A Comparison Between ARMPS and the New ARMPS–LAM Programs

Peng Zhang
Carlson Software
Watertown, MA

Keith A Heasley, Professor
Department of Mining Engineering
West Virginia University
Morgantown, WV

Zacharias G Agioutantis, Professor
School of Mineral Resources Engineering
Technical University
Crete, Greece

ABSTRACT

In previous research, the laminated overburden model from the LaModel program was effectively integrated with Analysis of Retreat Mining Pillar Stability (ARMPS) through ARMPS-like input to create a laboratory version of the new "ARMPS-LAM" program. This program takes the basic ARMPS geometric input for defining the mining plan and loading condition, and then automatically develops, grids, runs, and analyzes a full LaModel analysis of the mining geometry to output the section stability factor (SF), all without further user input. The initial ARMPS-LAM results were encouraging with a case history classification accuracy of 55% to 71%; however, a few of the input variables that were nominally included in the SF calculation showed independent significance in the classification accuracy.

Therefore, in order to further improve the accuracy of the ARMPS-LAM program, an investigation of the SFs calculated by the new ARMPS-LAM program and the ARMPS program is detailed in this paper. The initial results of a linear correlation between the ARMPS-LAM SF and the ARMPS SF showed a strong correlation ($R^2 = 0.88$), with the ARMPS-LAM SF averaging about 8% higher. The difference in SFs between the programs were further investigated, and, ultimately, the results indicated that the laminated overburden model as implemented in ARMPS-LAM distributes relatively more load on the section pillars for depths less than about 1,000 ft and less load for depths more than 1,000 ft. The results of this research highlight the potential for improving the ARMPS-LAM program in the future by implementing a more accurate loading calculation on the section pillars.

INTRODUCTION

A computer code, ARMPS-LAM, has been developed to effectively integrate the laminated overburden model into the ARMPS program (Zhang and Heasley, 2013). ARMPS-LAM functions as an automated solution for a LaModel analysis of an ARMPS-type mine design. Basically, the ARMPS-LAM program takes the typical ARMPS geometric input and empirical parameters for defining the mining plan and loading condition and then automatically conducts a complete LaModel analysis to calculate the stability factor of the Active Mining Zone (AMZ) (and barrier pillars), all without further user input. The program contains the necessary modules for covering all aspects and procedures of a full LaModel analysis, from pre-processing to post-processing. From the user perspective, only the traditional ARMPS input is required. Additionally, similar to ARMPS, the output contains the AMZ SF, barrier pillars SF, and other loading and strength data; however, these output values are now calculated using the laminated overburden model (Zhang and Heasley, 2013).

The ARMPS-LAM program consists of three primary modules: pre-processing, numerical solution, and post-processing. The pre-processing module includes the necessary subroutines to import data, develop, and calibrate the laminated overburden model (Heasley, 2008). The numerical solution module solves the laminated overburden model, and the post-processing module contains the subroutines to automatically extract and calculate the SFs and pillar loadings and then output the important data. The initial ARMPS-LAM program has been successfully validated (Zhang and Heasley, 2013); however, to further improve its classification accuracy of successful and unsuccessful cases in the future, the differences in the SFs calculated from the ARMPS program and the new ARMPS-LAM program are investigated in this paper.

STABILITY FACTOR INVESTIGATION

In previous research, the ARMPS 2010 and ARMPS-LAM programs were used to calculate the SFs for the 645 case histories in the original NIOSH ARMPS database (Zhang and Heasley, 2013). The results of the ARMPS analysis is based on the EXCEL version of ARMPS 2010, provided by the NIOSH for this research. It took only a couple of minutes of processing time to run the entire database with the EXCEL version of ARMPS. For the ARMPS-LAM analysis, the entire database took around 10 hours of processing time to run. The average running time for a single case history is 52 seconds, and the maximum running time of any case history in the database was 7 minutes. The ARMPS-LAM solution times depend on the complexity and size of the developed model. In this research, the SF criterion of 1.50 was used to separate the successful and unsuccessful case histories for both programs, and the calculated SFs between the two programs were compared to analyze their correlations and differences.

