Modeling Truck-Shovel Energy Efficiency under Uncertainty

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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 goal of this work was to apply stochastic process simulation to model the energy efficiency of a typical truck and shovel mining system and use the model to evaluate production strategies to improve energy efficiency. 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 fuel 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.

Valid fuel consumption models for shovel loading and truck haulage have been formulated based on the energy audit results. Valid stochastic process models of truck-and-shovel operations have been formulated to study energy efficiency. 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 energy efficiency.

1. Introduction

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 by using current best practice and a further 44.8 billion kWh/year with more research to make coal mining more energy efficient (US Department of Energy, 2007). This translates into 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 in the near future. According to US Department of Energy (2007), the most promising

[1] Paper submitted to Transactions of the Society of Mining, Metallurgy, and Exploration.

processes for energy efficiency improvement are grinding and materials handling, including loading and hauling.

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 the operating conditions. However, there is evidence that operator practices and mine operating conditions significantly affect the 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 and loading, for instance, are key factors in the energy efficiency of mining operations (Kecojevic and Komljenovic, 2010). Fig 1 shows, more comprehensively, the factors that affect energy consumption of mine equipment.

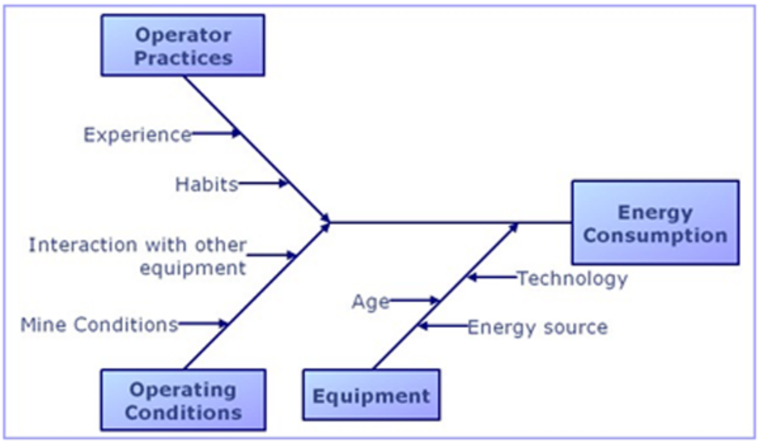

Fig 1. Factors affecting coal mine equipment energy consumption.

In order to understand the impact of operating conditions on energy efficiency, there is a need to conduct process specific, as opposed to system-wide, energy audits which account for operating conditions (Bogunovic, et al., 2009a). The knowledge can then be used to increase energy efficiency of mining operations and processes. Modeling and simulation is a cost effective and reliable way to assess the impact of different operating conditions on energy efficiency. Stochastic process simulation based on Monte Carlo simulation is capable of modeling process interactions and quantifying the uncertainty surrounding model outputs (Kelton, et al., 2003).

The objective of this research was to (i) apply stochastic process simulation to model the energy efficiency of a typical truck and shovel mining system; and (ii) evaluate production strategies to improve energy efficiency. The researchers conducted energy audits of the truck and shovel overburden removal operations at a surface coal mine. Following data analysis, they modeled the truck and shovel system in Arena® (Rockwell, 2010). The model was then validated with the field data and used to evaluate three improvement strategies.

Managing energy efficiency is an important goal in reducing process cost, which has become even more important due to concerns over energy availability and supply. Energy efficiency is defined as the ratio of effective energy to the total energy (Zhu and Yin, 2008). For loading and hauling, the amount of material loaded and hauled and the fuel consumed in the process are used as proxies for effective and total energies, respectively.

A fraction of the energy generated by an internal combustion engine is available for useful work as brake output due to heat, engine friction and pumping losses. In shovel loading, this output is used to overcome digging resistance and inertia, swing and spot, travel, and provide energy for accessories (Awuah-Offei, 2009). In trucking, the output is used to overcome aerodynamic drag, rolling resistance, drive train friction, inertial forces and accessory loads (Ang-Olson and Schroeer, 2002). For trucking, the contribution of each of these resistances to energy losses, and hence efficiency drops, depend on driving speed, truck weight, terrain, driver behavior, wind speed and direction, and road conditions (Ang-Olson and Schroeer, 2002). Researchers have evaluated the effect of reduced idling, speed reduction, driver training, and reduced empty runs through optimal truck scheduling on energy efficiency (Ang-Olson and Schroeer, 2002; Bates, et al., 2001; Hubbard, 2003; Leonardi and Baumgartner, 2004).

