

## Initial Results From Implementing a Laminated Overburden Model Into ARMPS

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### ABSTRACT

In a recent research effort, a laminated overburden loading model (as implemented in LaModel3.0) was compared with the results of ARMPS 2010, and the laminated overburden model was found to more accurately classify a ARMPS database of 52 deep cover case histories by a factor of 60% versus 54%. However, the LaModel analysis of each case study required several days to complete, as compared to a requirement of only several minutes for each ARMPS analysis. In the research presented in this paper, a computer code (ARMPS-LAM) has been developed to effectively implement the laminated overburden model into the ARMPS program. This program takes the basic ARMPS geometric input for defining the mining plan and loading condition and then automatically develops, runs, and analyzes a full LaModel analysis of the mining geometry to output the stability factor on the Active Mining Zone (AMZ), all without further user input. The present laboratory version of ARMPS-LAM can be run in batch mode; therefore, the ARMPS 2010 database of 645 case histories can be analyzed very quickly. In an initial logistic regression analysis of this database, the ARMPS-LAM program was seen to be slightly more accurate than ARMPS 2010 by a factor of 71% versus 63%.

### INTRODUCTION

#### ARMPS

The original version of ARMPS was developed by NIOSH in the mid-1990s (Mark and Chase, 1997) to aid in the design of room and pillar retreat mining operations in underground coal mines. ARMPS was created with a very user-friendly interface, and it was simple and fast to use. Over the years, it has been widely used in the United States, and undoubtedly, it has greatly improved the safety of retreat room and pillar mining operations. In the ARMPS program, the stability factor of the Active Mining Zone (AMZ) is determined by comparing the strength of the pillars (determined using the Mark-Bieniawski pillar strength formula) in the AMZ against the development loads (determined using the tributary-area method) and abutment loads (determined using the abutment angle concept) applied to those pillars. The value of the calculated pillar stability factor is then compared against a large database of successful and unsuccessful case histories to determine the chance of success of the chosen design. This large database of case

histories is the real strength of the program and provides very solid empirical support for the application of the ARMPS method.

In the wake of the widespread pillar failure at the Crandall Canyon mine, research efforts with ARMPS focused on improving the loading half of the stability factor determination. In particular, a “pressure arch” algorithm was added to the tributary-area loading calculation in the newest version of the ARMPS program (ARMPS 2010) in an effort to more accurately model deep cover mines (Mark, 2010). The pressure arch loading model takes the tributary area loading on the AMZ and reduces it by the “pressure arch factor” ( $F_{pa}$ ). The reduced AMZ loads are then transferred to the barrier pillars. If the barrier pillars are too small to carry all of the applied loads, then the pressure arch loads are transferred back to the AMZ. Initially, three different pressure arch loading functions were analyzed. Ultimately, the optimum pressure arch equation was determined to be the logarithmic function shown below (Mark, 2010), which only applies when the depth of cover is greater than the panel width plus 80 ft.

$$F_{pa} = 1 - \left[ 0.28 \times \ln \left( \frac{H}{P_w} \right) \right] \quad (1)$$

where:

- $F_{pa}$  = the pressure arch factor
- $H$  = overburden depth
- $P_w$  = panel width.

The manner in which the pressure arch factor was determined guarantees that the new pressure arch loading model provides the optimum separation between the successful and unsuccessful cases in the database. Further, the pressure arch loading model eliminates the previous depth effects in ARMPS 2002 and allows for the use of a constant value for the recommended stability factor (SF) regardless of depth. Based on the latest statistical analysis with an database of 645 case histories, the 2010 design criteria require a minimum ARMPS SF of 1.50 for depths less than 650 ft, and a minimum ARMPS SF of 1.50 and a minimum barrier pillar SF of

1.50 for depths over 650 ft. With these design criteria, ARMPS 2010 has a 82% accuracy in predicting the unsuccessful case histories, a 61% accuracy in predicting the successful cases, and an overall classification accuracy of 65% (Mark, 2010). The new ARMPS 2010 works very well as a guideline for designing room-and-pillar mines, but there is still plenty of room for improving the overall prediction accuracy of the program.

