FINAL TECHNICAL REPORT
January 1, 2010, through December 31, 2010

Project Title: **REDUCING ENERGY CONSUMPTION & CARBON FOOTPRINT THROUGH IMPROVED PRODUCTION PRACTICES**

ICCI Project Number: 10/ER9
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ABSTRACT

The US coal mining industry consumes approximately 142 billion kWh per year of energy. The US Department of Energy estimates that the industry's annual energy consumption can be reduced by 49% (24.6 billion kWh/year by using currently available best practices and a further 44.8 billion kWh/year with more research). This constitutes nearly $3.7 billion of potential savings on coal production costs at 5.3¢/kWh of energy. Additionally, with climate change regulation on the horizon, any benefits from energy savings in the near future are compounded by associated reductions in CO_2 emissions.

The overall goal of this project was to evaluate a variety of operational strategies and produce a ranked list of high impact energy saving improvement options for surface coal mining operations. The research team conducted energy audits of truck-and-shovel overburden removal and highwall miner operations. This information was used to develop regression models describing truck and shovel energy consumption. The research team then built a stochastic simulation model of the truck-and-shovel overburden removal operation and used it to assess a variety of improvement measures by simulation experimentation.

Results of energy audits show that the average fuel efficiency for trucks, shovels, and the overall truck-and-shovel system are 37.14, 39.29, and 19.09 tons/gal of diesel, respectively, for overburden removal at the study site. The highwall miner's energy efficiency is 0.443 tons/kWh. Valid fuel consumption models for shovel loading and truck haulage have been formulated based on these energy audit results. Valid stochastic process models of truck-and-shovel operations have been formulated to study fuel consumption.

The following strategies, in decreasing order of impact, provide the most energy savings for truck-and-shovel overburden removal at the mine: (1) shorten haul roads; (2) increase shovel capacity; and (3) increase shovel utilization through optimal truck matching. Additional data will be required to adequately describe operator effects on fuel consumption. There are indications that power quality affects the energy draw for highwall miner operations but further study is required to adequately understand this.

EXECUTIVE SUMMARY

Background

The US mining industry consumes approximately 365 billion kWh of energy annually to produce vital products supporting the US and world economies. Of this figure, coal mining accounts for approximately 142 billion kWh per year. The US Department of Energy (DOE) estimates that energy consumption can be reduced by 24.6 billion kWh/year using currently available best practices and a further 44.8 billion kWh/year with more research, making coal mining much more efficient (DOE, 2007). This translates into an almost 49% decrease in energy consumption or nearly $3.7 billion of potential savings on coal production costs at 5.3¢/kWh of energy. With climate change legislation on the horizon, the benefits of energy savings in any production endeavor will be compounded. The most promising processes for energy efficiency improvements are grinding and materials handling, *including loading and hauling* (DOE, 2007).

Almost all current energy-saving strategies in coal mining involve improvements in technology (e.g. improving engine performance) and overall energy audits and reporting to ensure increased energy efficiency. Research, however, shows that operator practices and mine operating conditions significantly affect energy consumption. Simulation experiments conducted by the research team on electric shovels, for instance, suggest that an operator who operates near optimal with a 58 yd^3 bucket can save over $114,000/year in electricity costs for the digging cycle alone, when compared to an average operator (Awuah-Offei and Frimpong, 2007; Awuah-Offei, 2009). Other research shows that equipment utilization is a key factor in the energy efficiency of mining operations. Consequently, this research explored operating conditions and operator practices to optimize energy savings with existing equipment.

Objectives

This project evaluated the feasibility of modeling and predicting energy consumption of coal mining processes and the effects of operator practices and operating conditions. Specific objectives were to:

1. Conduct energy audits that account for operating conditions and operator practices for three typical coal mining equipment units;
2. Develop models to predict the energy consumption of these equipment units and related processes; and
3. Assess the efficiency of different improvement strategies by simulation experimentation.

Experimental Procedures

Two Illinois coal mines were used as study sites for this project. Truck-and-shovel overburden removal operations were the focus at Mine 1 and highwall miner operations were the focus at Mine 2.

Original equipment manufacturer (OEM) onboard data logging, time and motion studies, digital power metering, and production data were used to conduct energy audits for shovel loading, truck haulage, and highwall miner extraction operations. The goal was to obtain energy consumption data that can be correlated to productivity, operating conditions, and operator effects. Statistical techniques were used to evaluate correlation, develop predictive models, and evaluate the effect of operator practices.

A stochastic process simulation model of the truck-and-shovel overburden removal operation was built in ARENA® (Rockwell Automation Inc., Milwaukee, WI). The chi-squared goodness-of-fit test was used to fit theoretical distributions to the cycle time and payload data. These distributions were then used to describe stochastic processes in the ARENA model. The model was validated with truck fuel consumptions. The validated model was then used to evaluate the effect of increasing shovel utilization through optimal truck matching, using a higher capacity shovel, and shortening haul distances. The goal was to produce a ranked list of energy improving strategies.

Results

Data from Mine 1 shows that the average load factor of the shovel engine is 66.78%, which corresponds to a fuel consumption rate of 35.36 gals/hr and fuel efficiency of 39.29 tons/gal (of diesel). The average truck fuel consumption is 3.68 gals/cycle. This leads to a fuel efficiency of 37.14 tons/gal. Overall, the fuel efficiency of the truck-and-shovel overburden removal operation is 19.09 tons/gal.

Table S1 shows that there is significant linear correlation (p-value less than $\alpha = 0.05$) between load factor and shovel front end utilization (ratio of time shovel front end was active during the shift). Equation (S1) represents the model to predict shovel load factor from front end utilization based on regression analysis.

Table S1: Shovel Load Factor Correlation Analysis

Independent variable	Pearson correlation coefficient	p-value ($\alpha = 0.05$)
Front end utilization	0.77948	0.0000
Ratio of travel time	-0.11818	0.1392

$$\text{Shovel load factor} = 0.2391 + 0.5337\left(\text{front end utilization}\right) \qquad \text{(S1)}$$

Table S2 shows that there is significant linear correlation between payload and fuel consumed per cycle and between cycle time components and the fuel consumed per ton per cycle. Equation (S2) represents the model to predict fuel consumption rate from cycle time components, t_i, (in minutes) where component i is described by subscripts *es*, *et*, *l*, *ls*, and *lt*, which mean empty stopped, empty travel, loading, loaded stopped, and loaded travel, respectively.

$$\text{Fuel/cycle/ton} = 0.0037 + 0.0005t_{es} + 0.0035t_{et} + 0.0008t_{l} + 0.0031t_{ls} + 0.0043t_{lt} \qquad \text{(S2)}$$

Table S2: Truck Fuel Consumption per Cycle per Ton Correlation Analysis

Independent variable	**Pearson correlation coefficient**	**p-value ($\alpha = 0.05$)**
Payload	0.1518[1]	0.0000
Loading time	0.1861	0.0049
Empty stopped time	0.3951	0.0000
Empty travel time	0.5206	0.0000
Loaded stopped time	0.1861	0.0049
Loaded travel time	0.3511	0.0000

[1] Correlation is between payload and fuel/cycle

The stochastic process model predicts fuel consumption per cycle and fuel efficiency of trucks with 1% error. Simulated shovel utilization over a shift was used as an estimate of the average shovel engine load factor in a shift. The model was then used to evaluate energy saving strategies. Figure S1 shows that decreasing average haul distance (provided haul grade is maintained) and using the larger Hitachi EX2500 (20.4 yd^3 dipper) instead of the EX1900 (14.4 yd^3 dipper) increases fuel efficiency. Adding one more truck (either a 100-ton or 150-ton truck) results in a marginal (1.3-1.5%) decrease in fuel efficiency but a significant (27-34%) increase in productivity.

The average fuel efficiency of the highwall miner is 0.443 tons/kWh. Available data suggests that power quality may be the cause of significant inefficiency. Drops in power factor, for instance, were observed to more than triple current demand.

Conclusions

- Process specific energy audits can help identify energy improving opportunities in a way that is not possible with global energy consumption figures. This is illustrated with the fuel consumption analysis of the truck-and-shovel system.
- At Mine 1, average truck and shovel fuel efficiencies are 37.14 and 39.29 tons/gal, respectively. The truck-and-shovel system's overall fuel efficiency is 19.09 tons/gal of diesel. At Mine 2, the highwall miner's energy efficiency is 0.443 tons/kWh.
- Equations (S1) and (S2) are valid fuel consumption models for shovel loading and truck haulage, respectively.
- Valid stochastic process models of truck-and-shovel operations have been formulated to study fuel efficiency.
- For Mine 1, the following strategies in decreasing order of impact, provide the most improvement in energy efficiency for truck-and-shovel overburden removal:
  - Shorten haul roads while keeping haul grade and dozer push distance similar.
  - Use a Hitachi EX2500 (20.4 yd^3 dipper) instead of the EX1900 (14.4 yd^3 dipper).
  - Increase shovel utilization through addition of one more truck (either a 100-ton or 150-ton truck). This change marginally decreases fuel efficiency but significantly increases production and shovel utilization.
- Operator effects cannot be adequately described without additional data.