Loading and hauling in surface mines is different from freight trucking because loading is a significant aspect of the energy demand due to significantly shorter distances. Consequently, the inefficiencies due to shovel-truck interactions (under-matched or over-matched shovels) are also significant. Bogunovic, et al. (2009b) show variability in energy consumption of trucks and shovels due to operating conditions (e.g. which coal seam is being mined) and operators.

Kecojevic and Komljenovic (2010) show that just 10% reduction in engine load factor can result in fuel savings ranging from $40,000 to $267,000 per year depending on the size of truck, based on original equipment manufacturer (OEM) data and existing literature. Various studies have also shown that shovel depth of cut, which is a function of operator experience and preferences, significantly affects shovel energy consumption (Awuah-Offei and Frimpong, 2007; Patnayak, et al., 2008). However, what is missing in the literature is predictive modeling of energy efficiency as a function of operating conditions under uncertainty to facilitate evaluation of improvement strategies. As far as the authors know, there has been no work that characterizes uncertainty in a model and also attempts to determine statistically significant correlations. This can be achieved with stochastic process simulation with adequate data for uncertainty characterization.

An important aspect of this study was the use of stochastic process simulation to evaluate energy saving production strategies, before implementation, and characterize uncertainty. 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 exist for modeling continuous, discrete and mixed continuous-discrete event systems. An important advantage of these packages is the use of Monte Carlo simulation to handle uncertainty modeling. In this work, we used Arena® (Rockwell, 2010), which is based on the SIMAN simulation language, to model the energy consumption of the truck-shovel system of the mine (Kelton, et al., 2003).

This work represents a novel attempt to model truck and shovel energy efficiency with uncertainty. Existing OEM software are deterministic and do not account for the inherent uncertainty. This approach to energy improvement planning will allow inexpensive experimentation prior to implementation so that the strategies that are implemented are likely to succeed and the risks are properly understood.

2. Experimental procedures

2.1. Study site

The study site is a strip mine in the Illinois basin 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 Caterpillar 785C (150-ton), rigid frame, haul trucks. Both the shovel and trucks had on-board data logging systems that were used to collect data on engine load factor and fuel consumption, respectively.

2.2. Shovel Energy Audit

Hitachi's onboard shovel data logging system, Machine Information Center (MIC) logs, among others, engine running time, the operating time of the front end[1], 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, we used the shift averages of the engine running time, the operating time of the front end, travel time, and engine load factor for data analysis. Since MIC does not log fuel consumed, Hitachi data on fuel consumption and load factors was used to establish the relationships in Eq. (1), which relates engine load factor to fuel consumption for the two shovel models analyzed in this study.

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

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

2.3. Truck energy audit

Caterpillar's Vital Information Management System (VIMS) 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 team downloaded data from May 3 to July 2, 2010. The summary performance was based on all this data. However, given the variability in haul distance, and haul road profile and conditions, the team only used the data from the experimental period (June 28-July 2) for detailed analysis. This was because the haul distances, profile and conditions were similar. The haul profile was surveyed with Topcon Hyperlite GPS units for real-time kinematic (RTK) surveying. Even though VIMS logged the cycle times, the team conducted manual time and motion studies of the trucks as well to confirm the VIMS data. The OEM data was proven to be reliable and better than the manual data and therefore all the analysis was based on that.

3. Data analysis and model input

3.1. Shovel data analysis and modeling

Statistical correlation analysis, at 95% confidence, was used to examine correlation between the load factor (the proxy for fuel consumption) and the engine running time, the operating time of the front end, 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 the time ratios in correlation analysis was to enable extension of the results to different shift lengths. Regression analysis was then used to determine the relationship between load factor and key independent variables.

Figs. 2-4 show plots of load factor against engine running time, front end operating time and travel time. As shown by Table 1, there is positive linear correlation between load factor and each of the variables except ratio of travel time (p-value is greater than α). 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.

