MODELING OF SLUMP VALUE AND DETERMINATION OF INFLUENTIAL VARIABLES WITH REGRESSION APPROACH

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ABSTRACT

There are many factors underlying the instability of the consistency of the concrete mixture. The consistency of the concrete mixture was measured using a slump test. Slump tests are commonly used in measuring the quality of fresh concrete. The instability of the slump value becomes an unsolved problem. To facilitate predicting slump values, modeling is needed to reduce variations in concrete job mix. Regression has been known as the basic method of predictive modeling. Collected data is divided according to the ratio of sand to: <38%, 38-44% and > 44%. The sand ratio data <38% is the most suitable model, because it has a value of R2 0.957, adj. R2 0.897 and MSE 0.31. The most influential variable is water and sand. The resulting modeling is adjusted to the range of data collected.

Keywords : slump, flexibility, consistency, regression, prediction, quality management

1. INTRODUCTION

Concrete is composite building material which adjustable character. Must be considered, the main properties of concrete are strength, workability and durability. Determining the nature of concrete can effect the proportion of material. Proportion of material based on structural requirement and construction conditions such as: ambient temperature, construction methods. Error measuring material proportions can cause concrete mixture problems such as: segregation, bleeding, less density (honeycomb), cracks, etc. The main material of concrete is paste as a binder and aggregate as a filler. Pasta is formed from water and cement, while the aggregates are sand and gravel. Other materials used to enrich the concrete properties are admixture and additive. Things to keep in mind, the more complex the materials used, control of concrete quality increasingly difficult.

The mixture result from batch to batch can be different (Murdock, 1986) [1]. There are many factors that affect for example: material especially water calculations, different material sources, material availability and way of storage, and etc. Management of concrete production supervision should be done carefully. As stated by JIS in JSCE, 2010 that the search process of concrete mixtures was carried out with several adjustment [2]. The adjustment are the amount of water, the amount of cement, the percentage of sand and the amount of additional material. Fine mixture resulted by tested the quality of concrete.

Concrete quality problems also occur when fresh concrete is transported from batchingplant to site. Changing ambient temperature, transit time, poor management in the field such as damaged pouring equipment or other things, can reduce the quality of fresh concrete. Fresh concrete can lose plasticity when not immediately poured. Murdock states that it is necessary to test the consistency of concrete to maintain workability. However, repeated testing procedures can interfere with the concrete production process. Inconsistent consistency values attract some researchers to examine modeling in helping determine the value of slump.

Previous research uses several methods, namely: regression, Artificial Neural Network (ANN), Group Data Handling Algorithm (GDMH), Partial Least Square (PLS), Least Square-Support Vector Regression (LS-SVR). The most common method is backpropagation ANN. All research that has been done is only looking for modeling that is accurate in predicting slump values.

This study will predict the slump value by multiple linear regression methods. This method was chosen because it is a basic method of prediction in statistics. The variables included are: cement, water, sand, 5-10mm gravel, 10-20mm gravel, 20-30mm gravel, rock dust, fly ash, retarder and superplatisizer. Varying compressive strenghts from BO, K-125, K-175, K-225, K-250, K-275, K-300, K-350, K-400, K-450 to K-500 used in this research. Data was obtained from several batchingplant in Malang and one batchingplant from Blitar. The final product of this study is to get the appropriate model in predicting the slump and the most influential predictor variable on the value of slump. This study is expected to facilitate the management of concrete quality later.

2. LITERATURE REVIEW

2.1. Workability

Workability means that it is easy to do. Fresh concrete is expected to be easily moved, transported, poured, filled in the mold. Concrete must be able to flow well to the corners of the formwork, fill it perfectly and tightly without holes. When fresh concrete is worked, the mixture is still homogeneous, coherent and stable when worked and easily compacted. So fresh concrete must be easily mobilized, compacted and have the right consistency to easily fill the mold well.

Concrete production that has consistent workability is an indication of good concrete quality management. Good performance will produce concrete with good standard deviation of compressive strength.

2.2. Slump Test

The slump value in the field cannot be closely monitored as in laboratory production (SNI 1972: 2008) [3]. Slump value has several classifications as in **Table 1**. Slump test results can be wrong if the testing process is not according to the procedure. The process of inserting concrete in an abrasive cone until stabbing and removal of the mold must be done well, should not be more than 5 seconds and must be straight.

