Modeling the Flow Properties of DDGS

V. Ganesan, 1 K. A. Rosentrater, 2,3 and K. Muthukumarappan 1

ABSTRACT

Distillers dried grains with solubles (DDGS) are one of the co-products obtained from the fermentation of corn for the production of ethanol. It is mainly used to improve the palatability and nutrient balance of animal feed rations. Significant quantities of distillers grains are now being produced due to increased demand for ethanol as a fuel additive. By 2008-2009, distillers grains are projected to displace more than 1 billion bu. of corn per year (NCGA 2006). It has been reported that DDGS has flowability issues (AURI 2005; Ganesan et al 2005, 2006a), which is problematic as these coproducts are often transported out of the Corn Belt. Moreover, DDGS can become hardened during transportation, which can lead to the damage of railcars while unloading. These issues impede the expansion of the DDGS market domestically. In addition to that, marketing of distillers grain products is hampered by variability in physical and chemical properties, both within a single plant over time, as well as between plants. Flow characteristics are of immense significance in bulk material handling and processing because the ease of conveying, blending, and packaging depends on them. Reliable flow is necessary to optimize designs and maximize profits. To ensure steady and reliable flow, it is crucial to accurately characterize the flow behavior of these materials (Kamath et al 1994). Quantification of properties is important because DDGS storage and flow behavior will depend on the physical and chemical characteristics, as well as environmental variables. The authors have previously investigated the flow properties of DDGS at various soluble levels, moisture contents, and flow agent levels using Carr and Jenike shear tests (Ganesan et al 2005, 2006a, 2007). We have observed that DDGS had flow problems at higher levels of solubles and moisture contents. 

Exploratory data analysis (EDA) is a versatile method to detect patterns in data. In brief, exploratory data analysis emphasizes flexible searching for clues and evidence (Hoaglin et al 1983). EDA is also referred as data mining, knowledge discovery, knowledge extraction, data dredging, data analysis, and so on. The data are analyzed in a stepwise manner in the EDA approach. An iterative exploratory procedure helps in defining and finding combinations of analysis conditions to completely understand the data. In each step, EDA maximizes insight into a data set, evaluates the appropriateness of developed models to explain the data, uncovers underlying relationships, extracts important variables, and gives new insight into numerous other important conditions that are necessary to reach valid conclusions. The application of data exploration is wide, and many reports are available on EDA (Leinhardt and Wasserman 1979; Kimber 1990; Bhandari et al 1997; Kleinberg et al 1998; Pietersma et al 2004).

Visual data mining (VDM) is one of the data exploration techniques that can be used to ease the analysis of large volumes of data. VDM also provides extensive insight into data, but in a visual form. This helps the analyst to directly interact with the data and draw effective conclusions. VDM has high potential in exploring large volume databases. This technique is very useful especially when little is known about the data and the exploration goals are vague. Many researchers have used these data mining techniques in various fields (Cox et al 1997; Brown and Mielke 2000; Macêdo et al 2000; Keim 2002; Wegman 2003; Rosentrater 2004).

Flowability of DDGS is one such problem that could benefit from EDA techniques, as it is a multivariate problem that includes synergistically acting variables such as air and product temperature, moisture content, soluble level, relative humidity, chemical constituents, etc. And a comprehensive model to predict the flowability of DDGS would be very useful for distillers grain producers, as it would allow them to predict when flow problems may occur. Currently there is no model available for predicting the flowability of DDGS. Therefore the objectives of this study were to 1) conduct an EDA on all data obtained from Ganesan et al (2005, 2006a, 2007) to examine the relationships between all key variables; and 2) develop a comprehensive model to predict flowability of DDGS that incorporates the information obtained from the EDA.

MATERIALS AND METHODS

The data obtained from the Carr test (Ganesan et al 2006a) and the Jenike test (Ganesan et al 2007) were compiled together into an electronic spreadsheet. The data set comprised 21 variables with 60 data points each. The independent variables were soluble level and moisture content. The dependent variables included angle of repose, angle of fall, angle of difference, angle of spatula, aerated bulk density, packed bulk density, compressibility-Carr, uniformity, dispersibility, flow index, flood index, compressibility-Jenike, unconfined yield strength, major consolidation stress, angle of internal friction, effective angle of friction, and color values ($L^*$, $a^*$, and $b^*$).