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

Table 1 Shovel fuel consumption 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

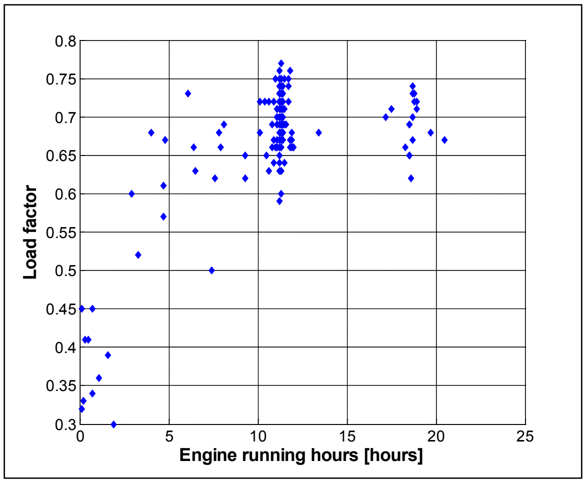

Fig 2. Plot of load factor against engine running hours for a shift.

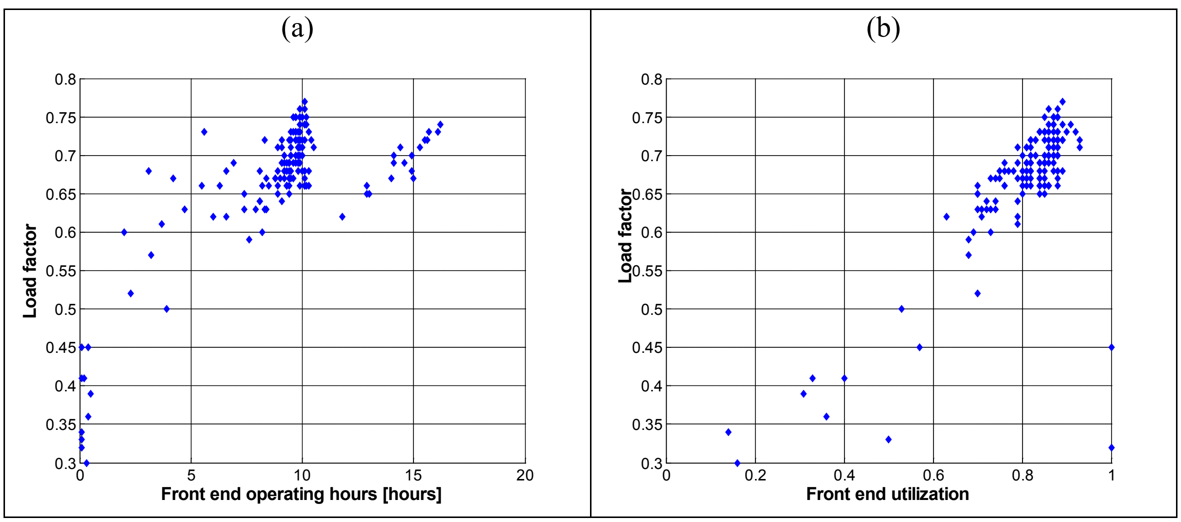

Fig 3. Plot of load factor against (a) front end operating time; (b) front end utilization.

Front end utilization allows one to extend the model to different shift times. Eq. (2) is the resulting regression model. Fig 5 shows the residuals of the model compared to the actual data. The mean residual for the 158 data points is 3.0918×10^{-17}%. Fig 5 shows only 3 out of 158 data points could not be predicted with confidence. The R^2, the F statistic and its p-value, and the error variance are 0.6062, 240.1482, 0, and 0.0030, respectively.