Stability Factor Correlations

To initially investigate the correlations between the two programs, the value of the calculated ARMPS-LAM SF was initially plotted versus the ARMPS SF, and a linear correlation was performed (see Figure 1). There was a fairly good correlation between their stability factors with an R^2 value of 0.8797 for the best-fit line (green dash line) and an R^2 value of 0.8794 for the best-fit line forced to go through the origin (blue solid line). This means that 88% of the variation of the ARMPS-LAM SF can be explained by the variation of the ARMPS SF for the given database. When the slope of the line is forced to go through the origin, the slope of the trend line (1.0811) indicates that the ARMPS-LAM SF averages about 8% higher than the ARMPS SF (blue line and equation, see Figure 1).

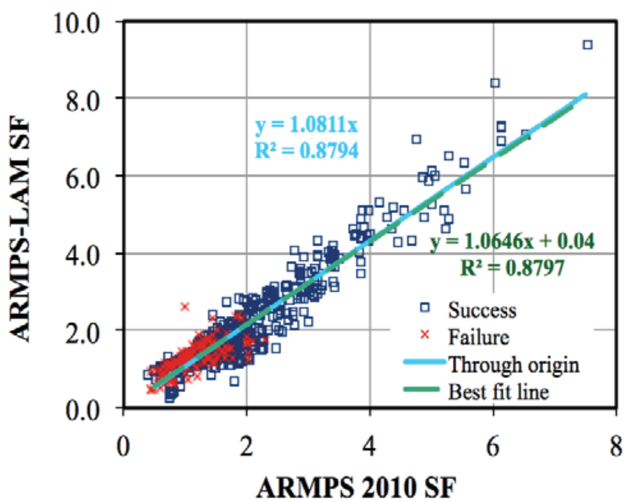

Figure 1. Relationship between ARMPS-LAM SF and ARMPS SF.

This strong correlation is not necessarily surprising. Both programs use the Mark-Bieniawski formula for determining the coal pillar strength. Also, both programs use the same abutment angle calculation for determining the magnitude of the abutment load. The big difference between the two programs is that ARMPS-LAM uses the laminated overburden model in a numerical determination of the relative stiffness of the support pillars (and gob) to ultimately determine the abutment (and overburden) load distribution, while ARMPS uses a number of empirically determined formulas for load distribution.

Although the ARMPS-LAM SF and the ARMPS SF show a strong correlation (trend line in Figure 1), some significant differences are also evident. Figure 1 indicates that some case histories have quite a different SF when comparing both programs. In order to further explore any significantly patterns in the differences between the ARMPS-LAM SF and the ARMPS SF, an SF ratio was created by dividing the ARMPS-LAM SF by the ARMPS SF for each case study (see Equation 1).

$$\text{SF Ratio} = \frac{\text{ARMPS - LAM SF}}{\text{ARMPS 2010 SF}} \tag{1}$$

Based on previous research and experience with the laminated overburden model (Esterhuizen, Dolinar, and Ellenberger, 2011; Heasley, 2012; Heasley et al., 2010; Sears and Heasley, 2013; Tulu, Heasley, and Mark, 2010), the SF ratio was analyzed against five potentially significant variables: depth, mining height, panel width, panel width-to-depth ratio, and pillar width-to-height ratio, looking for any significant trends. (For the pillar width-to height ratio (w/h), the average value of the section pillars is used. Because the strength of a rectangular pillar is different from that of a square pillar (Darling, 2011; Dolinar and Esterhuizen, 2007), the shape effect is considered by using a value four times the area (A) divided by perimeter (C) where w = 4A/C is a substitute for the pillar w/h ratio) (Wagner, 1980).