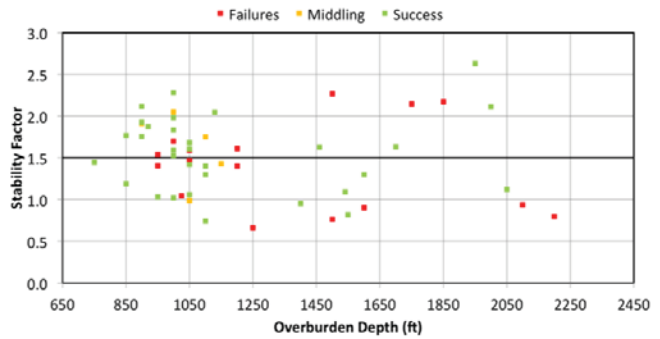
## LaModel

In contrast to the empirical ARMPS program, the LaModel program is a numerical program based on simplified overburden and seam mechanics. It simulates the overburden as a stack of homogeneous, frictionless plates (Heasley, 1998), and within the seam horizon, the elements are simulated with various stress-strain behaviors (elastic, elastic-plastic, strain-softening, and strain-hardening) intended to model the various behaviors of the in-seam coal and gob. When the program is executed, it takes the user input behavior of the overburden and balances it with the in-seam material behaviors and solves for the resulting displacements, stresses, pillar safety factors, etc. The LaModel program requires quite a bit more time, effort, and complexity to run than the ARMPS program, but with its ability to fairly accurately model complex mining geometries, variable topography, multiple-seams, and many other situations and/or detail beyond the capability of ARMPS, it has found quite extensive use throughout the coal mining industry.

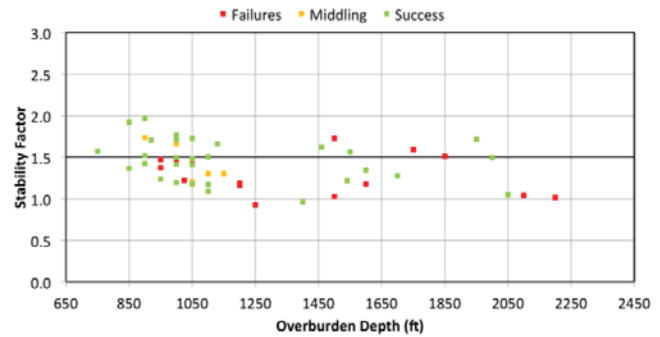
One of the difficulties of using LaModel (or any numerical model) is determining the appropriate values for the input parameters. Given the complexity of the geologic environment, laboratory determined parameter values are typically not accurate for simulating the *in situ* geomechanical behavior of the mine structure. Rather, the best way to produce an accurate numerical model is often to calibrate the critical input parameters against measurements and/or observations in the field. In the last few years, a formal procedure for calibrating the critical input parameters for LaModel versus field observations has been developed and implemented into the program's version 3.0 pre-processor (Heasley et al., 2010; Heasley, 2008). Essentially, the lamination stiffness in LaModel is calibrated against the measured/observed/empirical extent of the abutment stress, the gob stiffness is calibrated against the expected gob/abutment loading, and the *in situ* coal strength is input using the NIOSH default of 900 psi or is back-calculated (Heasley, 2008).

In a recent analysis of 52 deep-cover case histories, where the results from calibrated LaModel3.0 runs were compared with the results of ARMPS 2010, it was found that the LaModel program more accurately classified the case histories by an overall factor of 60% versus 54%. Further, the LaModel program more accurately classified the critical design failures by a factor of 76% versus 52% (Tulu et al., 2010).

The results of the database analysis are presented in Figure 1 (a and b). For the ARMPS 2010 analysis shown in Figure 1a, 52% of the failed case histories and 55% of the successful case histories were correctly classified for an overall classification accuracy of 54%. For LaModel3.0, as shown in Figure 1b, 76% of the failed case histories and 48% of the successful case histories were correctly classified for an overall classification accuracy of 60% (Tulu et al., 2010).



a. Stability factor analysis with ARMPS 2010



b. Stability factor analysis with LaModel 3.0

Figure 1. Comparison between ARMPS 2010 and LaModel3.0 (after Tulu et al, 2010).

In this analysis of the relatively small deep-cover database, the laminated overburden model showed significant promise for improving the accuracy of the ARMPS calculation; however, in this research, the LaModel analysis of each case study required several days to complete, as compared to a requirement of only a few minutes for each ARMPS analysis. Using LaModel3.0, the model input parameters and mine grid needed to be entered by hand, and the output needed to be specifically analyzed to determine the stability factor within the active mining zone. The user expertise and attention for LaModel required considerable more time and effort than performing a simple ARMPS analysis. However, if only a simple ARMPS type mining plan is to be analyzed, and the user is satisfied with a 900 psi Mark-Bieniawski coal pillar strength and a 21° abutment angle type of gob loading (as used in ARMPS and as used in the calibrated LaModel), then it is certainly possible to automate all of the parameter input, grid generation, and output analysis associated with the LaModel program. This automation would greatly increase the speed of using a laminated overburden model in an ARMPS-type room-and-pillar analysis and potentially increase the overall accuracy of the pillar design.

## ARMPS-LAM

In the research presented in this paper, a computer code (ARMPS-LAM) has been developed to effectively implement the laminated overburden model into the ARMPS program. This ARMPS-LAM program takes the basic ARMPS geometric input for defining the mining plan and loading condition and then

automatically develops and analyzes a complete LaModel file of the mining geometry to calculate the stability factor on the AMZ (and barrier pillars), all without further user input. For the user, only the traditional ARMPS input is required, and similar to ARMPS, the output is the stability factor of the AMZ and barrier pillars; however, it is now calculated using the laminated overburden model. Based on the deep-cover analysis described above, it was anticipated that this new ARMPS-LAM program would have the potential to significantly improve the accuracy of the mine design classification, and therefore, greatly improve the safety of the underground coal mines.