Table 1. Workability Classsification

Slump value	Workability	Function
0-25 mm	Dry	Road construction
10-40 mm	Low	Low streght foundation
50-90 mm	Medium	Normal concrete
>100 mm	High	

(Lyons, 2014) [4]

2.3. Influental Variable to Slump Value

In his research, Kardiyono referred to changes in the value of slump according to the amount of water, the ratio of aggregate cement, water-cement ratio and aggregate properties (Tjokrodimuljo, 1998) [5]. Based on Pielert, 2006, the value of slump depends on the number and type of cement, consistency, sand gradient, sand form, gradient and gravel shape, additional material, air percentage, number and characteristics of additional materials, quantity and characteristics of materials and transit time [6]

2.4. Regression

Regression analysis was chosen because multiple linear regression is the basic method of prediction in statistics. The stages of testing are carried out in 3 phases, namely:

- Test linearity using scatter diagrams that are useful for viewing data distribution.
- Classic assumption test in the form of: multicollinearity test, non autocorrelation test, non heteroscedasticity test and normality test which is useful to see the suitability of the data.
- Regression test to find the most appropriate modeling of slump values and determine the most influential predictor variables on the value of slump.

The linear regression equation is:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta nXn \quad (1)$$

The hypothesis of the regression model uses p-value

H0: $\beta j = 0$

H1: $\beta j \neq 0$

- α <0.05 then H0 is rejected if H1 $\neq$ 0 then the coefficient X contributes
- α> 0.05 then H0 is not rejected, even though H1 $\neq$ 0 X coefficient does not have a significant contribution to Y

The selection of regression is best sought by looking for the values the highest R^2 and adj. R^2 and its accuracy are validated in the diagram and the MSE value. The influential variable is obtained from the standard coefficient value with p-value <0.05.

3. RESEARCH METHODOLOGY

3.1. Research concept

Ideally the value of the slump must be stable starting from batching, mixing, transporting to pouring. The consistency of the concrete mixture can change due to the temperature and transit time in the site. The rotation of the mixer truck restrain hardening, but the nature of the plasticity will decrease. Therefore, modeling to predict slump values can be used to minimize the trial and error process when making job mix proportions. Appropriate modeling can be used to predict the value of the concrete mix slump as a form of quality management supervision.

3.2. Research Flow

This study produces appropriate modeling and the variables that most influence the slump value. Output is obtained by analyzing primary data in two stages, there is: test assumptions and regression analysis. Test assumptions are useful for verifying data, so that the resulting regression modeling is not biased. The second processing is regression analysis to get the appropriate prediction model and most influential variable. The appropriate model is selected from the highest R^2 and adj. R2 value and also the smallest Mse value and diagram. The output regression analysis not only R^2 but also standard coefficients for each predictor variable. The standard coefficient that have p-value <0.05 indicates that the variable has a significant effect on the value of slump.

4. RESULT AND DISCUSSION

4.1. Empirical Data

The data obtained is a mutual quality check. The mutual check sheet for each batching plant varies according to the company format. Data amounted to 56 mixes with variations in type and amount of material. Data has varying compressive strengths, namely: BO, K-125, K-175, K-225, K-250, K-275, K-300, K-350, K-450, K-500. The amount of each material based on compressive strenght also varies. Data is used entirely without being categorized based on strong characteristics.

To deepen the analysis of the study, the data will be divided according to the ratio of sand-aggregate with a division of <38%, 38-44% and >44%. Jobmix materials as predictor variables with the following names: cement (X1), water (X2), sand (X3), gravel 5-10mm (X4), gravel 10-20mm (X5), gravel 20-30mm (X6), rock dust (X7), fly ash (X8), retarder (X9) and superplasticizer (X10) and the response variable is the target slump (Y).

4.2. Analysis

Data divided into 3 part according sand ratio there is sand ratio <38%, ratio 38-44%, and >44% (**Table 2**). Each classification have vary compressive strenght and materials.

Table 2. Classification Data

Classification	Number	Variable predictor
Sand ratio <38%	18	10
Sand ratio 38-44%	29	10
Sand ratio >44%	7	8

4.2.1.Analysis of rasio pasir <38%

Data on sand ratio analysis <38% has 18 mixed data. Predictor variables that can be categorized are 10 variables. The sand ratio data range <38% is shown in **Table 3**. The collected data is included in medium and high workability.