After reviewing the results from all of the potentially significant variables, there appeared to be a slight significant trend with the depth ($R^2 = 0.21$). In particular, it appears that the SF ratio decrease as the depth increases (see Figure 2). This means that the ARMPS-LAM SF is generally greater than the ARMPS SF when the depth is less than about 1,200 ft (as calculated from the regression equation). However, when the depth is greater than 1,200 ft, the ARMPS-LAM SF is generally smaller than the ARMPS SF.

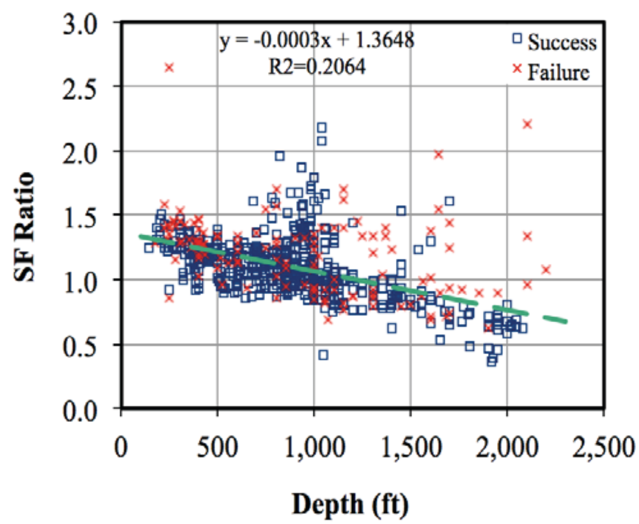

Figure 2. Influence of the depth on the stability factor ratio.

Any correlation between the SF ratio and the other potentially significant parameters, such as panel width, pillar width-to-height ratio, panel width-to-depth ratio, and mining height, was also investigated, and the results are presented in Figure 3, 4, 5 and 6, respectively. Figure 3 shows that the SF ratio is scattering around 1.08 at different panel widths with very little correlation ($R^2 = 0.008$). Figure 4 indicates that the SF ratio slightly decreases with increasing pillar width-to-height ratio, but the results are still very scattered, and the correlation is poor ($R^2 = 0.060$). In Figure 5, the SF ratio is seen to increase with the increase of panel width-to-depth ratio, but, again, the results are very scattered, and the correlation is poor ($R^2 = 0.050$). Finally, Figure 6 shows that the SF ratio is varying around 1.08 with different mining height and a poor correlation of $R^2 = 0.049$. Therefore, in comparing the ratio of the SFs between ARMPS-LAM and ARMPS, the only significant variable is the depth.

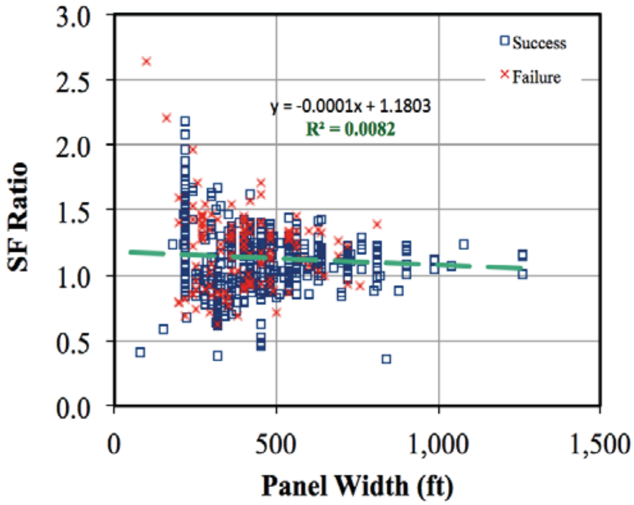

Figure 3. Influence of the panel width on the stability factor ratio.