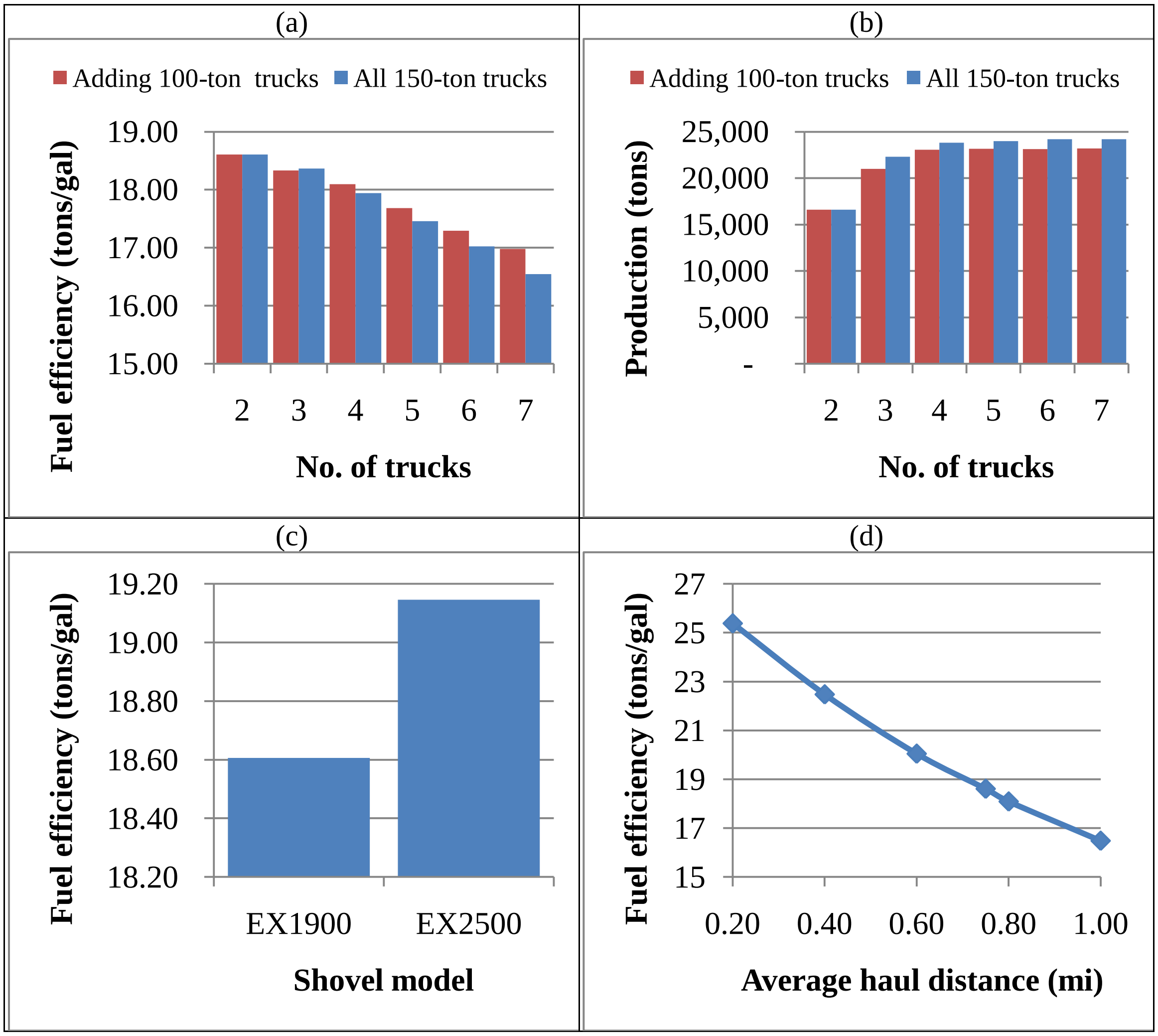

Figure S1: Simulation Results:

(a) Fuel Efficiency vs. Number of Trucks

(b) Shift Production vs. Number of Trucks

(c) Fuel Efficiency vs. Shovel Model

(d) Fuel Efficiency vs. Average Haul Distance

OBJECTIVES

The objective of this project was to conduct a study to understand the effect of operating conditions and operator practices on the energy used to produce coal. Specific objectives were to:

1. Conduct energy audits that account for operating conditions and operator practices for three typical equipment units used in surface coal mining;
2. Develop models to predict the energy consumption of these equipment units and related processes; and
3. Assess the impact different improvement strategies on energy efficiency using simulation experimentation.

The project was divided into three tasks, as follows:

- **Task 1 – Process specific energy audits:** Energy audits of shovel overburden loading, truck overburden haulage, and highwall coal mining.
- **Task 2 – Data analysis and modeling:** Statistical data analysis and regression modeling to describe energy consumption data. Stochastic process simulation modeling of truck-and-shovel overburden operations for evaluating improvement strategies.
- **Task 3 – Production improvement analysis:** Analysis of improvement strategies using simulation experimentation.

INTRODUCTION AND BACKGROUND

The US mining industry consumes approximately 365 billion kWh of energy annually to produce vital products to support the US economy. Of this, coal mining accounts for approximately 142 billion kWh per year. The US Department of Energy (DOE) estimates that energy consumption can be reduced by 24.6 billion kWh/year using currently available best practices and a further 44.8 billion kWh/year with more research to make coal mining more energy efficient (DOE, 2007). This translates into an almost 49% decrease in energy consumption or nearly $3.7 billion of potential savings on coal production costs at 5.3¢/kWh of energy. With climate change regulation on the horizon, the benefits of energy savings in any production endeavor will be compounded. According to DOE (2007), the most promising processes for energy efficiency improvement are grinding and *materials handling, including loading and hauling* (emphasis added).

Current energy-saving strategies in coal mining tend to involve improvements in technology (e.g. improving engine performance). Energy consumption monitoring and reporting emphasizes system performance without regard to operating conditions. However, there is evidence that operator practices and mine operating conditions significantly affect energy consumption. For instance, simulation experiments conducted by Awuah-Offei (2009) suggest that an electric shovel operator who operates near optimal with a 58 yd^3 bucket can save over $114,000/year in electricity costs for the digging cycle alone, when compared to an average operator. Other research shows that equipment utilization, for instance, is a key factor in the energy efficiency of mining operations. Figure 1 shows multiple factors that affect energy consumption. Consequently, this research considered operating conditions and operator practices to optimize energy savings with existing energy-saving technology.

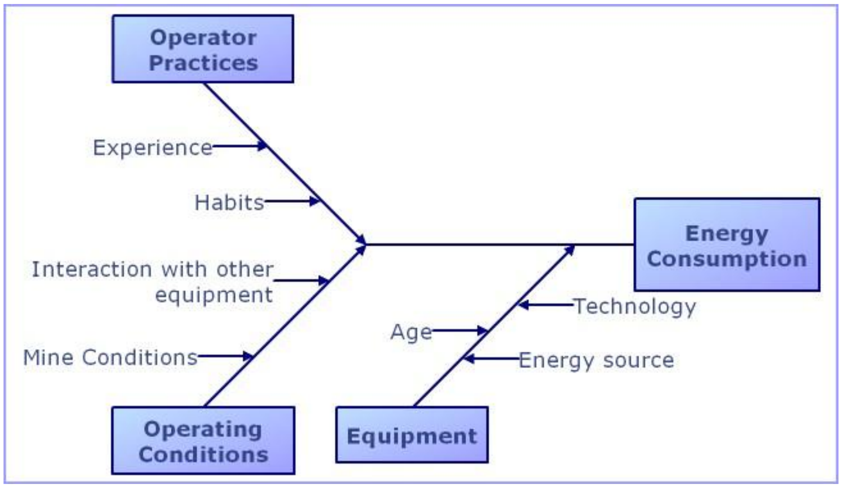

Figure 1: Factors Affecting Coal Mine Energy Consumption.

An important aspect of this study was the use of stochastic process simulation to evaluate energy saving production strategies before implementation. Stochastic simulation is a well known technique that has been used to study several mining systems (Awuah-Offei et al., 2003; Raj et al., 2009). Several special-purpose simulation languages like GPSS, Simscript, SLAM, and SIMAN have been developed to model continuous, discrete, and mixed continuous-discrete event systems. A key strength of these packages is the use of Monte Carlo simulation to introduce uncertainty into modeling. In this work, ARENA® software (Rockwell Automation Inc., Milwaukee, WI) was used to model the energy consumption of a truck-and-shovel mining system (Kelton et al., 2003). It is based on the SIMAN simulation language.

An ARENA model was developed in this project for evaluating energy saving production strategies of loading and hauling operations. This framework is applicable to Illinois coal with the base model based on an Illinois surface coal mine. By using a data-driven simulation approach, the uncertainty associated with predicting fuel consumption can be estimated. This allows users to judge the risks associated with implementation of particular operating strategies. The model is applicable to any loading and hauling scenario provided cycle time data is available to describe the system.

EXPERIMENTAL PROCEDURES

Mine Sites

Researchers collected data from two surface coal mine sites. Mine 1 is a strip mine and recovers coal mainly from the Murphysboro seam, with some coal mined from the Mount

Rorah seam. The mine produces about 600,000 tons of coal annually at an average stripping ratio of 17:1. The overburden is made up of grey, well-laminated, non-marine shales, overlain with up to 40 feet of glacial outwash clays and sand channels. The overburden is fragmented through blasting prior to removal. Overburden removal is mainly by carry dozers. However, the final overburden is removed by a Hitachi EX1900 hydraulic shovel (14.4 yd^3 dipper) and 150-ton, rigid frame, haul trucks. Both the shovel and trucks have on-board data logging systems that were used to collect data on engine load factor and fuel consumption, respectively.

Mine 2 is a surface and underground mine complex that employs a highwall miner to mine marginal strip/underground coal. The mine produces about 2.7 million tons of coal, annually, with approximately 200,000 tons from the highwall miner. The highwall miner is used only intermittently and is capable of 3,000 tons/day of coal production. Coal is recovered from the Herrin No. 6 coal seam with surface mining used to extract some coal from the Springfield No. 5 seam. The highwall miner is able to extract coal from surface highwalls without additional stripping thus economically extracting coal with minimal surface impact and cost.

Shovel Loading Energy Audit

The original equipment manufacturer (OEM) of the shovel, Hitachi, has an onboard data logging system called the machine information center (MIC) that logs, among other things, engine running time, front end operating time[*], travel time, and engine load factor. MIC data from January 1 to July 12, 2010 was downloaded from the shovel for this study. After careful review, the research team used shift averages of engine running time, front end operating time, travel time, and engine load factor for data analysis. Since MIC does not log fuel consumed, Hitachi data on fuel consumption and load factors were used to establish the relationships described in Equation (1), which relates engine load factor to fuel consumption for the two shovel models analyzed in this study.

$$\begin{aligned}&\text{EX1900 fuel consumption [gals/hr]} = 52.971\times\text{Load factor}+0.0133\\&\text{EX2500 fuel consumption [gals/hr]} = 71.304\times\text{Load factor}+0.0059\end{aligned}\qquad(1)$$

Additionally, researchers conducted time and motion studies of the shovel loading operation to obtain cycle times. Shovel productivity was obtained by correlating time stamps on the data with the truck OEM data logging system (discussed in the next section).

Statistical correlation analysis, at 95% confidence, was used to examine the correlation between load factor (a proxy for fuel consumption) and engine running time, front end operating time, front end utilization (ratio of time the front end was active in the shift), travel time, and ratio of time the shovel traveled in the shift. The decision to use time ratios in correlation analysis was to enable extension of results to different shift lengths.

[*] This time is cumulatively logged so long as any of the hydraulic pumps controlling cylinders on the front end of the shovel are active. Thus, the time logged is always more than actual shovel loading time.

Regression analysis was then used to determine the relationship between load factor and key independent variables.