The result of test classic assumption, there is variables having VIF value >10 (**Table 4**). It is indicate that there is correlation between independent variables. The variables were cement, sand, gravel 5-10mm, 10-20mm, gravel 20-30mm gravel, rock dust, fly ash and retarders.

Table 3. Data Range of Sand Ratio <38%

Variable	Min	Max
Cement	252	541
Water	146	215
Sand	472	761
Gravel 5-10mm	0	318
Gravel 10-20mm	384	1181
Gravel 20-30mm	0	471
Rock dust	0	194
Fly ash	0	135
Retarder	0	1,5
Superplasticizer	0	3,46
Slump value	5	12

Table 4. VIF Value Data Sand Ratio <38%

	Collinearity Statistics	
Variable	*Tolerance*	VIF
Cement	0,005	212,097
Water	0,150	6,647
Sand	0,007	137,006
Gravel 5-10mm	0,012	81,306
Gravel 10-20mm	0,001	704,613
Gravel 20-30mm	0,003	369,349
Rock dust	0,006	170,046
Fly ash	0,026	38,948
Retarder	0,004	271,527
Superplasticizer	0,151	6,606

Analysis regression using this data has a p-value less than 0.05 with values R^2 0.957 and adj. R^2 0.897. So, the model can used to predict slump value accurately as in equation 2. Multicollinearity only affects the partial test of independent variable.

$$Y = -146{,}837 + 0{,}079\,x_1 + 0{,}147\,x_2 + 0{,}114\,x_3 + 0{,}009\,x_4 + 0{,}029\,x_5 + 0{,}035\,x_6 + 0{,}065\,x_7 + 0{,}025\,x_8 - 7{,}253\,x_9 + 0{,}820\,x_{10} \quad (2)$$

If multicollinearity variables are issued, namely: cement, gravel 10-20mm, gravel 20-30mm. The results of the multicollinearity assumption test can be seen in **Table 5**. The test results show no assumption of test violations.

$$Y = -19{,}10 + 0{,}1457\,x_2 + 0{,}0075\,x_3 - 0{,}01502\,x_4 - 0{,}0312\,x_7 - 0{,}0212\,x_8 + 3{,}56\,x_9 + 0{,}494\,x_{10} \quad (3)$$

Modeling of sand ratio data <38% which has undergone improvement in assumption test consists of 7 predictor variables with values R^2 0.8236 and adj. R^2 0.7001. This result indicate that modelling data for predicting slump value on sand ratio <38% more accurately using equation 1. Based on standardized coefficient the variables influencing the slump value of model 1 are water and sand. The influential variables of model 2 are: water, rock dust and retarder.

Table 5. Data Value of Sand Ratio <38% Improvement

	Collinearity Statistics	
	Tolerance	VIF
Water	0,622	1,608
Sand	0,325	3,075
Gravel 5-10mm	0,147	6,822
Rock dust	0,107	9,377
fly ash	0,222	4,501
Retarder	0,305	3,277
Superplasticizer	0,633	1,579

4.2.2. Analysis of Sand Ratio 38-44%

Data on sand ratio analysis of 38-44% had 29 mixed data. Predictor variables that can be categorized are 10 variables. The data range at the sand ratio of 38-44% is shown in table 6. Data on this ratio are included in moderate to high workability.

The classic assumption test results on 38-44% sand ratio data also indicate the presence of multicollinearity characterized by a VIF value >10. Variable gravel 10-20mm and 20-30mm has multicollinearity problems.