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Exploratory data analysis was then performed on the data using VDM techniques (Cox et al. 1997; Macêdo et al. 2000; Keim 2002; Wegman 2003). The techniques employed included multiple linear regression, correlation analysis, and 3D response surface modeling. These steps were taken to explore and detect the possible patterns related to soluble and moisture effects on the flow properties of DDGS. Ultimately, the purpose of this study was to generate a comprehensive model that could be used to predict the flowability of DDGS.

To seek valuable information out of this data, the compiled data was first analyzed using stepwise multiple linear regression (SMLR) analysis. Regression analysis is valid when the dependent and independent variables are all quantitative and the mean conditional distribution of the dependent variable can be expressed as a mathematical function of the independent variables (Rao 1998). Multiple linear regression aids in investigating the relationship among one dependent variable and several independent variables simultaneously. Also, multiple linear regression is a robust tool for explanatory analysis, which helps in understanding the relationships between the response and predictor variables. SMLR was performed with inclusion and exclusion $P$ values of 0.1 and 0.05, respectively, to include only statistically significant parameters ($\alpha < 0.05$) in the model. SMLR was used to simultaneously test the data and model the multiple predictor variables.

Correlation is another statistical technique that examines the relationship between variables. Correlation can be used for data in which numbers are meaningful and cannot be used for categorical data. To measure the relationship between the variables in our data, the data was analyzed using linear correlation. Correlation coefficients ($r$) range from -1 to 1. Correlation coefficients with a value of -1 correspond to a strong negative correlation between variables, while a value of +1 characterizes a strong positive correlation. A value of 0 denotes a weak correlation between the variables. Flow properties with high correlation coefficient ($r$) values were plotted with bivariate scatterplots, and specific relationships were modeled using linear regression. Both SMLR and correlation analyses were done using SAS v.9.1 (SAS Institute, Cary, NC).

Dimensional analysis is a powerful technique for reforming the original dimensional variables into a set of dimensionless parameters. Additionally, this technique overcomes the limitations that are imposed on the variables by their dimensions. It requires a dimensional homogeneity in any relationship between the variables (Vignaux 1992). So the dimensional analysis method was used to form the dimensionless parameters by combining one or more properties (independent and response variables) that share the same dimensions. The relationship between the soluble-to-moisture ratio (SM) and each of the dimensionless parameters were then plotted in bivariate scatterplots, and their relationships