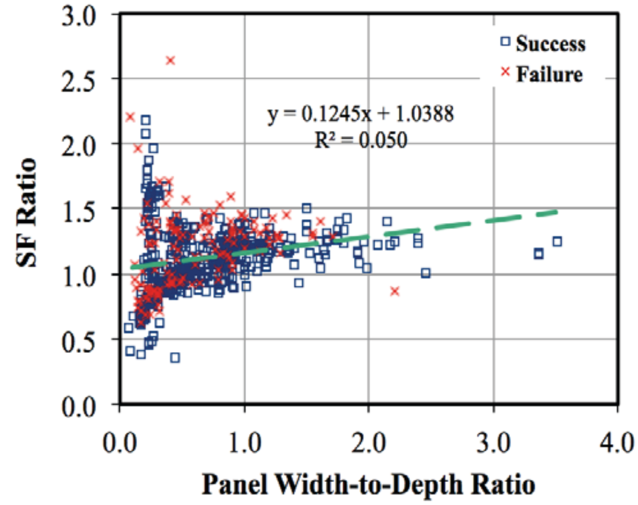

Figure 5. Influence of the panel width-to-depth ratio on the stability factor ratio.

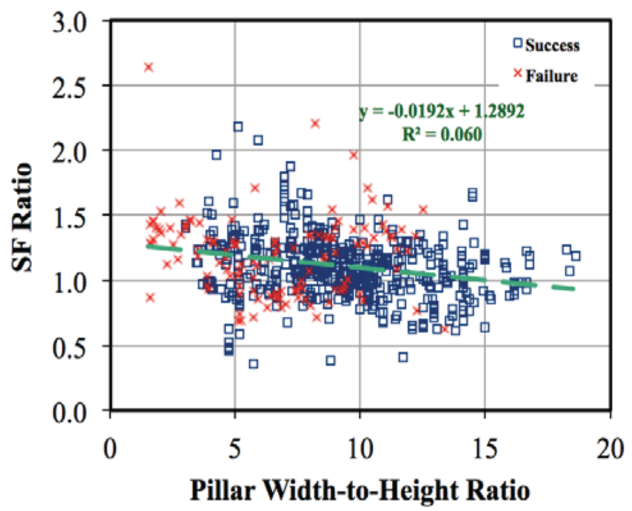

Figure 4. Influence of the pillar width-to-height ratio on the stability factor ratio.

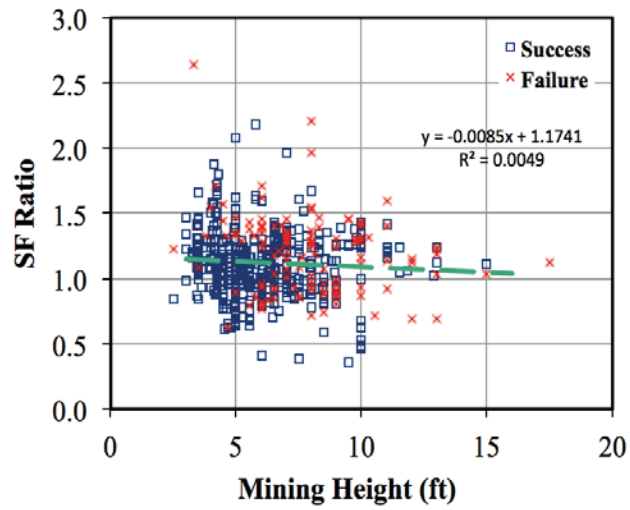

Figure 6. Influence of the mining height on the stability factor ratio.

Stability Factor Differences

To further analyze the differences between the SFs calculated by ARMPS-LAM and ARMPS, the differences in classification accuracy were examined. For both programs, the SF value of 1.50 was used to separate successful from unsuccessful case histories. In the classification accuracy analysis, it was found that both programs correctly classified 349 of the case histories (270 successes and 79 failures), and both programs incorrectly classified 187 of the case histories (172 successes and 15 failures). For the remaining 109 case histories, the two different programs gave opposite classifications. This means that, in these 109 case histories, when ARMPS-LAM classified the case history as a success, ARMPS classified it as a failure, or vice-versa. Thus, in these 109 cases, only one of the programs gives the correct classification. This small subset of the database was used to further explore the differences between the two programs with the intent of identifying potential improvements to the ARMPS-LAM program.