Table 6. Data Range of Sand Ratio 38-44%

Variable	Min	Max
Cement	237	512
Water	123	210
Sand	626	871
Gravel 5-10mm	0	288
Gravel 10-20mm	401	1081
Gravel 20-30mm	0	500
Rock dust	0	171
Fly ash	0	110
Retarder	0	1,3
Superplasticizer	0	3
Slump value	5	18

Table 7. VIF Value for Sand Ratio 38-44%

	Collinearity Statistics	
Variable	*Tolerance*	VIF
Cement	0,128	7,832
Water	0,442	2,264
Sand	0,167	5,998
Gravel 5-10mm	0,118	8,501
Gravel 10-20mm	0,010	95,889
Gravel 20-30mm	0,009	110,761
Rock dust	0,162	6,190
fly ash	0,200	5,011

The model formed from regression analysis for sand ratio data is 38-44%, seen from equation 4 with R^2 0,631 and adj. R^2 0.4394.

$$Y = -40{,}325 + 0{,}024\,x_1 + 0{,}058\,x_2 + 0{,}009\,x_3 + 0{,}030\,x_4 + 0{,}014\,x_5 + 0{,}025\,x_6 + 0{,}043\,x_7 + 0{,}063\,x_8 + 2{,}575\,x_9 + 1{,}507\,x_{10} \quad (4)$$

Test assumptions and regression analysis were carried out again by removing the multicollinearity variable. If one of the variables between gravel size 10-20mm or size 20-30mm is issued, multicollinearity does not occur. The highest value R^2 and adj. R^2 is obtained by removing the gravel material size 10-20mm.

Table 8. VIF Value of Sand Ratio 38-44% Improvement

	Collinearity Statistics	
Variable	*Tolerance*	VIF
Cement	0,202	4,940
Water	0,444	2,255
Sand	0,168	5,936
Gravel 5-10mm	0,389	2,572
Gravel 20-30mm	0,178	5,604
Rock dust	0,186	5,369
Fly ash	0,328	3,052
Retarder	0,190	5,259
Superplasticizer	0,340	2,945

The results of the improvement regression analysis for sand ratio data 38-44% have a value of R^2 0.6196 and adj. R^2 0.4394 on equation 5.

$$Y = -40{,}325 + 0{,}024\,x_1 + 0{,}058\,x_2 + 0{,}009\,x_3 + 0{,}030\,x_4 + 0{,}014\,x_5 + 0{,}025\,x_6 + 0{,}043\,x_7 + 0{,}063\,x_8 + 2{,}575\,x_9 + 1{,}507\,x_{10} \quad (5)$$

In this category, based on adj. R^2 value modelling has the same ability to predict the slump value. The R^2 value on equation 3 higher than equation 5 because the variables on equation 4 much more than equation 5. Based on standardized coefficient value, the most influencing variables on model 3 is fly ash and on model 4 are 20-30mm gravel and fly ash.

4.2.3.Analysis of sand ratio >44%

Analysis data on sand ratio >44% had 9 mixed data. Predictor variables that can be categorized are 8 variables. Variable rock dust and superplasticizer not included. The data range of the sand ratio >44% is shown in **Table 9**. The data included in moderate to high workability.

Table 9. Data Range of Sand Ratio >44%

Variable	Min	Max
Cement	210	394,23
Water	118	193,27
Sand	780	908
Gravel 5-10mm	129	291
Gravel 10-20mm	409	864
Gravel 20-30mm	0	456,87
Fly ash	0	85
Retarder	0	1
Target value	5	10

Analysis the classic assumption of data sand ratio >44% is failed. There is correlation between independent variables, autocorrelation and heteroskedastisitas occurs, and the data distribution is not normal. Regression analysis cannot be done because the data cannot be repaired. The method of improvement can be done by increasing the amount of data (n), but no empirical data can be added.

4.3. Appropriate model

The results of the analysis show that there are 4 equations that can be formed from 56 study data by dividing them according to the ratio of sand. The used variables can be reduced due to violations of assumptions. Comparison of the values of R^2, adj R^2 and MSE can be seen from table 10. Equations with the highest values of R^2 and adj. R^2 and the smallest MSE value is the equation for the data ratio <38% without improvement (model 1). The selection of sand ratio models <38% is strengthened by the diagram in Figure 1. The predicted slump value of the equation 1 has a pattern that approximates the actual slump pattern. So the appropriate model for predicting concrete slump values accurately is model sand ratio <38% (model 1). Modeling can be used to predict slump values for data that included in range data according to **Table 2**.