To completely automate the model building and analysis process, numerous complex algorithms and mathematical formulas needed to be developed and implemented. Fortunately, many of these algorithms and formulas associated with material properties and the stress solution had already been developed and implemented in previous research. However, to completely automate the mine plan gridding, quite a number of new algorithms needed to be developed. The major steps in the automated development and analysis of the LaModel file in ARMPS-LAM are listed below and further detailed in the following paragraphs:

## Pre-Process:

- **Data Import:** Read the input file containing the ARMPS 2010 data (primarily geometry).
- **Property Calibration:** Determine the appropriate properties for the overburden, coal, and gob materials based on the formal LaModel calibration procedure.
- **Boundary Pillar Sizing:** Based on the input mine geometry and calibrated overburden properties, determine the radius of displacement and stress influence and, thereby define the required size for the boundary pillars around the edge of the model.
- **Mine Model Sizing:** Based on the input mine geometry and the required boundary pillar sizes, determine the overall required size for the model grid.
- **Mine Plan Generation:** Based on the input mine geometry and the required boundary pillar sizes, generate the exact boundary lines for the pillars and gobs, and output as an AutoCAD file.
- **Element Sizing:** Based on the overall model dimensions and the dimensions of the entries and pillars, determine an optimum element size.
- **Grid Generation:** Insert the coal and gob materials into the mine grid based on the pillar and gob locations.
- **Yield Zone Application:** Apply the yield zones to the pillars based on the Mark-Bieniawski stress gradient.
- **Input File Generation:** Generate and output the LaModel input file based on the final material properties and mine grid (this input file is a fully compatible LaModel3.0 input file).

## Process:

- **Run the Model:** Solve the model using LaModel and generate the output file (this output file is a fully compatible LaModel3.0 output file).

## Post-Process:

- **Calculate Stability Factors:** From the LaModel output file, determine stability factors of the AMZ and barrier pillars.

## EXAMPLE CASE HISTORY

In order to illustrate the automated model building and analysis process of ARMPS-LAM, one example case history from the ARMPS database was selected and is presented in detail here. This case history, located in Kentucky, has a cover depth (H) of 860 ft, an entry height (h) of 7.7 ft, a crosscut angle of 60°, an entry width of 20 ft, a crosscut spacing of 60 ft, uses the default abutment angle of 21°, and has an active and one side gob (loading condition of three). There are five entries with the same center-to-center spacing of 55 ft. The front active gob extends in by the pillar line a distance of 1,000 ft, and the first side gob has a width of 340 ft with a 75 ft wide barrier pillar separating the two retreat sections that has slab cut of 50 ft.

### Pre-process – Data Import

The proceeding ARMPS parameters are stored in a one-line input file, which is read into ARMPS-LAM in the data import step.

### Pre-process – Property Calibration

Next, the program uses the formal LaModel calibration process (Hesley et al., 2010) to automatically calibrate the overburden, coal, and gob material properties. For this sample case history, a lamination thickness of 307 ft, a coal strength of 900 psi (as implemented in the Mark-Bieniawski formula), and a final gob modulus of  $1.66 \times 10^6$  psi (as implemented in the exponentially hardening gob) were developed.

### Pre-process – Boundary Pillar Sizing

To determine the appropriate width of boundary pillars to use around the LaModel grid, the radius of stress/displacement influence is determined. Given a lamination thickness of 307 feet and a depth of 860 ft, the radius of influence is determined as 2,087 ft (Hesley, 1998).

$$R_p = \sqrt{\frac{2tz \ln(1-p)}{\sqrt{3(1-v^2)}}} = \sqrt{\frac{2 * 307 \text{ ft} * 860 \text{ ft} * \ln(1-0.999999)}{\sqrt{3 * (1-0.25^2)}}} = 2,087 \text{ ft} \quad (2)$$

where:

$R_p$  = Radius of influence, ft

P = Percentage of displacement/stress influence that is included (99.9999%)

t = Lamination thickness, 307 ft

v = Poisson's Ratio of laminations, 0.25

z = Vertical distance between points, 860 ft

## Pre-process – Mine Model Sizing

The overall size of the LaModel mine grid is determined by the input mine geometry and the calculated boundary pillar width. The total mine grid width (TWM) in ARMPS-LAM is then the sum of the width of the first side edge boundary pillar (WEB(3)), the width of the first side gob (WSG(3)), the width of the first side bleeder pillar (WSBP(3)), the width of the first side barrier pillar (WBAR(3)), the width of the extraction panel (WEP), the width of the second side barrier pillar (WBAR(4)), the width of the second side bleeder pillar (WSBP(4)), the width of the second side gob (WSG(4)), and the width of the second edge boundary pillar (WEB(4)). See Equation 3 below. (For these width variables, as used in ARMPS, the first side is designated by the index of 3 and the second side is designated by the index of 4.) In the example case history, there were no bleeder pillars left in the first side gob, and there was no second side gob, and therefore no second side barrier pillar or second side bleeder pillars. As a result, their widths were assigned as zero. The equation for the total width of the mine grid model (TWM) is given below and calculates a total model width of 4,864 ft.