Table 1 further expands the analysis of the small subset of 109 case histories that were oppositely classified by ARMPS-LAM and ARMPS. In this subset, ARMPS-LAM correctly classified 47 of them (43%) compared with ARMPS which correctly classified the remaining 62 case histories (57%). Specifically, there are 78 successful case histories (72% of total) where ARMPS-LAM correctly predicted 38 (49%) of them (ARMPS fails), and ARMPS correctly predicted the remaining 40 (51%) successes (ARMPS-LAM fails). In addition, there are 31 failed case histories (28% of total) where ARMPS-LAM correctly predicts 9 (29%) of them (ARMPS fails), and ARMPS correctly predicts the remaining 22 (71%) failures (ARMPS-LAM fails).

To further explore the case histories in Table 1, the ARMPS-LAM SF was plotted versus the depth with the case histories divided into successes and failures and then further split into two sub-categories: ARMPS-LAM is correct, or ARMPS is correct

Table 1. Case histories where the two programs disagree on classification.

Program	Prediction Result	Case Histories with Opposite Results from Programs		
		Total Opposite	Case Success	Case Failure
		109	78	31
ARMPS-LAM	Correct	47	38 (<1,000 ft)	9 (>1,000 ft)
ARMPS 2010	Correct	62	40 (>1,000 ft)	22 (<1,000 ft)

(see Figure 7). This figure shows that the difference in prediction accuracy between the programs is strongly correlated to the depth (H). This figure indicates that, when the depth is less than around 1,000 ft, the ARMPS-LAM SF is greater than 1.50 for both successes and failures, and the ARMPS-LAM program predicts more successfully than ARMPS. However, when the depth is greater than 1,000 ft, the ARMPS-LAM SF is less than 1.50 for both successes and failures and is often incorrect. This trend (see Figure 7) partially explains why ARMPS-LAM correctly classified 49% of the successes from the subset of the database (because their depth is less than 1,000 ft, and ARMPS-LAM gets SFs larger than 1.50) and why ARMPS-LAM can only correctly classify 29% of the failures (because their depth is greater than 1,000 ft, and ARMPS-LAM gets SFs smaller than 1.50).

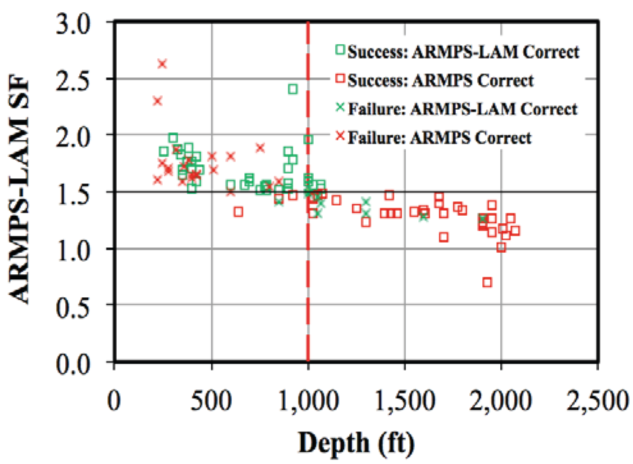

Figure 7. ARMPS-LAM SF vs. depth using the classification disagreement database.

Based on the analysis above, it can be seen that, when compared with ARMPS, ARMPS-LAM gets a higher SF for shallower cover (depths less than 1,000 ft) and gets a lower SF for deeper cover (depths greater than 1,000 ft). To further explore this trend, the results from ARMPS-LAM for the entire database were analyzed. Figure 8 is the plot of the ARMPS-LAM SF versus the depth with the case histories divided into the categories of successes and failures. These main categories are further split into two sub-categories: ARMPS-LAM is correct, or ARMPS-LAM is wrong. In this graph, it can be seen that most of the incorrectly classified successes occur with low ARMPS-LAM SF at deep cover and that most of the incorrectly classified failures occur with high ARMPS-LAM SF at shallow cover.