Truck Haulage Energy Audit

The OEM onboard data logging system logs payload, empty stopped time, empty travel time, empty travel distance, loading time, loaded stopped time, loaded travel time, loaded travel distance, total cycle distance, total cycle time, and fuel used for each cycle. The research team downloaded data from May 3 to July 2, 2010. The summary performance was based on all of this data. However, given the variability in haul distances, haul road profiles, and haul road conditions, only data from the June 28-July 2 experimental period were used for detailed analysis. This was because haul distances, profiles, and conditions were similar during that period. The haul profile was surveyed with Topcon Hyperlite GPS units for real-time kinematic (RTK) surveying. Even though the OEM system logged cycle times, manual time and motion studies of the trucks were conducted as well to validate data from the OEM system. The OEM data proved to be reliable and better than the manual data. Therefore, all analyses were based on OEM data.

First, statistical hypothesis testing at 95% confidence was used to determine if different operators and trucks had any impact on fuel consumption and total cycle time. Subsequently, statistical correlation analysis was used to evaluate the correlation between fuel consumption and payload, as well as between fuel/cycle per ton and the components of cycle time (i.e. empty stopped time, empty travel time, loading time, loaded stopped time, and loaded travel time). Regression analysis was then used to determine the relationship between fuel consumed/ton per cycle and components of cycle time.

Truck-and-Shovel Operations Modeling

Discrete systems, such as the truck-and-shovel system, are modeled in ARENA using the process orientation approach usually referred to as object-oriented simulation. In this type of model, the modeler identifies the system’s entities, processes, and resources. The system is then conceptualized by letting entities go through static processes in a logical way. At each process, entities wait their turn to use up required resources to go through the process (Awuah-Offei et al., 2003; and references therein). In ARENA, the modeler can create different entities which can be given characteristics by specifying attributes. The software provides numerous modules for model construction (Kelton et al., 2003).

Prior to modeling, chi-squared goodness-of-fit tests were used to fit appropriate theoretical distributions to cycle times (both shovel and truck) and payload. The selected distributions were provided as inputs to the model to describe various processes.

In modeling fuel consumption of the Mine 1 truck-and-shovel system, drivers/operators were identified as entities. Cycle times and payload were defined as attributes which were changed for each cycle by sampling from pre-defined distributions. Two *stations* were defined in the model and *transporters* (trucks) used to move entities between these stations. The shovel was defined as a resource which was needed for an entity to go through the loading process. The shovel schedule was used to enforce the 30-minute break during an 11-hour shift. The model was constructed using appropriate ARENA modules to mimic reality as closely as possible. In order to ensure accurate fuel consumption data, the model was set-up to write the fuel consumed by trucks in each cycle to a comma separated text file for processing at the end of the simulation. Appropriate data, including shovel utilization, were collected and reported at the end of the simulation. All simulation experiments were set up to run for 100 replications of eleven hours each (equivalent to 100 shifts).

This simulation model was then used to evaluate energy saving improvement strategies. The following strategies were evaluated:

- **Strategy 1:** Increase shovel utilization through optimal truck matching. This scenario involved increasing the number of trucks in the system in order to identify the *optimal* truck-shovel match. In an alternate scenario, additional 100-ton trucks were added to the fleet since the mine has two such trucks readily available. The mine is more likely to add these 100-ton trucks than purchase new 150-ton trucks. It is estimated that the shovel is able to load 100-ton trucks in five passes.
- **Strategy 2:** Increase shovel capacity. This scenario involved simulating the use of an EX2500 (20.4 yd^3 dipper), which, in Hitachi's fleet, is the next size up from the EX1900 shovel currently in use. In order to do this, it was assumed (after consultation with staff at the Hitachi dealer) that cycle times are the same for both shovels. The larger shovel will load 150-ton trucks in five passes.
- **Strategy 3:** Shorten haul roads. This can be achieved by reducing the size of the pit. This involved varying haul distance from 0.2 to 1.0 miles in steps of 0.2 miles while keeping everything else constant.

Highwall Miner Energy Audit

The highwall miner's energy consumption was monitored using a PowerLogic CM4250 circuit monitor (Square D, Palatine, IL). The unit is a multifunction, digital instrumentation, data acquisition and control device. The CM4250 was used in conjunction with a PowerLogic 3090 SCCT063 current transformer (CT). The meter has an accuracy of ±0.04% of reading plus 0.025% of full-scale current/voltage. The CT is rated at 1% accuracy.

Motors on the highwall miner run on a 995-volt, three-phase, three-wire, delta system. The meter was set up in a three-phase, three-wire, three-CT configuration. Since the meter is rated for only up to 600 volts, voltage was stepped down to 480 volts. An onboard data log file was prepared to store up to 32,000 entries. Every minute, the meter logged Phase A, B, and C current, average current, Phase A, B, and C voltage, average voltage, power factor, power, and energy, among several other items.

RESULTS AND DISCUSSION

Task 1: Process Specific Energy Audits

Tables 1 and 2 summarize fuel consumption data for trucks and the shovel, respectively. Table 1, covering the entire data range from May 3 to July 2, shows fuel efficiency to be 37 tons/gal. Table 2 shows the average load factor for the January 1 to July 12 period to be 67%. Based on Equation (1), average fuel consumption is estimated to be 35 gals/hr. Based on productivity, shovel fuel efficiency was estimated to be 39 tons/gal. Based on data in Tables 1 and 2, overall fuel efficiency of the truck-and-shovel system is estimated at 19.09 tons/gal.

The energy efficiency of the highwall miner is estimated to be 0.443 tons/kWh.

Table 1: Summary of Truck Fuel Consumption Data

Parameter	Truck #1	Truck #1	Average
Fuel per hour [gals]	19.51	17.94	18.72
Fuel per cycle [gals]	3.85	3.51	3.68
Fuel per mi [gals]	7.40	6.57	6.98
Fuel efficiency [tons/gal]	36.34	37.94	37.14

Table 2: Summary of Shovel Fuel Consumption Data

Parameter	Value
Average shift load factor	66.78%
Average fuel consumption [gals/hr]	35.36
Fuel efficiency [tons/gal]	39.29

Task 2: Data Analysis and Modeling

Shovel: Figures 2-4 show plots of load factor against engine running time, front end operating time, and travel time. As seen in Table 3, there is positive linear correlation between load factor and each of the variables, with the exception of ratio of travel time, where the p-value is greater than α.

Table 3: Shovel Fuel Correlation Analysis

Independent variable	Pearson correlation coefficient	p-value ($\alpha = 0.05$)
Engine running time	0.66979	0.0000
Front end operating time	0.76525	0.0000
Front end utilization	0.77948	0.0000
Travel time	0.51037	0.0000
Ratio of travel time	-0.11818	0.1392

The correlation between load factor and engine running time is due to the fact that short shifts (less than five hours) are usually for non-production related work and do not result in significant loading of the engine. Figure 2 shows that shifts greater than 10 hours do not exhibit this positive correlation. The positive correlation between load factor and travel time is really because longer shifts result in longer travel times. This is evidenced by the lack of statistically significant correlation between load factor and ratio of travel time (p-value greater than α). Hence the only significant and meaningful correlation is between load factor and front end operating time and utilization.

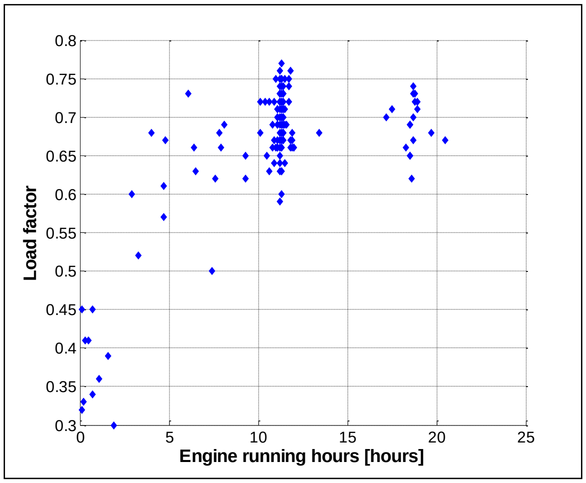

Figure 2: Load Factor vs. Engine Running Hours for a Shift

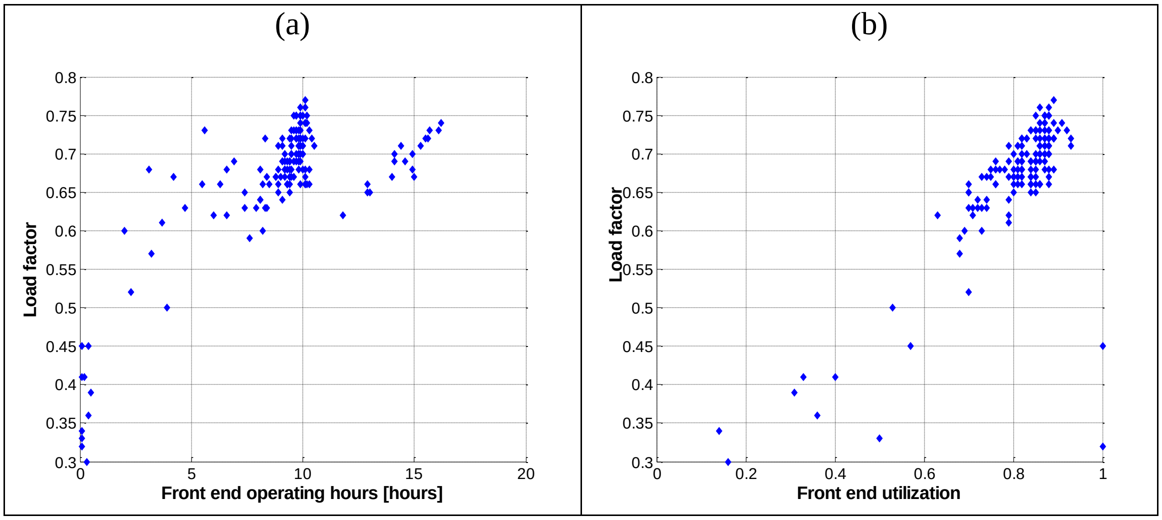

Figure 3: Load Factor vs. Front End (a) Operating Time; (b) Utilization

Front end utilization allows one to extend the model to different shift times. Equation (2) is the resulting regression model. Figure 5 shows residuals of the model compared to actual data. The mean residual for 158 data points is 3.0918×10^{-17}%. The red bars in

Figure 5 are residual intervals that do not include zero at 95% confidence. They show that only 3 out of 158 data points could not be predicted with confidence. R^2, the F statistic and its p-value, and the error variance are 0.6062, 240.1482, 0.0000, and 0.0030, respectively.

$$\text{Shovel load factor} = 0.2391 + 0.5337\left(\text{front end utilization}\right) \tag{2}$$