### TABLE I

<table>
<thead>
<tr>
<th>Property</th>
<th>Model</th>
<th>$R^2$</th>
<th>CV %</th>
</tr>
</thead>
<tbody>
<tr>
<td>AoR (deg)</td>
<td>$Y = 0.0023SM + 44.36$</td>
<td>0.33</td>
<td>4.78</td>
</tr>
<tr>
<td>ABD (g/cm³)</td>
<td>$Y = -0.0024M + 0.0032S + 0.559$</td>
<td>0.57</td>
<td>3.81</td>
</tr>
<tr>
<td>PBD (g/cm³)</td>
<td>$Y = 0.00016SM - 0.0043M + 0.6111$</td>
<td>0.52</td>
<td>3.74</td>
</tr>
<tr>
<td>Compressibility-Jenike (%)</td>
<td>$Y = 0.1618M - 0.547$</td>
<td>0.16</td>
<td>41.97</td>
</tr>
<tr>
<td>AoS (deg)</td>
<td>$Y = 0.188M + 55.59$</td>
<td>0.72</td>
<td>9.88</td>
</tr>
<tr>
<td>AoF (deg)</td>
<td>$Y = 0.146S + 35.95$</td>
<td>0.10</td>
<td>6.62</td>
</tr>
<tr>
<td>AoD (deg)</td>
<td>$Y = -0.1183S + 8.72$</td>
<td>0.06</td>
<td>41.99</td>
</tr>
<tr>
<td>Dispersibility (%)</td>
<td>$Y = -0.4312M + 19.19$</td>
<td>0.51</td>
<td>28.67</td>
</tr>
<tr>
<td>Flow index (·)</td>
<td>$Y = -0.165S + 80.40$</td>
<td>0.20</td>
<td>3.10</td>
</tr>
<tr>
<td>Flood index (·)</td>
<td>$Y = -0.014SM + 61.14$</td>
<td>0.23</td>
<td>7.84</td>
</tr>
<tr>
<td>$L^*$</td>
<td>$Y = -0.994S + 58.10$</td>
<td>0.64</td>
<td>10.39</td>
</tr>
<tr>
<td>$a^*$</td>
<td>$Y = 0.173SM + 13.67$</td>
<td>0.39</td>
<td>7.36</td>
</tr>
<tr>
<td>$b^*$</td>
<td>$Y = -1.40S + 92.16$</td>
<td>0.58</td>
<td>9.90</td>
</tr>
<tr>
<td>Compressibility-Jenike (cm⁻¹)</td>
<td>$Y = 0.96077M + 0.000040S - 0.000935$</td>
<td>0.96</td>
<td>9.62</td>
</tr>
<tr>
<td>Unconfined yield stress (UYS, kPa)</td>
<td>$Y = 0.18S + 3.11$</td>
<td>0.05</td>
<td>69.94</td>
</tr>
<tr>
<td>Major consolidation stress (MCS, kPa)</td>
<td>$Y = -0.229M + 24.12$</td>
<td>0.02</td>
<td>58.10</td>
</tr>
<tr>
<td>$\delta$ (deg)</td>
<td>$Y = -0.56SM + 52.29$</td>
<td>0.31</td>
<td>15.39</td>
</tr>
<tr>
<td>$\phi$ (deg)</td>
<td>$Y = -0.62M + 42.18$</td>
<td>0.24</td>
<td>26.68</td>
</tr>
</tbody>
</table>

### TABLE II

<table>
<thead>
<tr>
<th>Property Combinations</th>
<th>$r$</th>
<th>Variable Combinations</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soluble content</td>
<td>PBD</td>
<td>0.602</td>
<td>PBD</td>
</tr>
<tr>
<td>Soluble content</td>
<td>Uniformity</td>
<td>-0.848</td>
<td>Compressibility-Carr</td>
</tr>
<tr>
<td>Soluble content</td>
<td>$L^*$</td>
<td>-0.801</td>
<td>Uniformity</td>
</tr>
<tr>
<td>Soluble content</td>
<td>$a^*$</td>
<td>0.625</td>
<td>Uniformity</td>
</tr>
<tr>
<td>Soluble content</td>
<td>$b^*$</td>
<td>-0.764</td>
<td>AoF</td>
</tr>
<tr>
<td>Moisture content</td>
<td>Compressibility-Carr</td>
<td>0.718</td>
<td>AoF</td>
</tr>
<tr>
<td>Moisture content</td>
<td>Dispersibility</td>
<td>-0.715</td>
<td>AoD</td>
</tr>
<tr>
<td>Moisture content</td>
<td>Compressibility-Jenike</td>
<td>0.907</td>
<td>Dispersibility</td>
</tr>
<tr>
<td>Moisture content</td>
<td>MCS</td>
<td>-0.711</td>
<td>Dispersibility</td>
</tr>
<tr>
<td>Moisture content</td>
<td>$\delta$</td>
<td>-0.738</td>
<td>Dispersibility</td>
</tr>
<tr>
<td>Moisture content</td>
<td>$\phi$</td>
<td>-0.597</td>
<td>Compressibility-Jenike</td>
</tr>
<tr>
<td>AoR</td>
<td>Flow index</td>
<td>-0.598</td>
<td>Compressibility-Jenike</td>
</tr>
<tr>
<td>ABD</td>
<td>PBD</td>
<td>0.958</td>
<td>Compressibility-Jenike</td>
</tr>
<tr>
<td>ABD</td>
<td>$a^*$</td>
<td>0.598</td>
<td>Compressibility-Jenike</td>
</tr>
</tbody>
</table>


With inclusion $\alpha < 0.1$ and exclusion $\alpha > 0.05$.

S, soluble level; M, moisture content level; SM, interaction effect.
were determined by linear and nonlinear regression modeling using MS Excel v.2003. Also, to better understand the relationships, dimensionless parameters were analyzed using Tablecurve 3D (Systat Software, San Jose, CA), and three-dimensional response surfaces were constructed.

