing time, yielding more efficient space usage on site and many other benefits for the construction industry. Figure 2 gives an overview on RA testing using the normal and simplified procedures.

From Figure 2, it is clear that the number of tests is reduced from 23 to 4. Traditionally, RA samples have to undergo all tests. By using polynomial regression to study correlation among the test results, redundant tests can be identified. This means that after performing polynomial regression, it is possible to shorten the testing procedure. It should be noted that even though, 4 out of 23 tests are required to study RA properties, the selection of which tests is crucial. Figure 2 shows two possible choices: (1) One test out of Tests 3 to 20, and (2) One test out of Tests 21 to 23. Depending on a particular application, then particular tests in the test groups 3 to 20 and 21 to 23 are chosen.

To assess the effectiveness of the polynomial regression process, fitting errors of orders one to ten are estimated and plotted in Figure 3 and Figure 4 which give more insight to the effectiveness of all polynomial orders.

From Figure 3 and Figure 4, it is clear that the fitting errors of all orders vary uniformly among the tests. It should also be clear that for orders one to seven, the errors are more uniformly distributed than those of orders eight to ten, suggesting that high-order polynomials are not suitable for modeling the data in this case. This is evidently reflected by having large "harmonic" spikes in which it is clear that orders seven and eight yield the smallest fitting errors. In addition, it is also clear that the eighth-order polynomial possesses smaller fitting errors than those of the seventh-order, suggesting that the former may be a better choice to model the given data. However, one major advantage of the seventh-order polynomial over the eighth-order polynomial is that the errors of the former are more uniformly distributed which means that by using the seventh-order polynomial for the interpolation process, it is possible to roughly predict the fitting errors for different test inputs. The eighth-order polynomial possesses smaller fitting errors for test inputs 3, 4, 6, 14, 15, 17, 21 and 22, and

FIGURE 3. Normalised error matrix of all tests with orders 1 to 8.

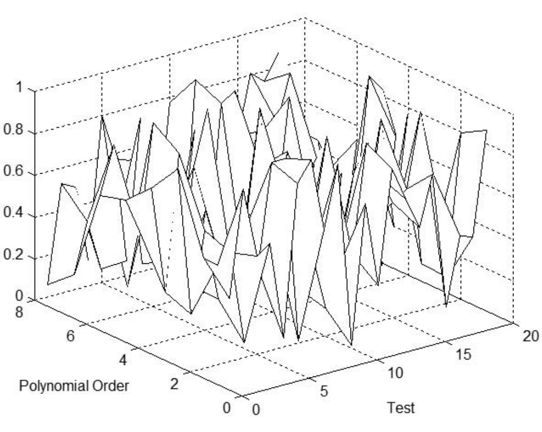


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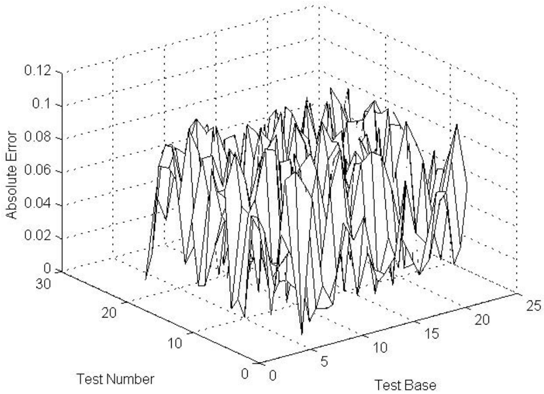
FIGURE 4. Error matrix of all tests with order 9.



larger errors for test inputs 7, 8 (apparent particle density), 10 (absorption time), 13 (moisture contents) and 19 (TFV) in which for test input 7, there is a sudden jump in the fitting error which suggests that the eighth-order is more unstable and unpredictable than the seventh-order. Further, it gave higher fitting errors for test input 19 which is an important test and should be accurately modeled. However, it should not be forgotten that the eighth-order polynomial does give smaller fitting errors at some other test inputs suggesting that it is also a useful polynomial for the interpolation process in this case. Thus, there exists a trade-off between unpredictability and error size at particular important tests. By considering all aspects of the seventh- and eighth-order polynomials, it can be suggested that the seventh-order is more suitable for this dataset. Apart from the seventh- and eighth-order polynomials, other smaller orders give fine results but with larger average errors. The ninth- and tenth-order polynomials possess larger fitting errors and thus they should not be employed for the interpolation process in this case. At this point, the answer to the question raised in Section 4 is due to the large fitting error generated by orders 9 and 10. Thus, it is recalled that orders seven or below should be used for the interpolation process to study the data presented in Figure 3.