$$\begin{aligned} \text{TWM} &= \text{WEB}(3) + \text{WSG}(3) + \text{WSBP}(3) + \text{WBAR}(3) + \text{WEP} \\ &\quad + \text{WBAR}(4) + \text{WSBP}(4) + \text{WSG}(4) + \text{WEB}(4) \\ &= 2,087\text{ft} + 340\text{ft} + 0 + 75\text{ft} + 275\text{ft} + 0 + 0 + 0 + 2,087\text{ft} \\ &= 4,864\text{ft} \end{aligned} \quad (3)$$

The total mine grid length (TLM) is the sum of length of top edge boundary pillar (LTEB), the length of central active gob (LCA), the breadth of the AMZ, and the length of bottom edge boundary pillars (LBP). The equation for the total length of the mine grid is given below and calculates a distance of 5,332 ft. Figure 2 shows a scaled schematic of the model case history with the distance parameters labeled.

$$\begin{aligned} \text{TLM} &= \text{LTEB} + \text{LCA} + \text{AMZ} + \text{LBP} \\ &= 2,087\text{ft} + 1,010\text{ft} + 148 + 2,087\text{ft} \\ &= 5,332\text{ft} \end{aligned} \quad (4)$$

## Pre-process – Mine Plan Generation

The total mine grid sizes determined in the previous step along with the input mine geometry and boundary pillars are then used to generate precise polygon outlines for the mine pillars and gob. This graphical pillar geometry is also saved as an AutoCAD DXF file. A sample of the case history mine geometry at the retreat line generated by ARMPS-LAM is shown in Figure 3a, where the coal pillars are shown with black polygons and the gob boundary is shown with a magenta polygon.

## Pre-process – Element Sizing

Next, a fairly complex algorithm examines the critical dimensions in the model (including the entry width, the production pillar dimensions, the barrier pillar widths, the remnant pillar widths, the gob dimensions, and the overall mine grid dimensions) and determines an optimum element size that will best fit all the

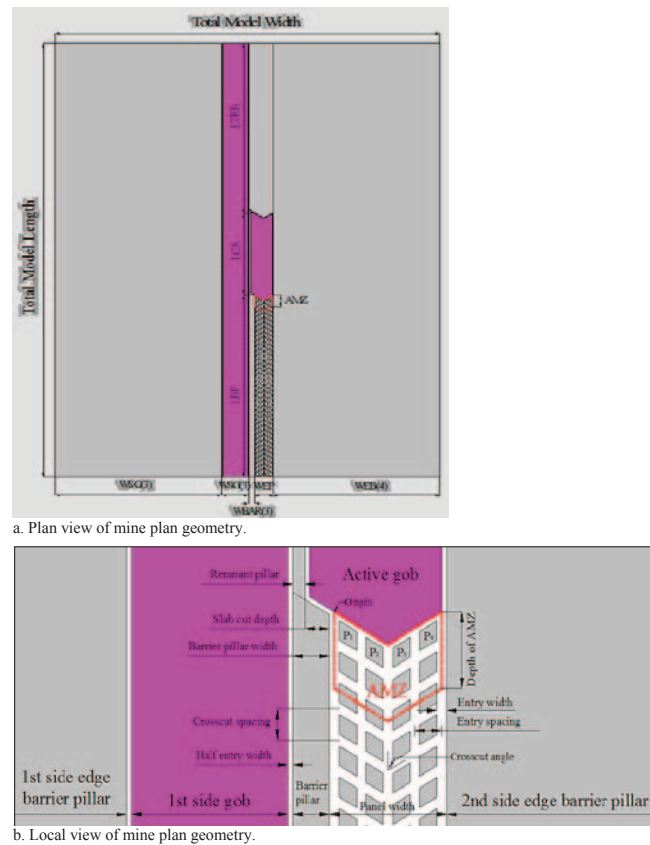


Figure 2. Mine plan geometry generated by ARMPS-LAM.

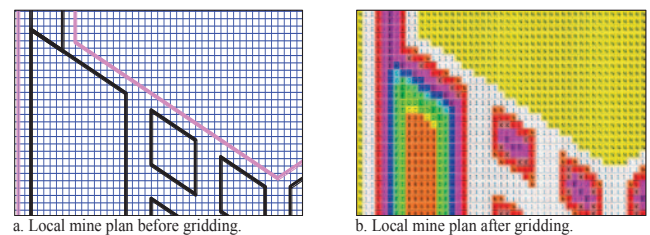


Figure 3. Plan view of mine plan gridding.

required dimensions. In this example case history, the algorithm determined that an element size of 5.0 ft was appropriate. With this element size, the final mine grid has 965 elements in the X direction and 1,066 elements in the Y direction.