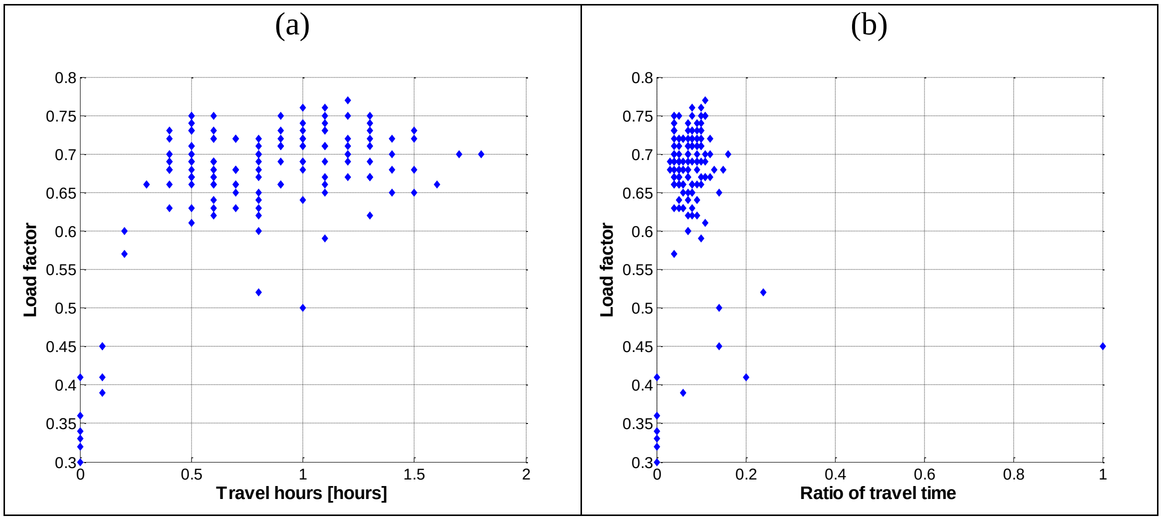

Figure 4: Load Factor vs. (a) Travel Time; (b) Ratio of Travel Time in a Shift

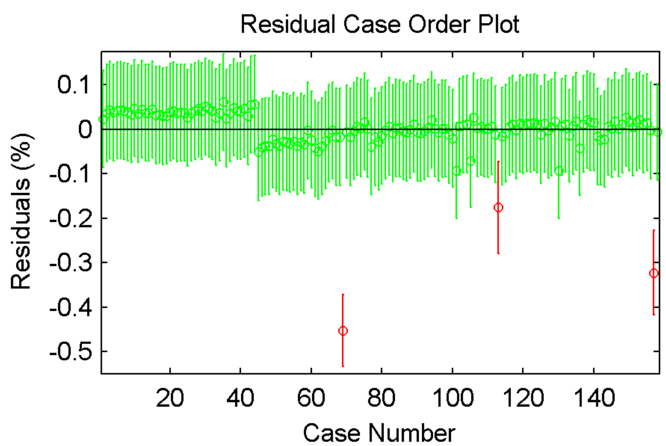

Figure 5: Residuals and Their 95% Confidence Intervals for Equation (2) Model

Trucks: To determine if different trucks and different operators had any effect on fuel consumption, the research team used two-sample, unequal variances, t-test hypothesis testing (NIST/SEMATECH, 2010). Data was collected by switching operators to ensure that different operators drove different trucks. Tables 4 and 5 summarize input to and output from the t-test. The null hypothesis was accepted for both cycle time and fuel per cycle when comparing two trucks (Table 4). Hence, it is concluded that there is not enough evidence at 95% confidence to reject the notion that means of cycle times and fuel consumption for both trucks are the same, given the available data.

Table 4: Truck Comparison t-test Summary

	Cycle time [mins]		Fuel/cycle [gals]	
	Truck 1	Truck 2	Truck 1	Truck 2
No. of samples	115	113	115	113
Mean	11.66	11.44	4.36	4.22
Standard deviation	5.05	4.15	0.60	0.51
Degrees of freedom	226		226	
Pooled standard deviation	4.62		0.56	
t-statistic	0.3591		1.8615	
H_0	$\mu_1 = \mu_2$		$\mu_1 = \mu_2$	
H_1	$\mu_1 > \mu_2$		$\mu_1 > \mu_2$	

Table 5: Operator Comparison t-test Summary

	Cycle time [mins]		Fuel/cycle [gals]	
	Operator A	Operator B	Operator A	Operator B
No. of samples	116	112	116	112
Mean	11.29	11.83	4.36	4.21
Standard deviation	3.98	5.20	0.55	0.56
Degrees of freedom	226		226	
Pooled standard deviation	4.62		0.56	
t-statistic	0.3591		2.0944	
H_0	$\mu_A = \mu_B$		$\mu_A = \mu_B$ ($\mu_A > \mu_B$)	
H_1	$\mu_A < \mu_B$		$\mu_A > \mu_B$ ($\mu_A \leq \mu_B$)	

The null hypothesis was accepted in the test to compare cycle time means for the two operators (Table 5). However, when comparing fuel consumptions with the null hypothesis, $H_0 : \mu_A = \mu_B$, the hypothesis was rejected. The research team then proceeded to test the hypothesis that operator A was consuming more fuel/cycle than operator B (null hypothesis and corresponding alternate hypothesis shown in parenthesis in Table 5). Again, there was enough evidence to reject the null hypothesis. One would have to conclude based on these t-tests at 95% confidence, that: (i) means of cycle times for the two operators are equal; (ii) means of fuel/cycle for the two operators are not equal; and (iii) the mean fuel/cycle for operator A is not greater than the mean fuel/cycle for operator B. This leads to an inconclusive overall conclusion. On the one hand, cycle times for the two operators are similar but there are indications that the fuel/cycle is not the same. Yet, one cannot definitively say that the fuel consumption of operator A is higher than that of operator B. More data over a longer period, and possibly involving more operators, is needed to better characterize the impact of operators on fuel consumption. Given the foregoing, the research team concluded that different trucks and different operators made no significant difference and, hence, all data will be treated as one population.

The research team then proceeded to conduct linear correlation analysis to determine the correlation between fuel/cycle and cycle time components and payload. Table 6 and Figures 6-9 show correlation coefficients with their corresponding p-values and scatter plots, respectively. Surprisingly, there was no statistically significant correlation between payloads for the experimental period and fuel/cycle as indicated by the p-value of 0.1801 (greater than $\alpha = 0.05$). This was contrary to expectation and hence the correlation between payload for the entire available data set (May 3 to July2) and fuel/cycle was also analyzed. This yielded a statistically significant correlation (p-value of 0.0000). Modeling fuel/cycle per ton is desirable so that the model can be extended to different truck payloads. In fact, it is expected that fuel consumption should correlate to amount of material carried since more work is done. Hence, correlations between cycle time components in Table 6 and fuel/cycle/ton was tested and statistically significant positive correlation was found. Based on this, the regression model in Equation (3) was formulated. In this model, t_i is cycle time in minutes for component i. Subscripts *es*, *et*, *l*, *ls*, and *lt* mean empty stopped, empty travel, loading, loaded stopped, and loaded travel.

$$\text{Fuel/cycle/ton} = 0.0037 + 0.0005t_{es} + 0.0035t_{et} + 0.0008t_{l} + 0.0031t_{ls} + 0.0043t_{lt} \qquad (3)$$

Table 6: Truck Fuel Correlation Analysis

Independent variable	**Pearson correlation coefficient**	**p-value (α = 0.05)**
Payload (June 28-July 2)	0.0891[1]	0.1801
Payload (May 3-July 2)	0.1518[1]	0.0000
Loading time	0.1861	0.0049
Empty stopped time	0.3951	0.0000
Empty travel time	0.5206	0.0000
Loaded stopped time	0.1861	0.0049
Loaded travel time	0.3511	0.0000

[1] Correlation is between the independent variable and fuel/cycle.

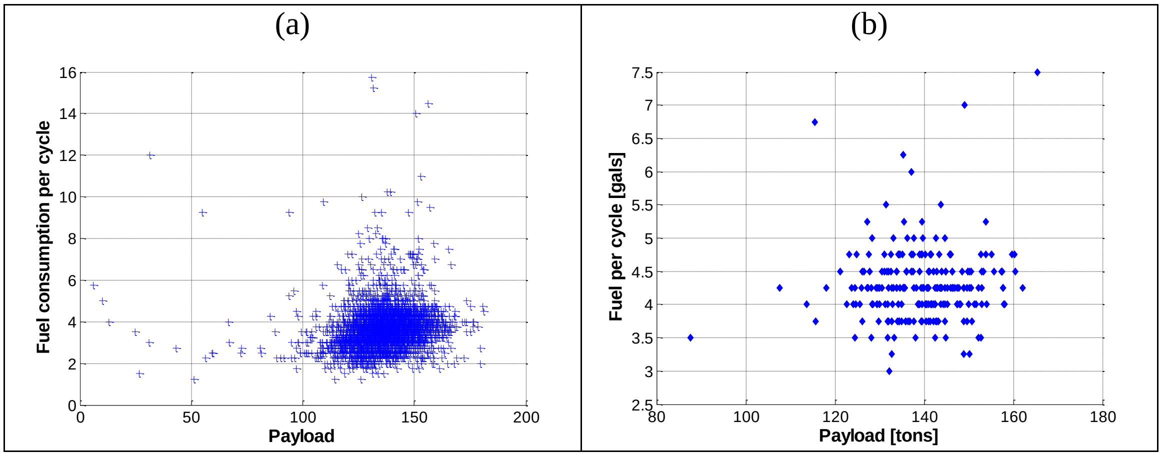

Figure 6: Fuel/cycle vs. (a) Payload 5/3-7/2 Period; (b) Payload for 6/28-7/2 Period