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

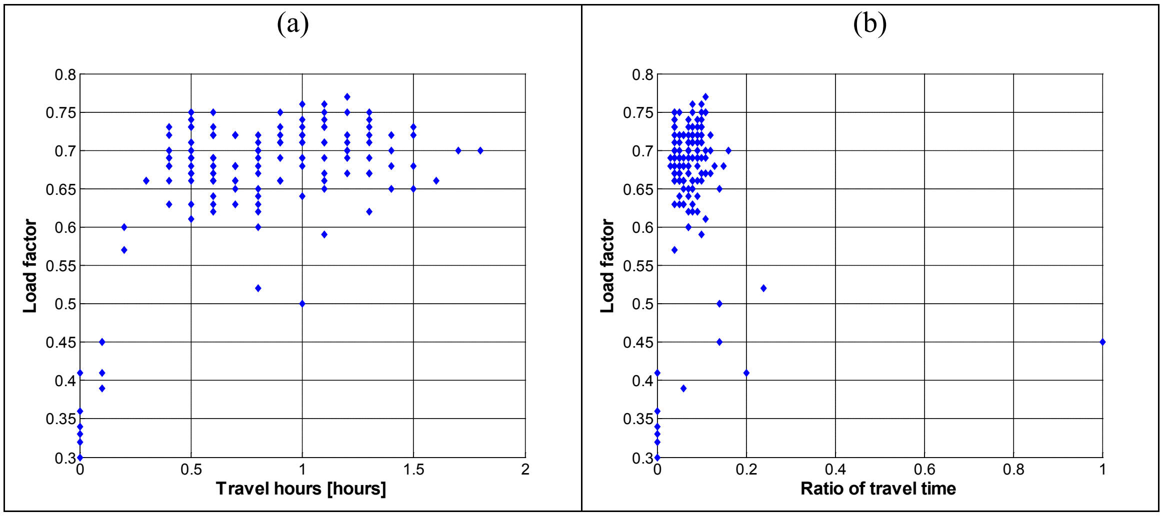

Fig 4. Plot of load factor against: (a) travel time; (b) ratio of travel time in a shift.

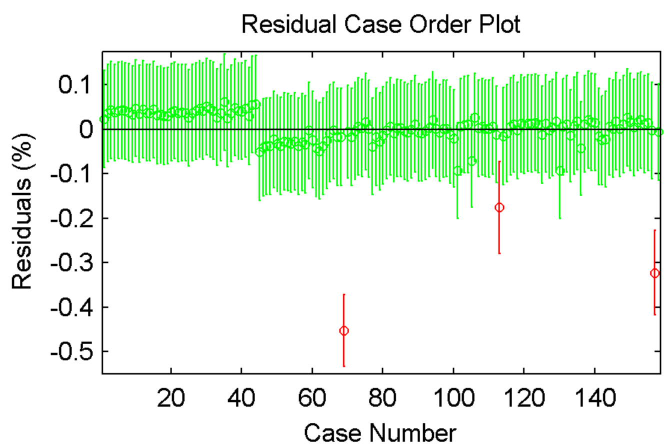

Fig 5. Residuals and 95% confidence intervals of residuals for Equation (2) model. Red data points are residual intervals that do not include zero.

3.2. Truck data analysis and modeling

First, we used statistical hypothesis testing at 95% confidence to determine if the different operators and trucks had any impact on the fuel consumption and total cycle time. We used two sample, unequal variances, t-test hypothesis testing (NIST/SEMATECH, 2010). The data was collected by switching operators to ensure that different operators drove the different trucks. Tables 2 and 3 show the summary of the input and output from the t-test. The null hypothesis was accepted for both cycle time and fuel when comparing the two trucks (Table 2).

Hence, we conclude that there is not enough evidence at 95% confidence to reject the notion that the means of the cycle times and fuel consumption for both trucks are the same, given the available data.

The null hypothesis was accepted in the test to compare the means of cycle times of the two operators (Table 3). However, when comparing the fuel consumptions with the null hypothesis, $H_0 : \mu_A = \mu_B$, the hypothesis was rejected. The 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 3).

Table 2. t-test summary for comparing trucks.

	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 3. t-test summary for comparing operators.

	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	$\mu_A < \mu_B$		$\mu_A > \mu_B$ ($\mu_A \leq \mu_B$)	

Again, there was enough evidence to reject the null hypothesis. One would have to conclude based on the t-tests at 95% confidence, that: (i) the means of the cycle times of the two operators are equal; (ii) the means of the fuel/cycle for the two operators are not equal; and (ii) the mean fuel/cycle of operator A is not greater than the mean of operator B. This leads to an inconclusive overall conclusion. On one hand, cycle times of 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 team concluded that the different trucks and operators made no significant difference and, hence, all the data will be treated as one population.

We then proceeded to conduct linear correlation analysis to determine the correlation between fuel/cycle and the cycle time components and payload. Table 4 and Figs 6-9 show the correlation coefficients with their corresponding p-values and the scatter plots, respectively. Surprisingly, there was no statistically significant correlation between the payloads for the experimental period and the 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). 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 be correlated to amount of material carried since more work is done. Hence, we proceeded to test the correlations between the cycle time components in Table 4 and fuel/cycle/ton. There was, statistically significant, positive correlation between the cycle time components and the fuel/cycle/ton. Based on this, the regression model in Eq. (3) was formulated. t_i is cycle time in minutes for component *i*. The subscripts *es, et, l, ls,* and *lt* mean empty stopped, empty travel, loading, loaded stopped, and loaded travel.

Table 4. Truck fuel correlation analysis.