## Pre-process – Yield Zone Application

With the grid geometry and element size known, as shown in Figure 3a, the next step is to apply the materials to the mine grid. Using the pillar (or gob) polygons and associated grid element squares, an integrated scan line filling algorithm developed by Foley (1996) and a polygon clipping method developed by Vatti (1992) are used to apply the appropriate material code to the grid elements. Essentially, each grid element will be checked to determine how much of its area is within a pillar or gob polygon. If the enclosed element area is more than 50%, the element will be assigned the same material as the polygon. This is the same

procedure used in the LaModel automatic grid generation function written for AutoCAD.

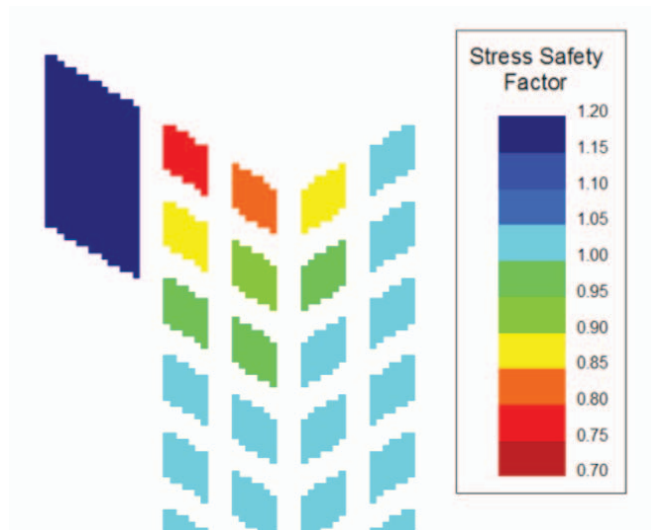
After all of the base coal and gob materials and remaining openings are applied to the mine grid, an appropriate set of material properties for a yield zone is applied to the coal pillars. This yield zone provides a stress gradient on the pillar consistent with the Mark-Bieniawski pillar strength formula. Initially, when the coal materials were generated, the material properties for each yield material were designed to coincide with a specific distance/location within a coal pillar. Now, once the location of the coal elements are known, these yield materials are applied to the coal elements based on the location of the given element within the coal pillar. The results of the material and yield zone application are shown in Figure 3b.

### *Pre-process – Input File Generation*

Finally, with all of the pre-processing steps completed and the final material properties and mine grid developed, ARMPS-LAM outputs the LaModel input file of the example case history. This input file is a fully compatible LaModel3.0 input file and could be further modified or enhanced using the LaModel pre-processor program, LamPre.

### *Process – Run the Model*

LaModel is then run using the input file, and the classic LaModel output file (.out file) is produced. This output file could be analyzed using the LaModel post-processor program, LamPlt, as shown in Figure 4, which presents the colored square plot of the pillar stress safety factor on the pillar line of the example case history.



**Figure 4. Colored square plot of stress safety factor.**

### *Post Process – Calculate Stability Factors*

With the LaModel output file, ARMPS-LAM then calculates and reports the stability factor of the AMZ and the barrier pillars (comparable to an ARMPS analysis). To determine the stability factor of the AMZ, an area-weighted average of the stability factor

of the pillars and partial pillars within the AMZ is used. For the example case history, the first two complete rows of pillars and about 40% of the third row of pillars are included in the AMZ. Table 1 details how the pillar safety factor for each pillar is weighted by the given pillar's percentage of area within the AMZ, and then the weighted stability factor from each pillar is summed to get the average stability factor for the AMZ. For this case history, the final AMZ SF is determined to be 0.93.

For this example case study, the complete ARMPS-LAM analysis took about five minutes of computer time, with most of that being taken to solve the LaModel grid. To develop the model, run the analysis, and calculate the AMZ stability factor would have taken several hours by hand. Thus, the automation functions of ARMPS-LAM can save the user considerable time and effort. From the user perspective, only the traditional ARMPS input is required, and the output is comparable to the traditional ARMPS stability factor of the AMZ.

### **ARMPS 2010 DATABASE**

The ARMPS 2010 database is supplied in the installation directory of ARMPS 2010. This 2010 database includes 645 case histories covering all of the United States coal fields. The 645 cases histories in the ARMPS 2010 database were extracted from the original 692 case histories by excluding the "borderline" and "floor heave" cases. Figure 5 shows the entire ARMPS 2010 database with the ARMPS 2010 SF plotted against the depth, with the suggested design criterion of 1.50 marked (Mark, 2010).

Within the ARMPS 2010 database, the mining height ranges from 3 ft to 18 ft with an average of 6 ft; the depth of cover ranges from 145 ft to 2,200 ft with an average of 892 ft; the entry width ranges from 9 ft to 37 ft with an average of 20 ft; the crosscut spacing ranges from 30 ft to 150 ft with an average of 78 ft; the center-to-center entry spacing ranges from 25 ft to 140 ft with an average of 70 ft; the crosscut angle ranges from 60° to 90° with an average of 85°; and the number of entries ranges from 2 to 10 with an average of 7. Also, all of the case histories use the same abutment angle of 21°. Table 2 presents the ranges of the input parameters of the ARMPS 2010 database.