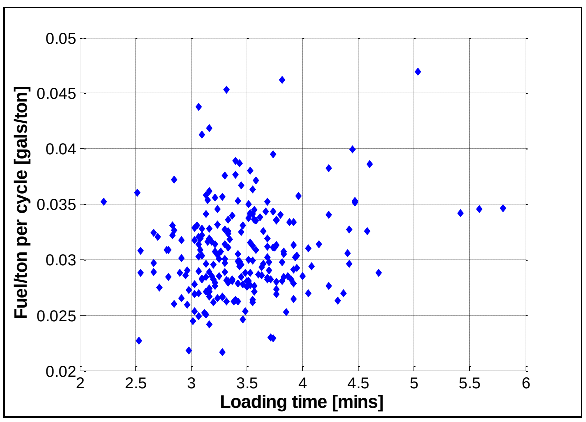

Figure 7: Fuel/cycle/ton vs. Loading Time

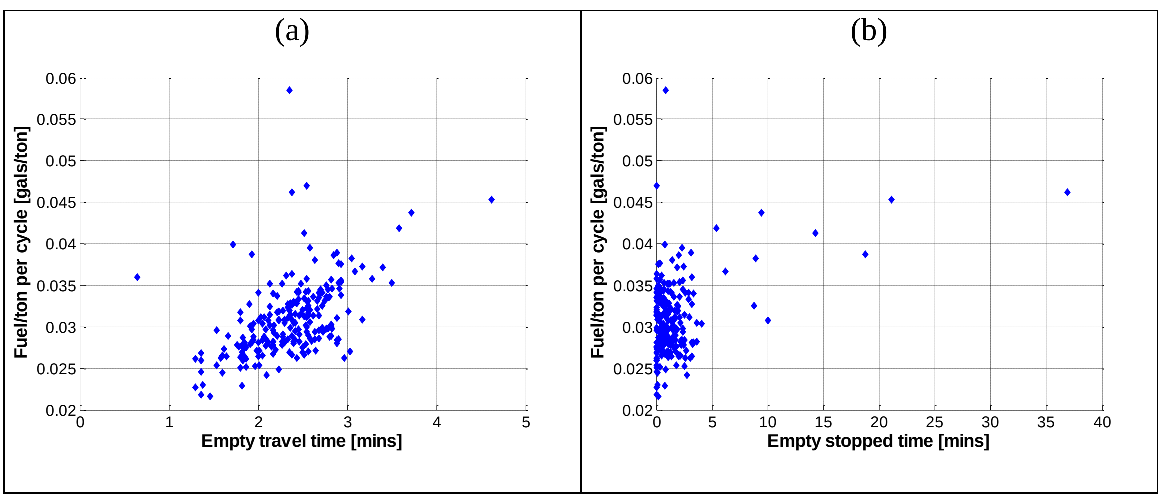

Figure 8: Fuel/cycle/ton vs. (a) Empty Travel Time; (b) Empty Stopped Time

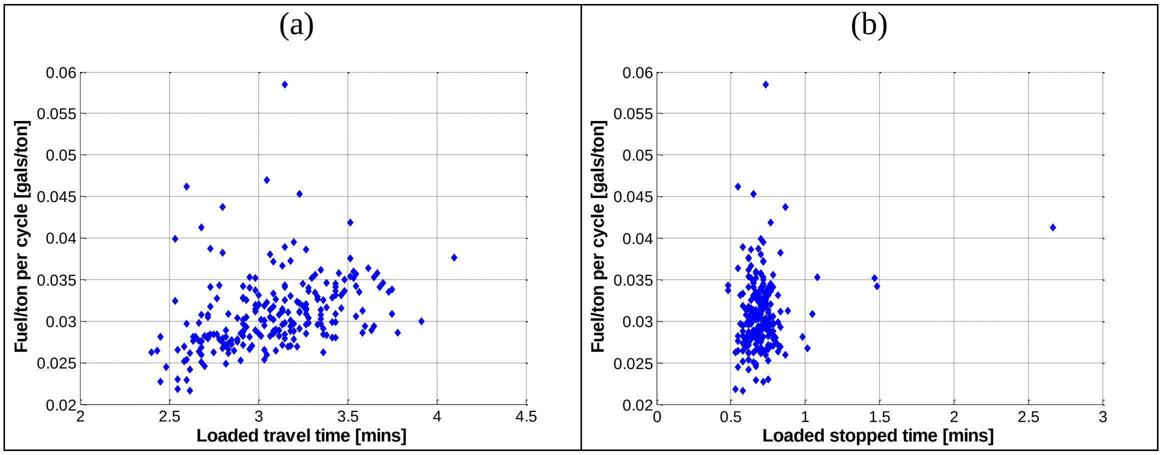

Figure 9: Fuel/cycle/ton vs. (a) Loaded Travel Time; (b) Loaded Stopped Time

Figure 10 shows residuals of the model compared to actual data. The mean residual for 143 data points is -8.6857×10^{-18}%. As before, red bars are residual intervals that do not include zero at 95% confidence. Figure 10 shows only 6 out of 143 data points compared could not be predicted with confidence. R^2 statistic, the F statistic and its p-value, and the error variance are 0.8356, 139.2678, 0.0000, and 0.0519, respectively.

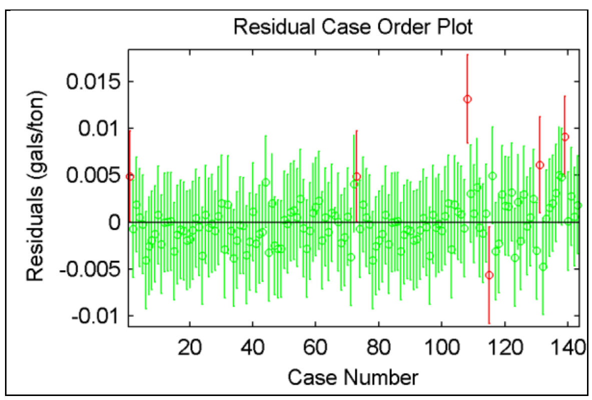

Figure 10: Residuals and Their 95% Confidence Intervals for Equation (3) Model

Simulation: Table 7a-b show results of distribution fitting using data from time and motion studies and OEM onboard data loggers. Expressions in Table 7 were used to describe activity times. The average haul distance for the experimental period was surveyed to be 0.75 miles (3,960 ft). Transporters in the ARENA model were hence specified to travel this distance at a speed equal to the ratio of the distance to the distribution of travel times.

Table 7a: Shovel Distribution Fitting Results

Process	Distribution	Expression	Square Error
Dumping time	Lognormal	LOGN(0.0349, 0.0156)	0.093891
Return time	Lognormal	LOGN(0.173, 0.0969)	0.019817
Loading time	Gamma	GAMM(0.0464, 3.05)	0.027245
Spotting time	Lognormal	LOGN(0.155, 0.109)	0.047969

Table 7b: Truck Distribution Fitting Results

Process	Distribution	Expression	Square Error
Payload	Normal	NORM(139, 10.8)	0.001313
Empty stopped time	Beta	37 × BETA(0.171, 2.31)	0.011708
Empty travel time	Normal	NORM(2.3, 0.471)	0.006764
Loaded stopped time	Erlang	ERLA(0.458, 2)	0.000268
Loaded travel time	Beta	2.26 + 1.66 × BETA(3.3, 4.06)	0.003836

The model was verified with animation and validated by comparison with field data. Table 8 shows the comparison of actual truck data for the experimental period and average values after 100 replications. The model was validated using truck data from OEM data loggers because it was more detailed and useful. Average shovel front end utilization for a shift and load factor from MIC data is 80.31% and 66.78%, respectively. Since cycle time data did not capture any action of the front end apart from loading activities, it was not possible to predict front end utilization from the simulation. The simulation model, however, predicts shovel utilization for a shift to be 67.43%, which is less than front end utilization, as expected. Given, the similarity between shovel utilization and load factor, it was assumed that shovel utilization is a good predictor of engine load factor for subsequent analysis. On the basis of truck predictions, the model was deemed validated as it was able to predict fuel efficiency and fuel consumed per cycle to within 1%.

Table 8: Simulation Model Validation

	Actual	Simulated	Error
Production [tons]	15,887	16,590	4%
Number of loads	114	120	5%
Total fuel consumption [gals]	488.87	502.60	3%
Average fuel consumption per cycle [gals]	4.24	4.27	1%
Truck fuel efficiency [tons/gal]	32.56	33.01	1%

Highwall miner: Figures 11-14 show sample signals collected for the highwall miner on November 10, 2010. On that day, there were two production shifts – one from 7:00AM to 4:30PM and one from 4:30PM to 10:30PM. Figure 11 shows periods of increased current draw, which correspond to production activities – mining, retracting, drilling down, etc.

Figure 12 shows that this increased load corresponds to an increase in power factor from approximately 88% to near 100%.

Of note is that even during production periods when all motors are included in the load, there are still significant drops in power factor. These drops cause spikes in current demand to compensate for the inefficiency. Figure 13 shows a histogram of power factors (logged every minute) during the production period. While less than 1.5% are below 90%, almost 25% are below 95%. The real issue is the increase in current draw that results. Average current (over three phases) is expected to be 600 amps, but as Figure 11 shows, there are significant spikes including one in excess of 1,500 amps. More work is necessary to fully quantify and understand the effect of power quality on highwall miner operations, including capturing the full spectrum of power quality indices (voltage and current swells and sags, frequency variation, harmonics, etc.) in addition to power factor.