Table 10. Value of R^2, adj. R^2 AND MSE

Equation	R^2	Adj. R^2	MSE
<38%	0,957	0,897	0,31
<38% improvement	0,8236	0,7001	1,29
38-44%	0,631	0,426	3,10
38-44% improvement	0,426	0,4394	3,19

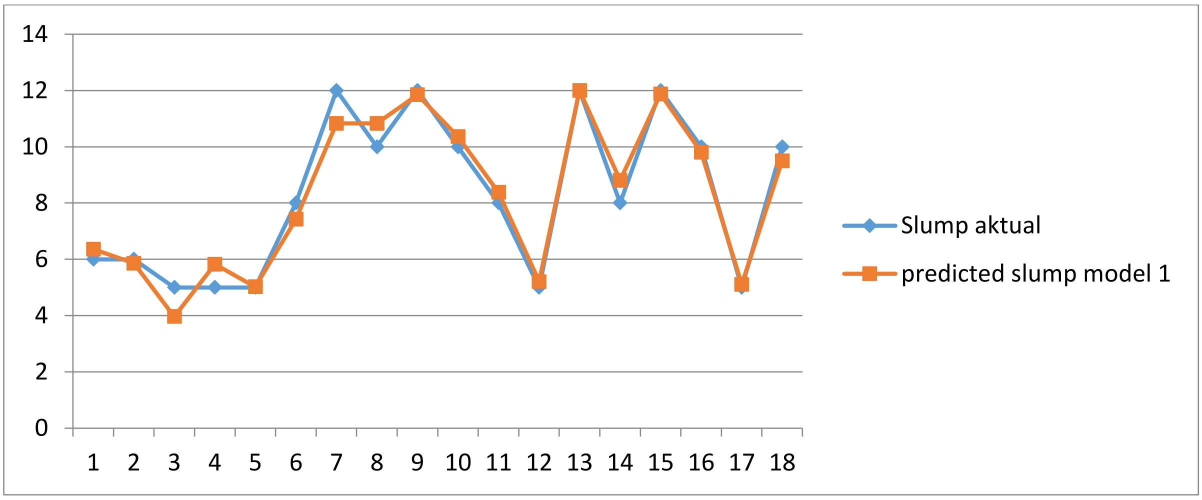

Figure 1. Comparison of Actual Slump Values With Slump Predictions of Model 1 (Data Sand Ratio <38%)

4.4. Influential variable of slump value

Based on the standard coefficients in the regression analysis, the p-value <0.05 of model 1 was seen in the variable water and sand. These variables show the highest influential variable on the predicted slump value based on statistic. In equation the most influencing variables having large coefficient than other materials. Water and sand have positif simbol and great coefficient. Every 1 kg/m^3 of each water dan sand added will increase the slump value by 0,147cm and 0,114cm. In theory, consistency of fresh concrete is related to water content. Measurement water content depends on moisture content of materials, gradation of aggregate and temperature variation.

Measurement moisture content of solid material related to the water arbsorption of material it selves. The highest effect of moisture content on aggregate, because the amount of this variable in job mix approximately 70-80%. The ideal moisture content of aggregate in saturated condition, but it is too difficult to measure. Cement also need water for hydration.

Aggregate gradation influencing water measurement based on dimension and quantity. The larger size of aggregate will require more water to lubricate the surface, but in concrete mass the number is less. Thats why, the more little size with a great number of quantity required more water than the larger one.

On fresh concrete there are two temperature that influencing water requirement. Concrete temperature due to hydration and ambient temperature. That temperature related to evaporation of water.

5. CONCLUDING AND SUGGESTION

5.1. Conclusion

Based on the results and discussion can be drawn as follows:

1. The most suitable modeling can be obtained using multiple linear regression. Model 1 is the most suitable and accurate in predicting the actual slump value. Degree of accuracy reaches 0,957 for R^2 and 0,897 for adj. R^2.

2. The most influential variables on slump value in equation 1 is water and sand. Both of it have lerger coefficient than other material and the simbol is positif. Which means, every 1 kg/m^3 of each water dan sand added will increase the slump value by 0,147 cm and 0,114 cm.

5.2. Suggestion

To deepen the analysis of the next study, more than 10 variables can be used. The deeper variables increase affect the slump value such as: evaporation, hydration, transit time, aggregate absorption rate, concrete temperature, ambient temperature and moisture content, will increase sharpness study. Other variables such as aggregate-cement ratio, FAS, aggregate max, aggregate gradient can be used for grouping data as in this study. To sharpen the next study, additional amount of data is much better.

6. REFERENCES

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