### **STATISTICAL ANALYSIS**

#### *Logistic Regression*

The present version of ARMPS-LAM discussed in this paper is a research-oriented design that is capable of batch solving numerous case histories. When ARMPS-LAM was initially coded, it was validated against some of the ARMPS case histories by manually performing the analysis and then comparing the results to the automated ARMPS-LAM results, as demonstrated with the example case history above. To further evaluate the overall accuracy of the ARMPS-LAM program and compare it to the accuracy of the previous ARMPS 2010 program, a statistical analysis of the ARMPS-LAM results for the complete ARMPS 2010 database was performed. To be consistent with the previous accuracy evaluation of ARMPS 2010 (Mark, 2010; Mark, Chase, and Pappas, 2007), a similar technique of logistic regression is used to evaluate the ARMPS-LAM results.

Table 1. AMZ stability factor determination.

Pillar	Row	Col.	Stress Safety Factor	Area Percentage within AMZ	Weighted SF
1	1	1	0.79	10.38%	0.08
2		2	0.83	10.38%	0.09
3		3	0.89	10.38%	0.09
4		4	1.01	10.38%	0.10
5	2	1	0.90	10.38%	0.09
6		2	0.92	10.38%	0.10
7		3	0.99	10.38%	0.10
8		4	1.02	10.38%	0.11
9	3	1	0.98	4.24%	0.04
10		2	0.98	4.24%	0.04
11		3	1.01	4.24%	0.04
12		4	1.02	4.24%	0.04
Sum				100.00%	0.93

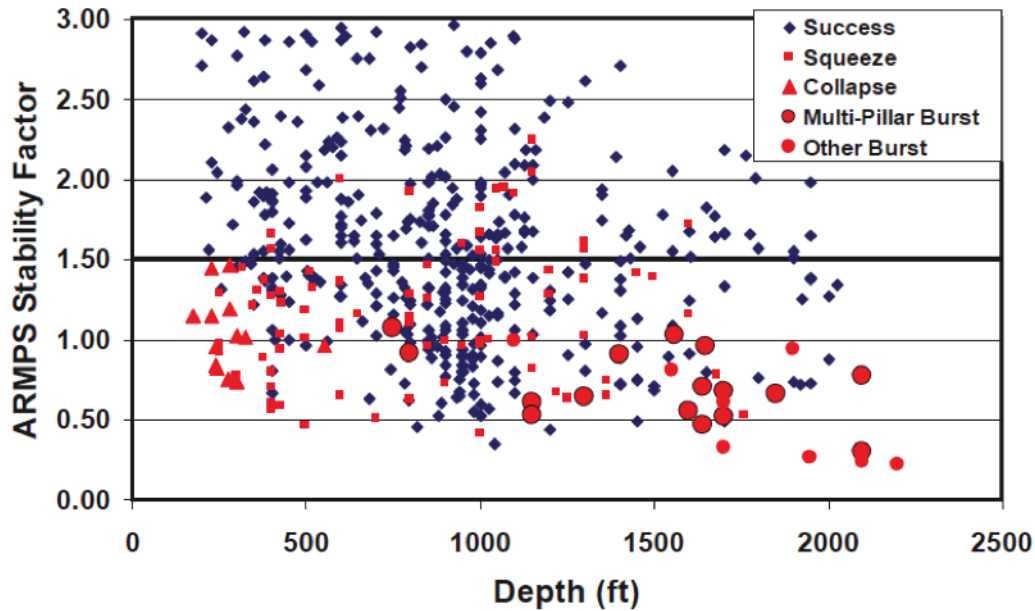


Figure 5. Recommended ARMPS SF (after Mark, 2010).

Table 2. Range of the input parameters of the ARMPS 2010 database.

Item	Min	Max	Average	Standard Deviation
Mining Height (ft)	3	18	6	2
Depth of Cover (ft)	145	2,200	892	436
Entry Width (ft)	9	37	20	1
Crosscut Spacing (ft)	30	150	78	18
Crosscut Angle (°)	60	90	85	11
Number of Entries	2	10	7	2

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Logistic regression is the most commonly used multivariate statistical technique when the outcome, or dependent, variable is binary (in this case “success” or “failure”). In order to obtain the coefficients of the independent variable, the outcome has to be in “binary” form (i.e., “1” or “0”); therefore, the panel success was chosen to be equal to “1,” while the panel failure was chosen to be “0.” The goal of logistic regression analysis is to develop a model that can best fit the “outcome” using a combination of the independent variables. In the regression analysis, different mathematical models need to be compared to determine the best fit model. To compare the goodness-of-fit of different logistic regression models, the Receiver Operating Characteristic (ROC) curve is employed. Specifically, the area under the ROC curve (AUC) is proportional to the ability of a given model to achieve a correct discrimination between the two outcomes (success or failure) within the database. The AUC of the ROC curve ranges from 0.5 (no discrimination or same as chance) to 1 (perfect discrimination) and provides a goodness of fit parameter that is somewhat analogous to the R-squared parameter in linear regression (Hosmer and Lemeshow, 2000).