RESULTS AND DISCUSSION

Multiple Linear Regression

To begin the EDA, the dataset was analyzed by the stepwise multiple linear regression technique (Table I, Fig. 1). Multiple linear regression (MLR) is a widely used method to model the relationships between a dependent variable and one or more independent variables. Most of the resulting models had poor regression coefficient ($R^2$) and coefficient of variation (CV) values. The highest $R^2$ value was obtained for compressibility-Jenike ($R^2 = 0.96$), followed by uniformity ($R^2 = 0.72$). The lowest CV was obtained for flow index ($CV = 3.10$), followed by packed bulk density ($CV = 3.74$). For some properties, such as uniformity, angle of fall, angle of difference, $L_a$, $a^*$, $b^*$, and unconfined yield strength, the soluble content had a significant effect. For some other properties, such as angle of repose, compressibility-Carr, angle of spatula, dispersibility, flow index, major consolidation stress, $\delta$, and $\phi$, moisture had a significant effect. On the other hand, the aerated bulk density, packed bulk density, flood index, and compressibility-Jenike were noticeably affected by the combination of soluble level to moisture content. As the soluble level increased, DDGS particles tend to form agglomerates and uni-

Fig. 1. Linear regression results for relationships between soluble content, moisture content, physical, and flow properties of DDGS using all collected data from Ganesan et al (2006a, 2007).
formity of particles decreased. This is reflected in the model obtained for uniformity of DDGS (Table I). Dispersibility of DDGS decreased with an increase in moisture content. In fact, moisture content had a significant effect ($R^2 = 0.51$) on dispersibility. Also, compressibility of DDGS increased with an increase in moisture content during Carr testing. This is reproduced in the model with a moderate $R^2$ value of 0.52. Overall, the results obtained from MLR showed a lack of explanation regarding the relationships between the dependent and independent variables. Any discrepancy from linearity leads to poor prediction. The linearity assumption itself may not hold for many cases in the data set. Regression analyses thus become immaterial when nonlinear relationships cannot be transformed into linear relationships. These limitations of MLR may have caused the poor prediction of variables.

**Property Relationships**

The relationships between all variables were then examined using linear correlation analysis, as the MLR did not perform well by itself. Correlation looks at the indirect relationships between two variables and can help in impartially evaluating the degree to which two variables are linearly proportional to each other. This

![Relationships between soluble-to-moisture ratio and various dimensionless variables using all data collected from Ganesan et al (2006a, 2007).](image)

**Fig. 2.** Relationships between soluble-to-moisture ratio and various dimensionless variables using all data collected from Ganesan et al (2006a, 2007).
could help to provide a discriminatory analysis of the variables. Out of all the relationships, 27 variable combinations (Fig. 1, Table II) were significant \((P < 0.05)\) and had a correlation coefficient \((r) > 0.59\). Bivariate scatterplots for the variable combinations with high correlation coefficients were plotted. A few of these correlations were expected before the analysis. As the soluble level increased, there was a noticeable decrease in the brightness \((L^*)\) and bluish-yellow tint \((b^*)\) of the DDGS. These led to the fairly high negative correlation between them. Also, there was a high positive correlation \((r = 0.99)\) between \(L^*\) and \(b^*\) values. This was due to the fact that \(L^*\) and \(b^*\) were higher for lower soluble levels, while \(a^*\) values were lower. This made the DDGS fall in between the axes of \(L^* = 100\) and positive \(b^*\) on the CIE Lab color space. The reddish-green \((a^*)\) value increased proportionally with an increase in soluble level and showed a positive correlation with soluble level. The high correlation \((r = 0.92)\) between ABD and PBD was also expected, as both measure the mass of DDGS per unit volume in the experimental container.