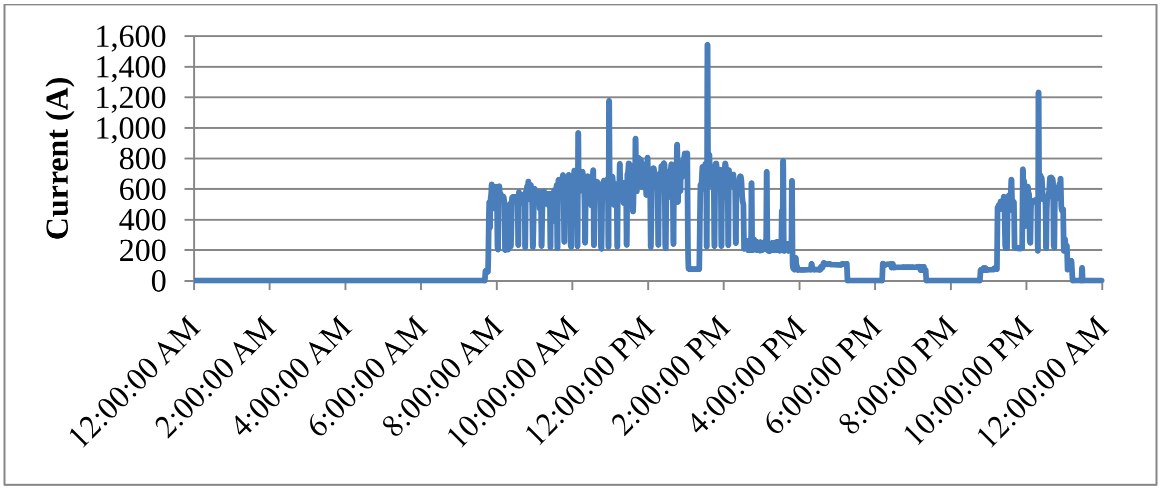

Figure 11: Average Current Draw for Highwall Miner on November 10, 2010

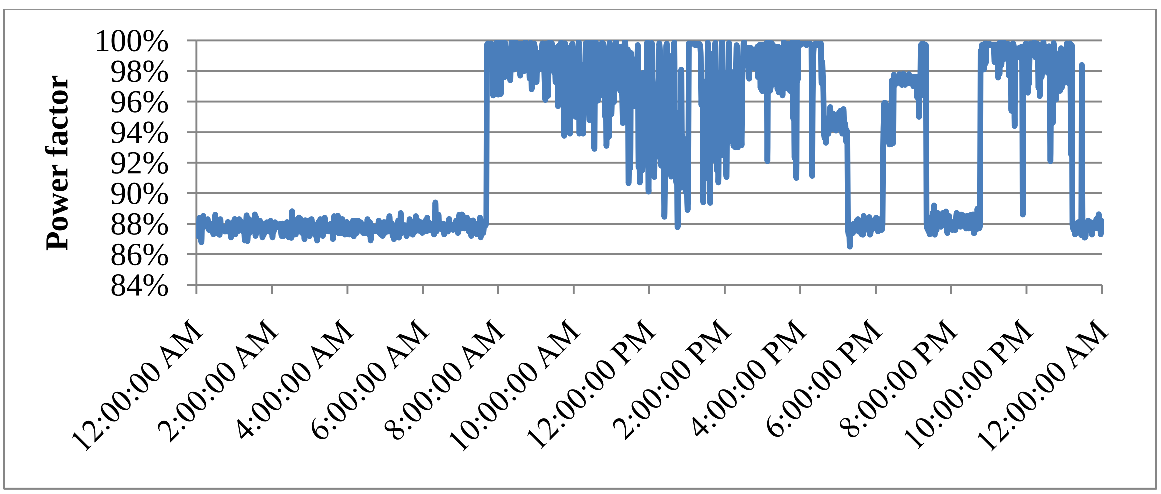

Figure 12: Power Factor for Highwall Miner on November 10, 2010

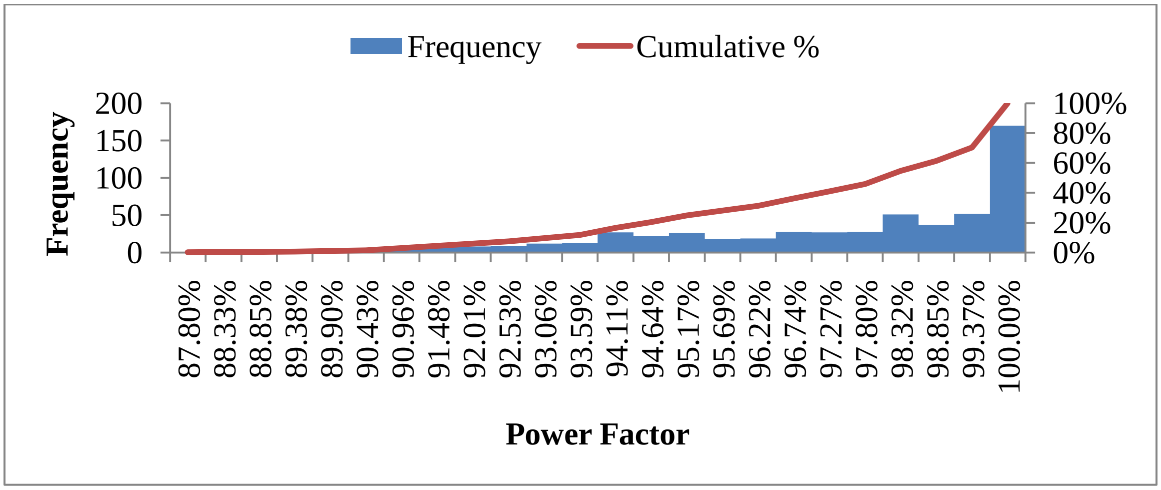

Figure 13: Highwall Miner Power Factor Analysis for November 10, 2010

Figure 14 is a plot of cumulative energy consumption, which increased from 490.10 kWh to 6,325.00 kWh during production. Overall production for the day was 2,609 tons resulting in energy efficiency of 0.447 tons/kWh. Similar data for a third production shift sampled on November 11 shows energy efficiency to be 0.439 tons/kWh. Thus, average energy efficiency for highwall miner operations is estimated to be 0.443 tons/kWh.

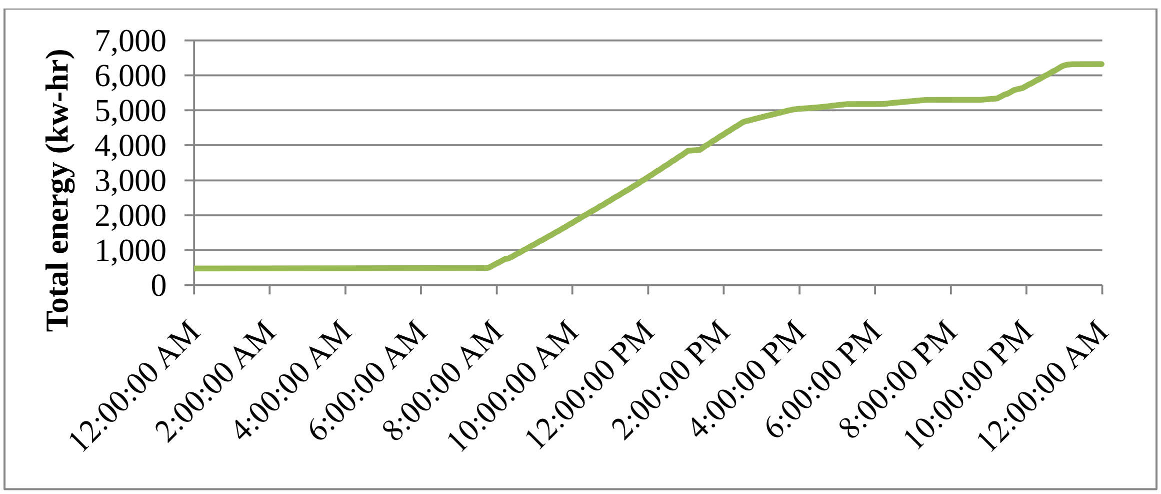

Figure 14: Highwall Miner Energy Draw for November 10, 2010

Task 3: Production Improvement Analysis

Three potential energy saving production strategies were evaluated through simulation experimentation. Each scenario was evaluated using results from 100 replications of the simulation model.

Strategy 1 – Increase shovel utilization through optimal truck matching: This strategy involves increasing the number of trucks in the system in an effort to identify the *optimal* truck-shovel match. Two scenarios are considered. The first (Scenario 1) is to add smaller 100-ton trucks since the mine has two such trucks readily available. The second (Scenario 2) is to add trucks of the same size (150-ton) as are currently being used. It should be noted that the mine is more likely to add the available 100-ton trucks than purchase new 150-ton trucks.

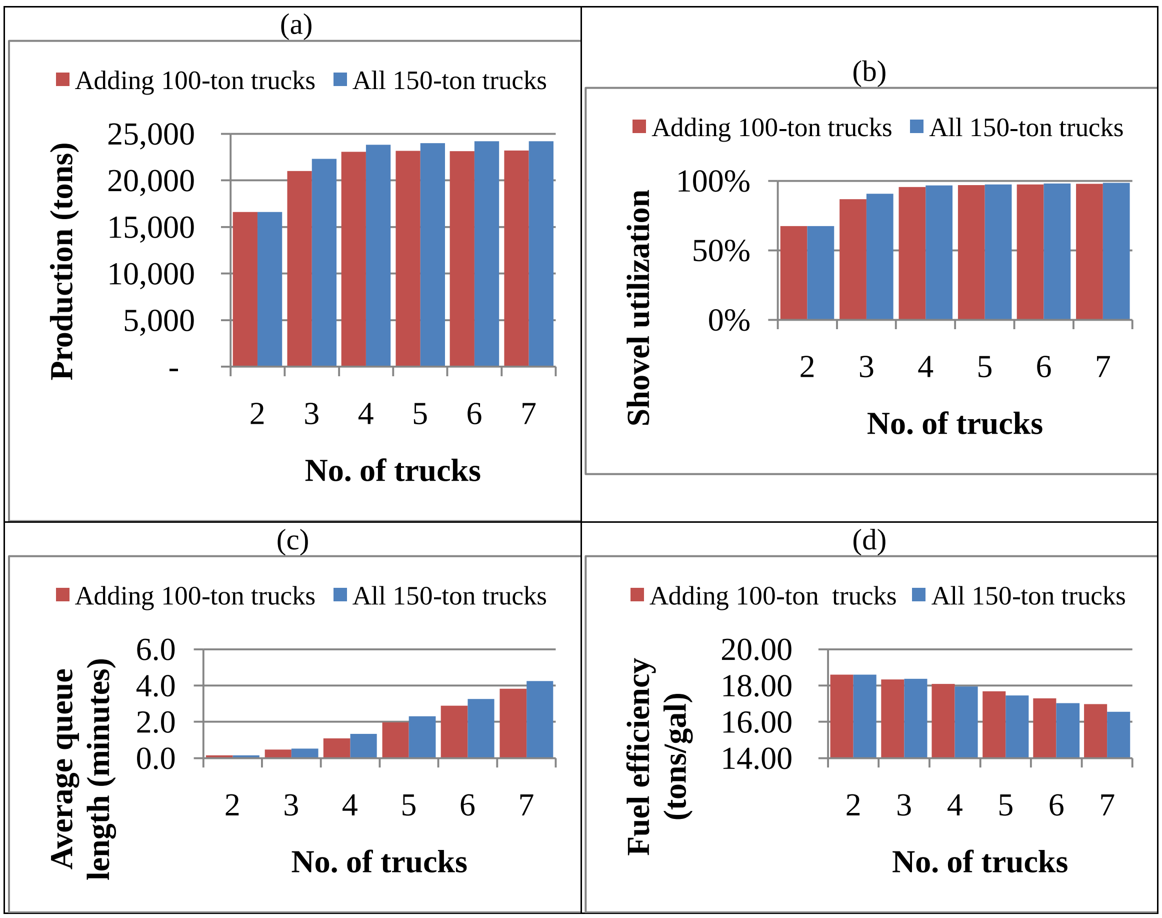

Figure 15: Simulation Results for Strategy 1 – Adding Trucks

Figure 15 shows there are potential gains in production and shovel utilization from adding trucks as expected. The largest gain comes when the number of trucks is increased from two to three – production increases by 4,400 and 5,700 tons/shift (Figure 15a), and shovel utilization increases by 19.53 and 23.26% (Figure 15b) for Scenarios 1 and 2, respectively. However, increasing the number of trucks increases queue lengths or time spent waiting at the shovel (Figure 15c) and longer queue lengths cause fuel efficiency to decline (Figure 15d). Adding one 100-ton or 150-ton truck decreases fuel efficiency by 1.5 and 1.3%, respectively.