The details of the classification accuracy related to depth, as shown in Figure 8, are tabulated in Table 2. The trends observed in Figure 8 are duplicated in the table where ARMPS-LAM is seen

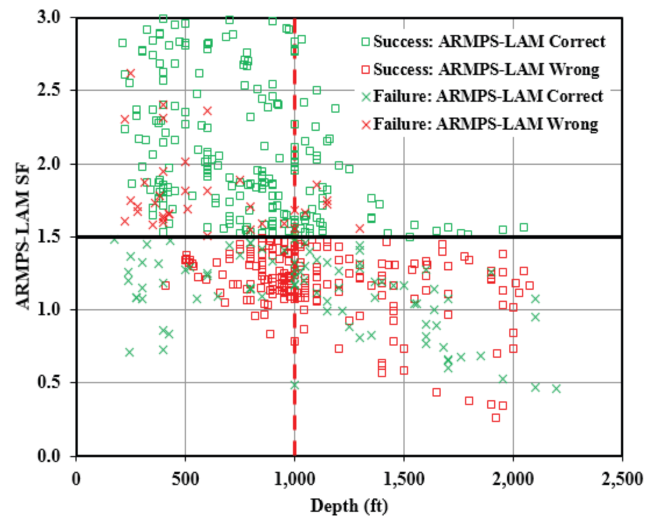

Figure 8. ARMPS-LAM SF vs. depth using ARMPS database.

to be good at classifying the shallow (less than 1,000 ft) successes (258 out of 372, 69%) and the deep (greater than 1,000 ft) failures (47 out of 52, 90%). Of course, the corollary is also true (see Table 2). ARMPS-LAM incorrectly classifies: 44% of shallow failures (32 out of 73) and 66% of deep successes (98 out of 148). It should be noted that it is not absolute that ARMPS-LAM has a greater SF for shallow mines and smaller SF for deeper mines, but there is a definite trend.

The highlighted trend in classification accuracy with ARMPS-LAM with depth is more than likely caused by the loading mechanics of the laminated overburden model, which, apparently, distributes less load on the AMZ for shallower cover (depths less than 1,000 ft), resulting in a higher stability factor, and more load on the AMZ for deeper cover (depth greater than 1,000 ft), resulting in a lower stability factor. This observation suggests that one of the potential future improvements to ARMPS-LAM (and LaModel) is to distribute more load on the AMZ for shallower cover and less load for deeper cover. This change would help ARMPS-LAM more accurately identify the failures with shallow cover and the successes with deep cover (see Figure 7). (However, it should be noted that this change could cause LaModel to fail to predict some successes with shallow cover and some failures with deep cover.)

SUMMARY AND CONCLUSIONS

Pillar stability is critical to safe and economic operations of room-and-pillar retreat mines. In previous research, a computer code, ARMPS-LAM, was developed to effectively implement the laminated overburden model (from LaModel) into the ARMPS program. This ARMPS-LAM program automatically develops,

Table 2. Classification accuracy of ARMPS-LAM using the SF guideline of 1.5.

Case History Category	ARMPS-LAM SF	ARMPS-LAM Prediction	Total		H <= 1,000		H > 1,000	
			Val.	Per.	Val.	Per.	Val.	Per.
Successes	> 1.5	Correct	308	59%	258	69%	50	34%
	<= 1.5	Wrong	212	41%	114	31%	98	66%
	Total		520	100%	372	100%	148	100%
Failures	<= 1.5	Correct	88	70%	41	56%	47	90%
	> 1.5	Wrong	37	30%	32	44%	5	10%
	Total		125	100%	73	100%	52	100%

runs, and analyzes a full LaModel analysis of an ARMPS-type mine design. An analysis of the SFs calculated by the new ARMPS-LAM and the ARMPS programs was performed and discussed in this paper. Based on the results of the analysis, it was seen that there is a strong correlation between the two stability factors (R^2 = 0.88) and that the ARMPS-LAM SF averages about 8% higher than the ARMP SF. In a more detailed analysis of the two SFs, depth was found to be a significant variable, with the ARMPS-LAM SF generally decreasing with depth in relation to the ARMPS SF.