CONCLUSION

By proposing a simpler RA testing procedure, this paper has shown that it is possible to further improve RA quality by using the polynomial regression technique. To widely propose RA for structural applications, it is important to improve its strength and quality. By saying that, it is essential to carefully assess RA properties such as particle density, porosity and absorption, particle shape, strength and toughness, and chemical composition. Sieve analysis is also important to improve concrete workability. It has been found that there is strong correlation among some of the parameters which can be used to simplify aggregate testing processes. From the findings in this paper, it has been shown that Tests 1, 2, one test out of Tests 3 to 20, and one test out of Tests 21 to 23 are required in the new RA testing procedure. Out of the ten polynomial orders, order seven has the smallest fitting errors for the given dataset. This paper has shown that polynomial regression can be successfully used to process data in the field of construction material and management.

REFERENCES

BS 812: Part 2 (1995) Methods for determination of density. British Standards Institution, London, United Kingdom.

BS 812: Part 105.1 (1989) Flakiness index. British Standards Institution, London, United Kingdom.

BS 812: Part 105.2 (1989) Elongation index of coarse aggregate. British Standards Institution, London, United Kingdom.

BS 812: Part 109 (1990) Method for determination of moisture content. British Standards Institution, London, United Kingdom.

BS 812: Part 111 (1990) Methods for determination of ten per cent fines value (TFV). British Standards Institution, London, United Kingdom.

BS 812: Part 112 (1990) Methods for determination of aggregate impact value (AIV). British Standards Institution, London, United Kingdom.

BS 812: Part 117 (1988) Methods for determination of water-soluble chloride salts. British Standards Institution, London, United Kingdom

BS 882 (1992) Specification for aggregates from natural sources for concrete. British Standards Institution, London, United Kingdom.

Cheung, H K (2003) Use of recycled asphalt pavement—a practical approach to asphalt recycling, Materials Science and Technology in Engineering Conference: Now, New and Next, 15-17 January 2003.

Crentsil, K S and Brown, T (1998) Guide for specification of recycled concrete aggregate (RCA) for concrete production: final report, From Victoria, http://www.ecorecycle.vic.gov.au/asset/1/upload/Guide_for_Specification_of_Recycled_Concrete_Aggregates_(RCA).pdf

Hassan, K E, Brooks, J J and Erdman, M (2000) The use of reclaimed asphalt pavement aggregates in concrete, Waste Materials in Construction: WASCON 2000: Proceedings of the International Conference on the Science and Engineering of Recycling for Environmental Protection, Harrogate, England, 31May, 1-2 June 2000, 121-128.

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Hewlett, P C (1998) Lea's chemistry of cement and concrete. London: Arnold

Howard Humphreys and Partners (1994) Managing demolition and construction wastes: report of the study on the recycling of demolition and construction wastes in the UK. London: HMSO

Mehta, P K and Monteiro, J M (1993) Concrete: structure, properties, and materials.

Mindess, S, Young, F and Darwin, D (2003) Concrete. Upper Saddle River, NJ: Prentice Hall.

Neville, A M (1995) Properties of concrete. Burnt Mill, Harlow, Essex; New York, Longman.

Noguchi, T and Tamura, M (2001) 'Concrete design towards complete recycling'. Structural Concrete, 3(2); 155-167.

Oklahoma State University (2006) Recycled Aggregate, From http://osu.okstate.edu/

Poon, C S, Azhar, S and Kou, S C (2003) Recycled aggregates for concrete applications, Materials Science and Technology in Engineering Conference—Now, New and Next, 15-17 January 2003.

Press, W H, Teukolsky, S A, Vetterling, W T and Flannery, B P (1994) Numerical Recipes in C. Cambridge University Press.

Reusser, R R (1994) Recycling portland cement concrete pavement at the contractor's option, Aviation crossroads: challenges in a changing world: proceedings of the 23rd air transport conference, Arlington, Virginia, 22-24 June 1994, 86-91.

Tam, W Y V and Le, K N (2007a) 'Aggregate testing using second-, seventh- and tenth-order interpolation polynomials'. Resources, Conservation and Recycling, In Press, Accepted on 14 February 2007.

Tam, W Y V and Le, K N (2007b) 'Optimal aggregate testing using Vandermonde polynomials and spectral methods'. Journal of Hazardous Materials, In Press, Accepted on 1 November 2006.

Troxell, G E and Davis, H E (1968) Composition and properties of concrete. New York: McGraw-Hill.

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