In general, the higher the angle of repose, the lower the flowability of a granular material. This was observed with DDGS and this is supported by the negative correlation between the angle of repose and the flow index. As discussed, uniformity, \(L^*\), and \(b^*\) of DDGS decreased with an increase in soluble level; this might be the reason behind the fairly high positive correlation of \(L^*\) and \(b^*\) with soluble level. Uniformity of DDGS showed a negative correlation \((r = 0.72)\) with soluble level. Compressibility of DDGS increased with an increase in the moisture index and showed a positive correlation for both Carr \((r = 0.72)\) and Jenike \((r = 0.91)\) testing. The same trend was observed by Moreyra and Peleg (1981) and Yan and Barbosa (1997) for food powders. Increases in moisture content can often lead bulk materials to gain strength (Marinelli and Carson 1992). Due to this, the dispersibility of DDGS decreased with an increase in moisture content. Angle of internal friction \((\phi)\) and effective angle of internal friction \((\delta)\) showed a high positive correlation with each other \((r = 0.80)\) and both of them had a negative correlation with moisture content \((r = -0.60, r = -0.74,\) respectively). The higher the angle of internal friction \((\phi)\), the higher the flow, and the lower the compressibility. This is reflected with the compressibility values obtained from the Jenike test, but not from the Carr test where the values were fairly randomly scattered.

Both the MLR and correlation analyses produced some physically meaningful relationships between the predictor (soluble level and moisture content) variables and the dependent variables (i.e., the flow properties). But we were not able to adequately model the flowability of DDGS using only these relationships. So it was decided to construct dimensionless parameters out of these variables, as dimensional analysis is often very useful in examining empirical relationships in data.

### Dimensional Analysis

All variables in the data set were converted into dimensionless quantities by combining one or more variables sharing the same dimensions, using the techniques of dimensional analysis. Soluble-to-moisture (SM) ratio was used as the primary independent variable and its relationships with the other dimensionless parameters were modeled. The results are shown in Fig. 2. Because of previous EDA work, a few of these relationships were expected before analysis: SM and \((L^*/b^*)\); SM and \((L^* \times b^*)\); SM and \((L^* \times \text{Uniformity})\); SM and \((\text{ABD/PBD})\); SM and \((\text{Compressibility/Dispersibility})\); SM and \((b^* \times \text{Uniformity})\); SM and \((a^* \times \text{ABD/PBD})\). ABD and PBD increased slightly with an increase in soluble level, but decreased with moisture content. Data exhibited an increasing polynomial trend between SM and \((\text{ABD/PBD})\) but a decreasing trend with \((\text{PBD/ABD})\) ratio. Moisture content did not have a significant effect on the color values \((L^*, a^*, \text{or } b^*)\) but soluble levels had a noticeable impact on color values. \(L^*\) and \(b^*\) decreased with an increase in soluble level but \(a^*\) increased. Thus, decreasing trends were found for SM and \((L^*/b^*)\), \((L^* \times b^*)\), and \((b^* \times \text{Uniformity})\). On the other hand, \((a^* \times \text{ABD/PBD})\) had an increasing power law trend with SM. Compressibility of DDGS increased with increase in moisture content, whereas dispersibility decreased with moisture content. But soluble levels did not have a striking impact on these two variables. This forced the (compressibility/dispersibility) ratio to follow a decreasing trend with SM. There was no visible trend between SM and \((\delta/\phi)\) ratio but there was an increasing trend for \((\text{dispersibility/compressibility})\) ratio with SM. Due to this, the product \((\delta/\phi)\) \((\times \text{dispersibility/compressibility})\) had an overall positive trend with SM.

In two-dimensional analysis, none of the relationships between the dimensionless parameters produced a high \(R^2\). The highest was observed between SM and \((\delta/\phi)\) \((\times \text{dispersibility/compressibility})\) with an \(R^2\) of 0.47. To further delve into potential relationships, data were also analyzed using three-dimensional response surface regression. Software used multiple surface fitting techniques.
to explore relationships between the three variables simultaneously. Many combinations of explanatory variables and response variables were investigated during the EDA (most of these results are not shown). Ultimately a combination of the dimensionless parameters \( X = \frac{PBD}{ABD}; Y = \frac{soluble}{moisture}; Z = (compressibility/\text{dispersibility}) \times (\delta/\phi) \) produced a very good model with an \( R^2 \) value of 0.93, \( F \) value of 139.42, and a standard error value of 0.12. The resulting model equation obtained was

\[
Z = a + \frac{b}{X} + c(\ln Y) + \frac{d}{X^2} + e(\ln Y)^2 + f(\ln Y)
\]

where \( a = 201.628, b = -391.92, c = -8.10, d = 190.28, e = -0.159, \) and \( f = 8.25. \)