In an analysis of the classification accuracy of ARMPS-LAM, it was seen that ARMPS-LAM generally calculated a higher SF and was more successful at shallow cover (depths less than 1,000 ft), while it generally calculated a lower SF and was less successful at deeper cover (depths greater than 1,000 ft). This analysis indicates that the laminated overburden model (as implemented in LaModel/ARMPS-LAM) distributes less load for shallow cover and more load for deep cover than may be accurate. This observation indicates that a potential improvement for the laminated overburden model might be to enhance the accuracy of its load distribution mechanisms by increasing the AMZ load at shallow cover and decreasing the AMZ load at deeper cover. For instance, the new abutment loading algorithm proposed by Tulu and Heasley, (2012) could achieve this result. Also, in the future, more accurate coal pillar strength models (for instance strain-softening) could potentially improve the accuracy of ARMPS-LAM.

REFERENCES

Darling, P. (2011). *SME Mining Engineering Handbook: 3rd Edition.* Englewood, CO: Society for Mining, Metallurgy, and Exploration, pp. 1840.

Dolinar, D. R. and Esterhuizen, G. S. (2007). "Evaluation of the effect of length on the strength of slender pillars in limestone mines using numerical modeling." In: *Proceedings of the 26th International Conference on Ground Control in Mining*. Morgantown, WV: West Virginia University, pp. 304–313.

Esterhuizen, G. S., Dolinar, D. R., and Ellenberger, J. (2011). "Pillar strength in underground stone mines in the United States." *International Journal of Rock Mechanics and Mining Sciences 48* (1): 42–50.

Heasley, K.A. (2008). "Some thoughts on calibrating LaModel." In: *Proceedings of the 27th International Conference on Ground Control in Mining*, pp. 29–31.

Heasley, K. A. (2012). "Calibrating the LaModel program for site specific conditions." In: *Proceedings of the 31st International Conference on Ground Control in Mining*. Morgantown, WV: West Virginia University, pp. 1–8.

Heasley, K. A., Sears, M. M., Tulu, I. B., Calderon-Arteaga, C. H., and Jimison II, L. W. (2010). "Calibrating the LaModel program for deep cover pillar retreat coal mining." In: *Proceedings of the ICGCM Pillar Design Workshop*. Morgantown, WV: West Virginia University, pp. 47–57.

Sears, M. M. and Heasley, K. A. (2013). "Calibrating the LaModel program for shallow cover multiple-seam mines." In: *Proceedings of the 32nd International Conference on Ground Control in Mining*. Morgantown, WV: West Virginia University, pp. 99–106.

Tulu, I. B. and Heasley, K. A. (2012). "Investigating abutment load." In: *Proceedings of the 31th International Conference on Ground Control in Mining*. Morgantown, WV" West Virginia University, pp. 1–10.

Tulu, I. B., Heasley, K. A., Mark, C. (2010). "A comparison of the overburden loading in ARMPS and LaModel." In: *Proceedings of the 29th International Conference on Ground Control in Mining*. Morgantown, WV: West Virginia Universiy, pp. 28–37.

Wagner, H. (1980). "Pillar design in coal mines." *Journal of the South African Institute of Mining and Metallurgy Jan. 1980*: 37–45.

Zhang, P. and Heasley, K. A. (2013). "Initial results from implementing a laminated overburden model into ARMPS." In: *Proceedings of the 32st International Conference on Ground Control in Mining*. Morgantown, WV: West Virginia University, pp. 239–247.