In the initial part of the logistic regression analysis, numerous independent variables and various ways of representing those variables were examined in order to determine the variables that most significantly affect the outcome (success or failure of the section). Ultimately, the five most significant variables, in order of significance, were found to be:

1. Stability factor of the AMZ (AMZ SF)
2. Mining height (h)
3. Stability factor of the barrier pillar (BP SF)
4. Depth of cover (H)
5. Panel width ( $P_w$ )

Table 3 presents the logistic regression results with the above variables. In the table, the coefficients represent the multiplicative factor of the variable; the standard error is an estimate of the data standard deviation; the z-value (z) is calculated by dividing the coefficient by the standard error, which provides an assessment of the portion of the standard error in the answer caused by each variable; and the P-value denotes the significance of the individual variable, where a variable is more significant as its P-value decreases. It was very assuring to see that the AMZ SF was the most significant variable, followed two spots down by the BP SF. However, the fact that the seam thickness (h) showed as being second most significant leads to a number of questions that will probably be addressed in future research.

**Table 3. Logistic regression results for the model containing five variables.**

Variable	Coefficient	Standard Error	z	P
AMZ SF	1.679	0.2905	5.781	7.42E-09
h	-0.2453	0.05689	-4.312	1.62E-05
BPSF	0.7733	0.2436	3.174	1.50E-03
H	1.406	0.3262	4.309	1.64E-05
$P_w$	0.0005436	0.0008502	0.6390	0.5226
Intercept	-1.185	0.7886	-1.503	0.1328

In the database, there were many ARMPS case histories (loading condition 1 and 2) where there was no barrier pillar,

but rather a solid block of coal. In this situation, it was not clear how to accurately determine/input a “barrier pillar” stability factor. Obviously this solid block of coal would have a very high stability factor, but the exact value was unknown. To handle this conundrum, it was decided to input the barrier pillar safety factor in a “binary” form around the safety factor of 1.5, where the BP SF is equal to 0, if the BP SF is smaller than 1.5 (unstable), and the BP SF is equals to 1 if the BP SF is larger than 1.5 (stable). The BP SF was input in this binary manner for the results shown in Table 3. Similarly, there appeared to be a binary effect in the database with the depth, so the depth of cover (H) was also input in binary form around 650 ft, with H equal to 0 if the depth was less than 650 ft, and H equals to 1 if the depth was greater than 650 ft. The other three variables—AMZ SF, h, and  $P_w$ —were input consistent with their real values.

Based on the relative significance of the above variables, six different logistic regression models with an increasing number of independent variables were developed and analyzed in order to determine the practical accuracy of the different models. Model No.1 only has the most significant independent variable, AMZ SF, and Model No. 2 has both the AMZ SF and the seam thickness (h). Model Nos.3 and 4 each have three variables; however, Model No.3 uses the depth (H) as the third variable and Model No. 4 uses the BP SF as the third variable. Model No. 5 has the four most significant variables, while Model No.6 contains all five of the significant variables. Table 4 contains the equations with the regression coefficients for each of the trial models.

### Database Classification Comparison

According to the logistic regression performed by Mark (2010), ARMPS 2010 with only the one variable of stability factor(SF) achieved an AUC value of 0.7569, which implies good discrimination between the two outcomes (success or failure) within the database (see Table 5). In this initial logistic regression analysis of ARMPS-LAM, the single variable model with the AMZ SF only obtained an AUC value of 0.7026. However, Model No. 2, which contained both ARMPS SF and seam thickness (h) has an AUC value of 0.7958, a significant improvement and slightly better than ARMPS 2010. The next models, Nos. 3 and 4, only show a slight increase in the AUC with the additional variable (see Table 5). However, Model No. 5, with all four of the most significant variables, shows essentially the best AUC of 0.8206, since Model No. 6, with the addition of the panel width ( $P_w$ ) does not show any significant improvement.

For ARMPS 2010, the design criteria were ultimately determined to be an ARMPS SF of 1.5 where 82% of the failed

**Table 4. Logistic regression models with different variables.**

Model No.	Model Equation
1	$g(x) = 1.331*AMZ\_SF - 0.6285$
2	$g(x) = 1.172*AMZ\_SF - 0.3300*h + 1.876$
3	$g(x) = 1.823*AMZ\_SF - 0.2268*h + 1.410*H - 0.7674$
4	$g(x) = 1.060*AMZ\_SF - 0.3424*h + 0.7625*BP\_SF + 1.588$
5	$g(x) = 1.730*AMZ\_SF - 0.2367*h + 0.7736*BP\_SF + 1.442*H - 1.123$
6	$g(x) = 1.679*AMZ\_SF - 0.2453*h + 0.7733*BP\_SF + 1.406*H + 0.0005436*P_w - 1.185$