According to Carr Indices, the higher the dispersibility and the lower the compressibility, the higher the flow index and the flood index. And according to Jenike, \( \delta \) is equal to \( \phi \), so \( (\delta/\phi) = 1 \) for noncohesive materials such as dry sand. As a result, the higher the \( \phi \) of a material, the higher its free flow, and vice versa. Interestingly, the PBD/ABD ratio is defined as the Hausner ratio (HR), which is commonly used for measuring the flowability of bulk solids. The higher the ratio, the lower the flow.

The surface fit for Equation 1 is shown in Fig. 3. The \( Z \) variable in Equation 1 combines the parameters from Carr and Jenike testing and is a new dimensionless parameter. We called this a flowability indicator (\( \zeta \)), which indicates the propensity of a bulk solid to flow (in this case DDGS). The higher the value of the flowability indicator (\( \zeta \)), the higher the chance of flow problems with a sample of DDGS. To pursue this further, flowability indicator values were calculated for different values of HR and SM from Equation 1 and are plotted in Fig. 4. The flow and flood indices from the data set were then imposed on the obtained curves to help delineate the flowability of DDGS (Fig. 5). Typically, good flowing DDGS data points were concentrated near the bottom region of the curves, whereas the DDGS with problematic flow was typically near the upper region of the curves. Thus the regression curves could be divided into three general flow regions. The bottom region of the curves represents DDGS with good flow (HR 1.0–1.03), the middle region appears to represent DDGS with a potentially probable flow problem (HR 1.03–1.05), and the upper region appears to represent DDGS with definite flow problems (HR > 1.05).

To validate this regression model, data obtained from Ganesan et al (2005) and another hard unload DDGS, called the HLD sample, were used. The HLD sample was obtained from an actual railcar where it had hardened and was unloadable. Both the soluble and moisture content of the HLD sample were determined to obtain SM values. The soluble level of the HLD sample was determined using the method developed by Ganesan et al (2006b), while moisture content was determined using (air oven) Approved Method 44-19 (AACC International 2000). Flowability indicator (\( \zeta \)) values for the data were then calculated from Equation 1 for different HR values. For the data of Ganesan et al (2005), Fig. 6 shows that DDGS without any flow problems, with probable flow problems, and with definite flow problems fall respectively in the good, medium, and poor flow regions of the model, which was anticipated. On the other hand, for the HLD sample there was a little variation between the actual and predicted values (Table III). The model developed was solely based on the properties of DDGS obtained from Dakota Ethanol (Wentworth, SD). The HLD sample was obtained from a different ethanol plant. DDGS properties differ between plants and this might be the reason for the variation. But still the data point falls in the region of poor flow, which was
expected. As the DDGS properties differ between plants, the Carr and Jenike properties of DDGS will have to be determined and a similar model should be developed for each plant. With this model, plant managers will be able to predict the flowability of DDGS for each batch and then transport or store them accordingly.

CONCLUSIONS

The application of exploratory data analysis to all the data obtained from the authors’ previous studies was used to find relationships between soluble level, moisture content, and various flow properties of DDGS. The data was meticulously investigated using stepwise multiple linear regression, correlation analysis, and dimensional analysis. All these analyses provided useful information about the relationships between the variables and paved the way for generating an empirical model to predict flowability of DDGS that combines both the Carr and Jenike information. This model can be used to predict the potential flowability of DDGS produced from a batch with a given set of properties at an ethanol plant. This model, however, was developed solely based on the DDGS properties of one ethanol plant. The flow properties of DDGS will differ somewhat from plant to plant. Therefore, it is recommended that users should determine the Carr and Jenike properties of DDGS for their particular ethanol plant and then use this methodology to develop a similar model to obtain a flowability indicator (C). This information will be vital to DDGS transportation and storage issues. Future studies will investigate the time and temperature effect on the flow properties of DDGS. This could lead to the development of a versatile model to predict the flowability of DDGS.

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