This phenomenon is described more clearly in Figure 16, which shows that the only cycle time component that varies as trucks are added to the system is empty stopped time. The increase in empty stopped time is smallest when a third truck is added to the system, but it rises sharply as additional trucks are added and the resulting inefficiencies outweigh any gains in productivity and shovel utilization. The conclusion is that for Mine 1, having more than three trucks in the system is sub-optimal.

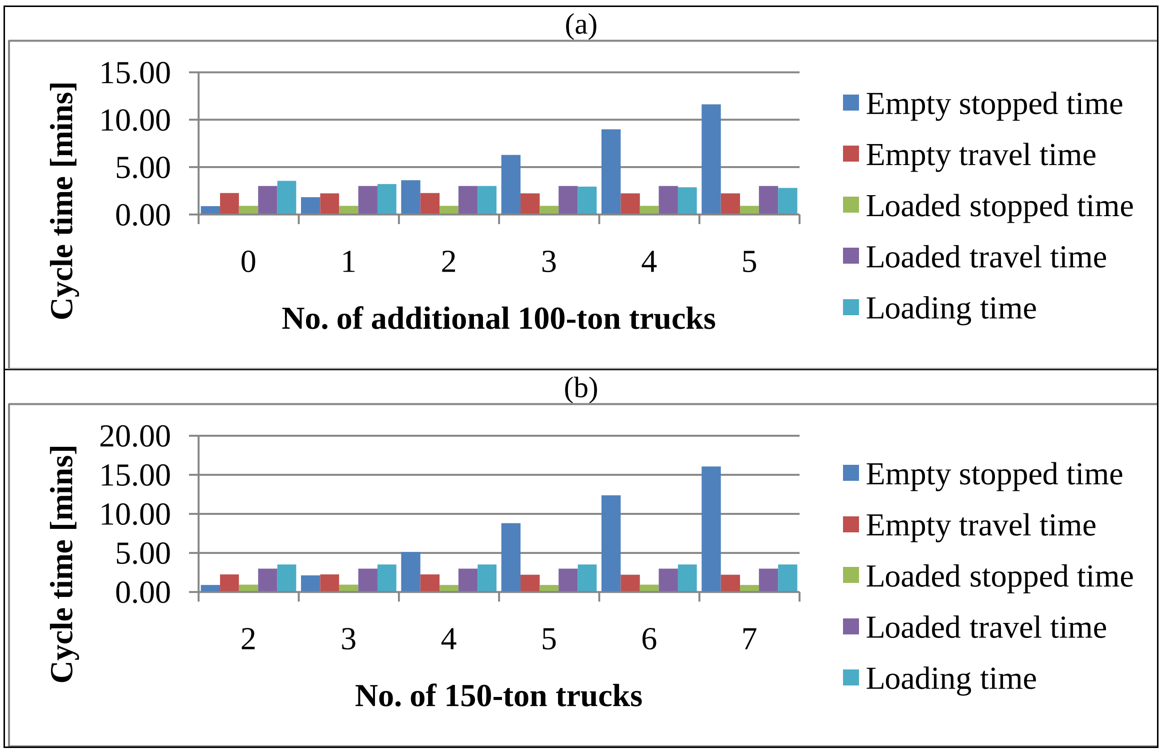

Figure 16: Simulated Cycle Time Components for Trucks: (a) 100-ton; (b) 150-ton

Strategy 2 – Increase shovel capacity: Figure 17 gives results when use of the larger EX2500 shovel, instead of the currently used EX1900, was evaluated. It shows an increase in production (Figure 17a) and decreases in shovel utilization (Figure 17b) and average queue length (Figure 17c), which lead to a 2.9% increase in fuel efficiency (Figure 17d). Even though shovel utilization is lower for the larger shovel, fuel consumption is 38.8 gals/hr compared to 35.4 gals/hr for the smaller shovel. This is due to a higher consumption rate for the larger engine. While the increase in production more than compensates for the increase in fuel consumption rate, lower utilization of the larger shovel is economically undesirable given its higher ownership costs.

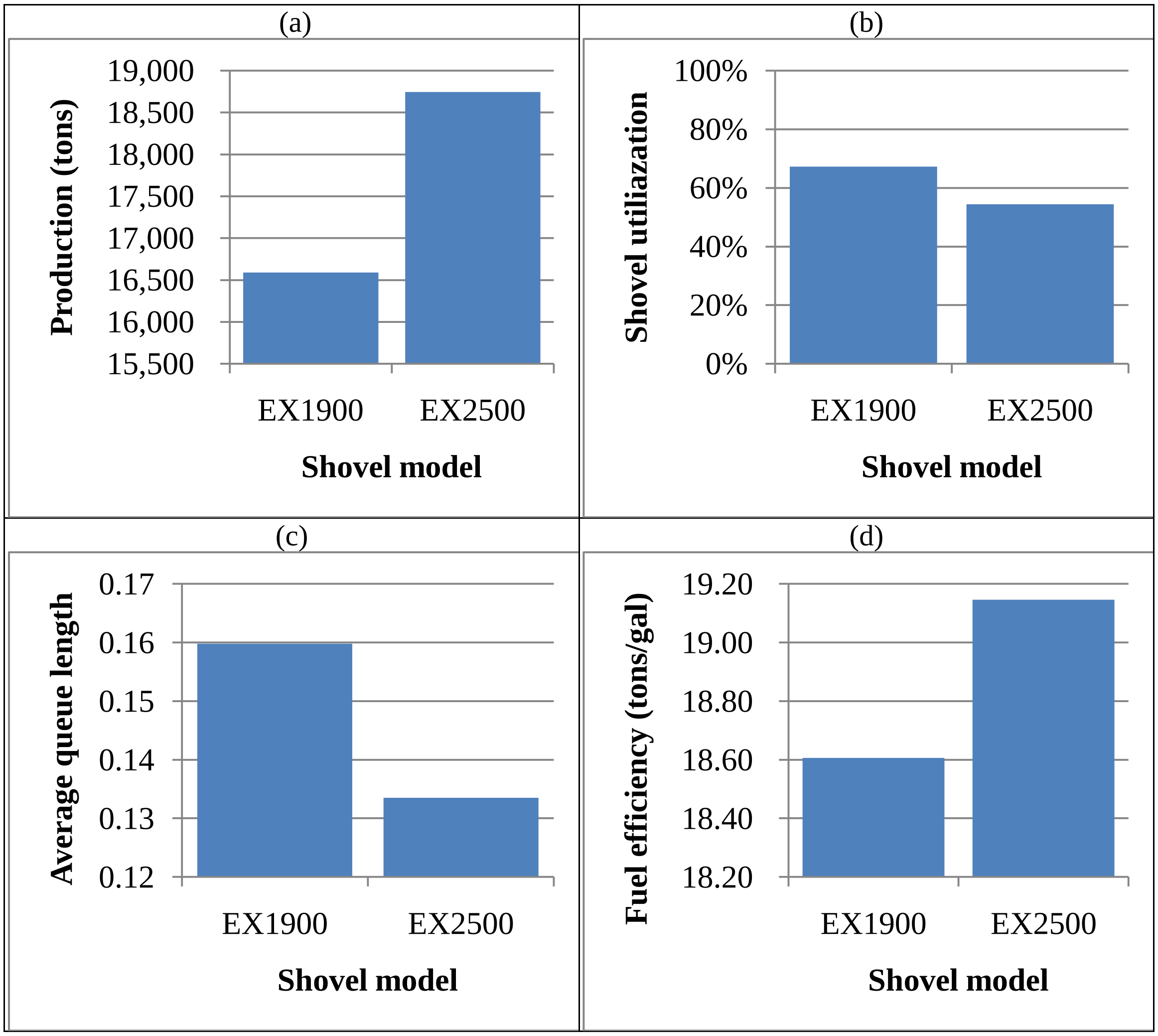

Figure 17: Simulation Results for Strategy 2 – Larger Shovel

Figure 18 shows average cycle time components for trucks working with the two shovels. Average travel time and loaded stopped time (dumping time) remain the same. Loading time and empty stopped time (waiting on shovel) decrease with use of the larger shovel. Consequently, truck fuel consumption is reduced from 4.27 to 4.14 gals/cycle. The result is increased fuel efficiency when using the EX2500 shovel.

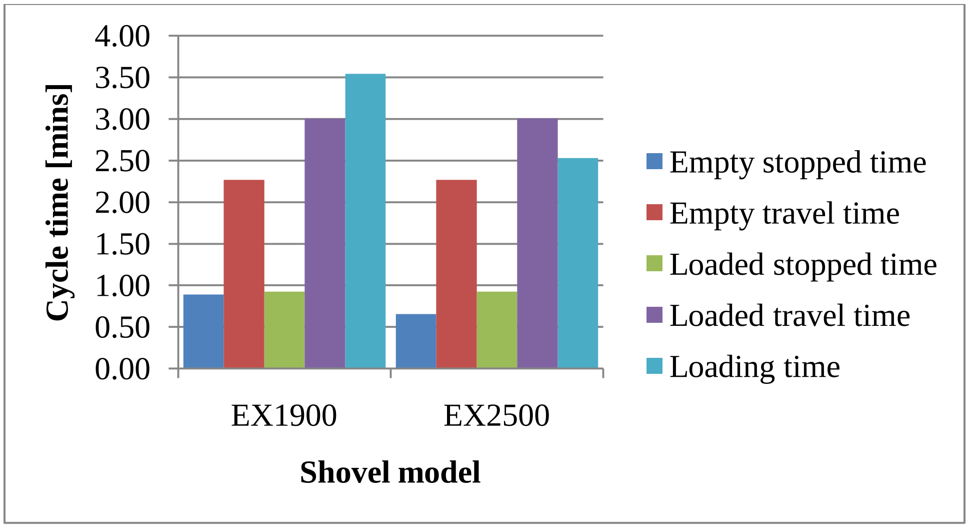

Figure 18: Truck Cycle Time Components When Different Shovels Are Used

Strategy 3 – Shorten haul roads: The variation in truck fuel consumption and average haul distance over a shift is evident in OEM ('Actual') data shown in Figure 19. However, it cannot be solely attributed to changes in haul distance since other factors (e.g. haul road conditions and profiles) were not kept constant. This explains the different fuel consumptions for the same truck (Truck 2) at 0.3 miles observed on June 19 and 20. Consequently, simulation experiments were conducted to quantify the relation between fuel consumption and haul distance when only the haul road distance is varied in a controlled experiment ('Simulated' data points and line in Figure 19).