**Table 5. Logistic regression results of different models.**

Model	Variables of equation	Area under ROC curve (AUC)
ARMPS 2010	AMZ SF	0.7569
1	AMZ SF	0.7026
2	AMZ SF, h	0.7958
3	AMZ SF, h, H	0.8079
4	AMZ SF, h, BP SF	0.8061
5	AMZ SF, h, BP SF, H	0.8206
6	AMZ SF, h, BP SF, H, P <sub>w</sub>	0.8207

case histories and 59% of the successful case histories were correctly classified, for an overall classification accuracy of 63% (see Table 6). The 1.5 value of stability factor for ARMPS 2010 was not the optimum overall classification point, but rather, the recommended stability factor was raised to more accurately classify the critical unsuccessful case histories. For the regression models of ARMPS-LAM, the same criteria of 82% accuracy in classifying the failure cases was applied, and the results are shown in Table 6. For Model No. 1 using only the ARMPS-LAM SF, the overall accuracy is only 55% (compared to 63% for ARMPS 2010). However, for Model Nos. 2 and 4, the overall accuracy is 66%, and for Model Nos. 5 and 6, the overall accuracy is 71%, significantly better than ARMPS 2010. Because Model No. 5 has essentially the same classification accuracy as Model No. 6 but with fewer variables, it is the preferred option.

Although, this is only a preliminary analysis of the ARMPS-LAM results, and a number of potential improved ARMPS-LAM algorithms will be tried in the near future, these initial results are very encouraging. In a direct comparison with ARMPS 2010, which correctly classified 82% of the failed case histories and 59% of the successful case histories, for an overall classification accuracy of 63%, the ARMPS-LAM analysis was able to accurately classify 82% of the failed case histories and 69% of the successful case histories for an overall classification accuracy of 71%. In the future, this classification accuracy may yet increase with more research efforts.

**SUMMARY AND FUTURE WORK**

In the research presented in this paper, a computer code (ARMPS-LAM) has been developed to effectively implement the laminated overburden model into the ARMPS program. This program takes the basic ARMPS geometric input for defining the mining plan and loading condition and then automatically develops, runs, and analyzes a full LaModel analysis of the mining geometry to output the stability factor on the AMZ, all without further user input. In particular, the program automatically calibrates the material properties, sizes the boundary pillars, sizes the mine model, generates the pillar and gob polygons, sizes the elements, fills the mine grid with material codes, creates a LaModel input file, runs the LaModel file, and determines the stability factor of the AMZ and barrier pillars. What would take a user several hours to accomplish manually, the ARMPS-LAM program accomplishes in about 5 minutes. From the user perspective, only

**Table 6. Different models with same classification accuracy for failures.**

Model	Successes, % of success/% of total cases		Failures, % of failures/% of total cases		Total, % of total cases	
	Correct classification	Incorrect classification	Correct classification	Incorrect classification	Correct classification	Incorrect classification
ARMPS 2010	59%/48%	41%/33%	82%/16%	18%/4%	63%	37%
1	49%/39%	51%/41%	82%/16%	18%/4%	55%	45%
2	62%/50%	38%/31%	82%/16%	18%/4%	66%	34%
3	59%/48%	41%/33%	82%/16%	18%/4%	64%	36%
4	63%/50%	38%/30%	82%/16%	18%/4%	66%	34%
5	68%/55%	32%/26%	82%/16%	18%/4%	71%	29%
6	69%/56%	31%/25%	82%/16%	18%/4%	71%	29%



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the traditional ARMPS input is required, and the output is the traditional stability factor of the AMZ.

The present laboratory version of ARMPS-LAM can be run in batch mode; therefore, the large ARMPS database of 645 case histories can be analyzed very quickly. In an initial logistic regression analysis of this database, the ARMPS-LAM program was seen to be slightly more accurate than ARMPS 2010 by a factor of 71% versus 63%.

Beyond just improving the accuracy of the ARMPS loading algorithm by implementation of a laminated overburden, the combination of the ARMPS-LAM implementation and the capability of batch analysis of the ARMPS database has the potential to quickly evaluate the utility of any number of new ground control approaches. For instance, the utility of a new abutment loading algorithm proposed by Tulu (2012), or the utility of using strain-softening coal properties (Karabin and Evanto, 1999) can both be quickly evaluated with the new program. Further, the ARMPS-LAM program outputs an AutoCAD drawing of the mine plan, as well as the input and output files from the LaModel analysis. This feature potentially allows the ARMPS-LAM program to be used as a preprocessor for further refinement of the mine plan or model input parameters beyond the initial automatic inputs, and the output file can be further analyzed beyond just the pillar stability factors. With all of this potential, it is anticipated in the future that the new ARMPS-LAM program will follow in the path of ARMPS and LaModel and further improve the safety of retreat room and pillar mining operations in the United States.

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