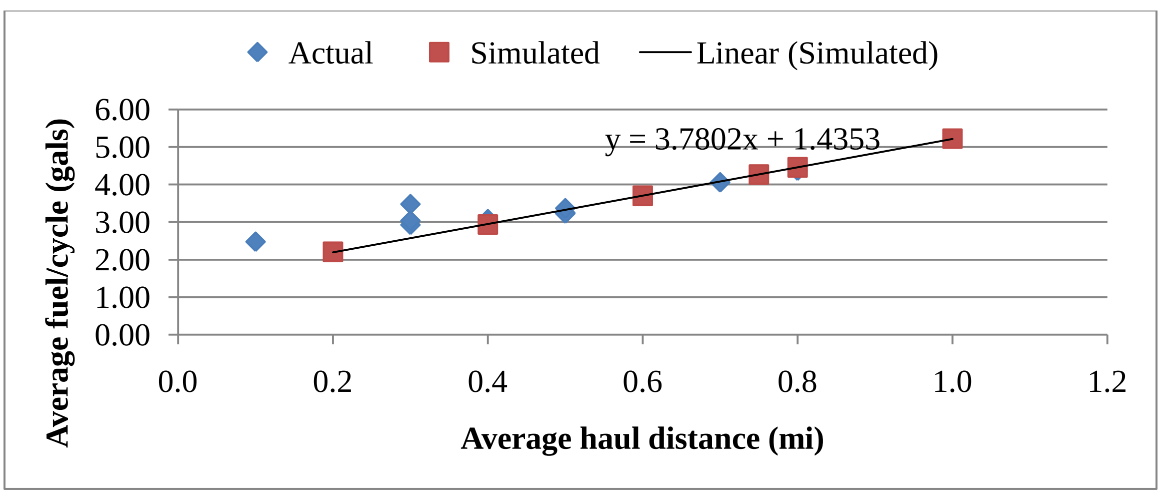

Figure 19: Variation in Truck Fuel/cycle with Average Haul Distance

Figure 20 shows that production, shovel utilization, queue length, and fuel efficiency decrease with increasing haul distance. The only one of these that is an efficiency gain from increasing haul distance is the reduction in queuing or truck waiting. This decrease in empty stopped time diminishes with increasing haul distance, as shown in Figure 21, such that beyond approximately 0.8 miles, empty stopped time is not dependent on haul distance. Figure 21 shows both travel times increasing with longer haul distances. This predictably increases the overall cycle time.

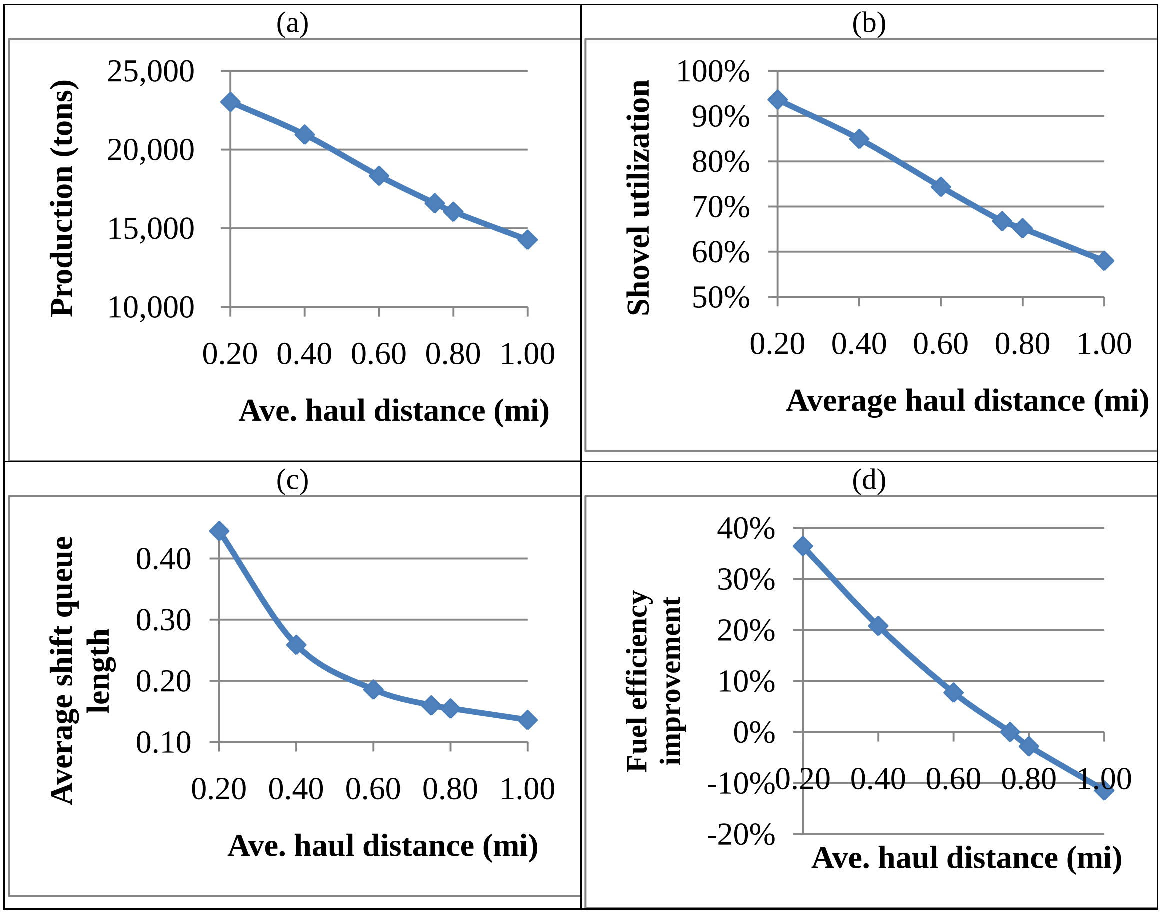

Figure 20: Simulation Results for Strategy 3 – Shorten Haul Distance

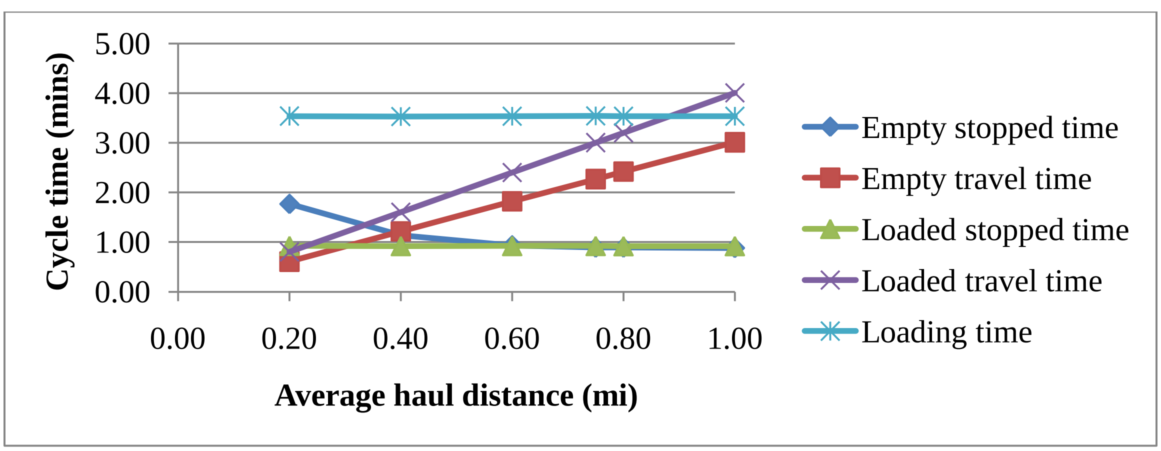

Figure 21: Variation in Truck Cycle Time Components with Haul Distance

While significant gains can be achieve by shortening haul distances, a systems approach should be taken in implementing this strategy. In reducing haul road length, the mine operator must be careful not to significantly increase either the haul road grade or the dozer push distance. A limitation of this analysis is that it did not include dozer fuel consumption.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The following conclusions are drawn from the results and discussion presented:

- Process specific energy audits provide insights into improving operations in a way that is not possible with global energy consumption figures. This was illustrated by the fuel consumption analysis of the truck-and-shovel system.
- Average fuel efficiency for trucks, the shovel, and the overall truck-and-shovel system used for overburden removal at Mine 1 are 37.14, 39.29, and 19.09 tons/gal of diesel, respectively. At Mine 2, average energy efficiency of the highwall miner is 0.443 tons/kWh.
- Equations (2) and (3) are valid fuel consumption models for shovel loading and truck haulage, respectively.
- Valid stochastic process models of truck-and-shovel operations have been formulated to study fuel efficiency.
- For Mine 1, the following strategies, in decreasing order of impact, provide the most improvement in energy efficiency for truck-and-shovel overburden removal:
    - Shorten haul road lengths while maintaining similar haul road grades and dozer push distances.
    - Increase shovel capacity by using next larger model (Hitachi EX2500).
    - Increase shovel utilization by adding one more truck. While adding one more truck actually results in 1.5 and 1.3% decreases in fuel efficiency, for the 100- and 150-ton trucks, respectively, this is compensated for by 4,400 and 5,700 tons/shift increases in production, and by 19.53 and 23.26% increases in shovel utilization.
- The effect of operators cannot be adequately described without additional data.

Recommendations

The following recommendations for future work and improvements are warranted:

- More work is necessary to acquire more data over longer periods to build confidence in the results and models.
- Future work should gather data from systems with more operators or over longer periods to adequately describe operator effects. The current data set shows inconclusive results on whether different operators have any significant impact on cycle time and fuel consumption. It may well be that the two operators studied do not operate any differently due to their experience and training; however, more data is required to test this hypothesis, definitively. Also, in mines with significant disparity

in experience and training, operator effects can be studied and quantified with more confidence.

- More study is needed to understand the effect of different parts of the highwall miner cycle on energy consumption. Analyses similar to what was done in this study for trucks can be done for the highwall miner so long as a method is derived to acquire start and end times of various processes. This can be done by applying data mining techniques on current and voltage signals, by conducting time and motion studies while monitoring energy consumption, or both with the manual time and motion studies serving as validation.
- The effect of power quality on the energy consumption of the highwall miner needs further study. As indicated in the analysis of power factors, power quality issues may be the cause of energy inefficiency and present an opportunity for improvement.
- Further work should be done to model the energy efficiency of other surface coal mining equipment units (e.g. draglines).

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