Independent variable	**Pearson correlation coefficient**	**p-value ($\alpha = 0.05$)**
Payload (June 28-July 2)	0.0891[1]	0.1801
Payload (May 3-July 2)	0.1518	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.

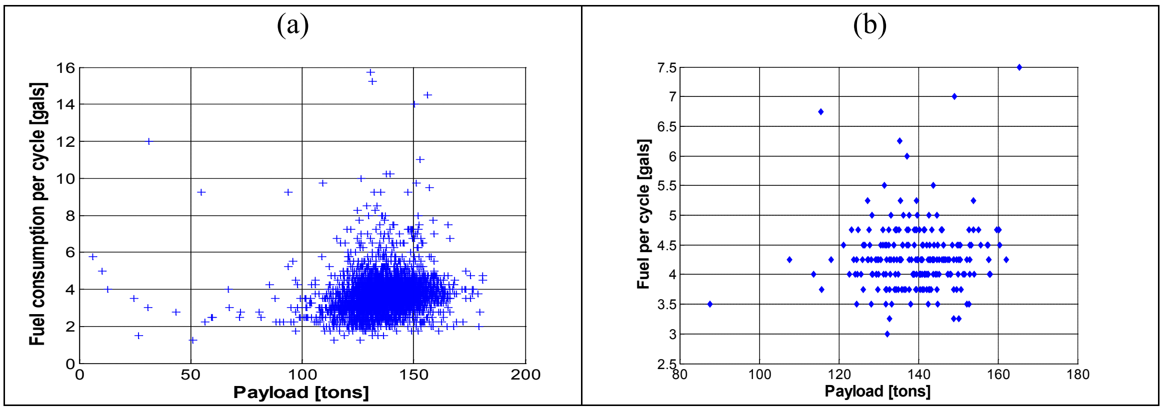

Fig 6. Fuel/cycle against: (a) payload over the period 6/28-7/2; (b) payload over the period 6/28-7/2.

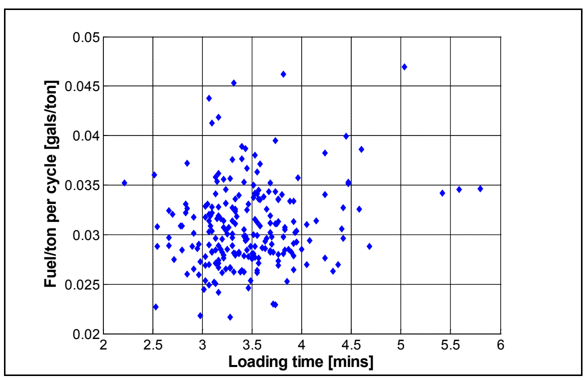

Fig 7. Fuel/cycle/ton against loading time.

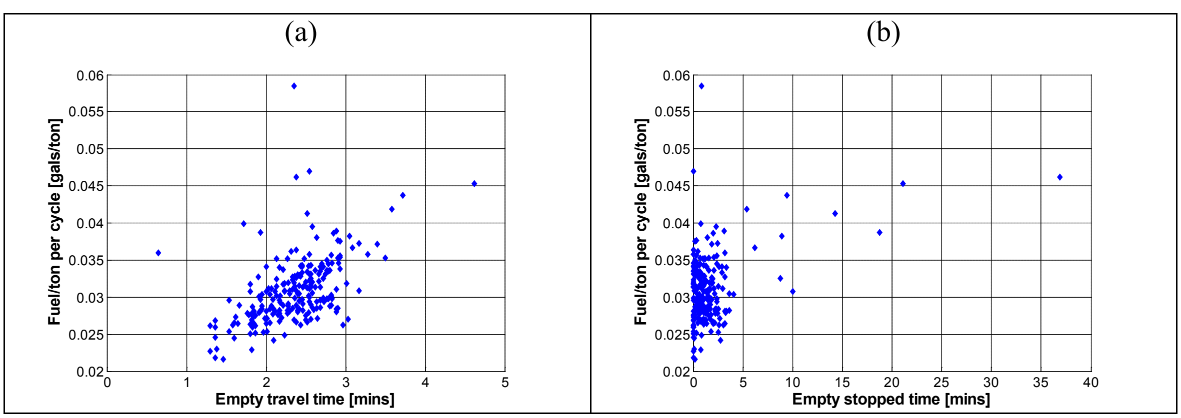

Fig 8. Fuel/cycle/ton against: (a) empty travel time; (b) empty stopped time.

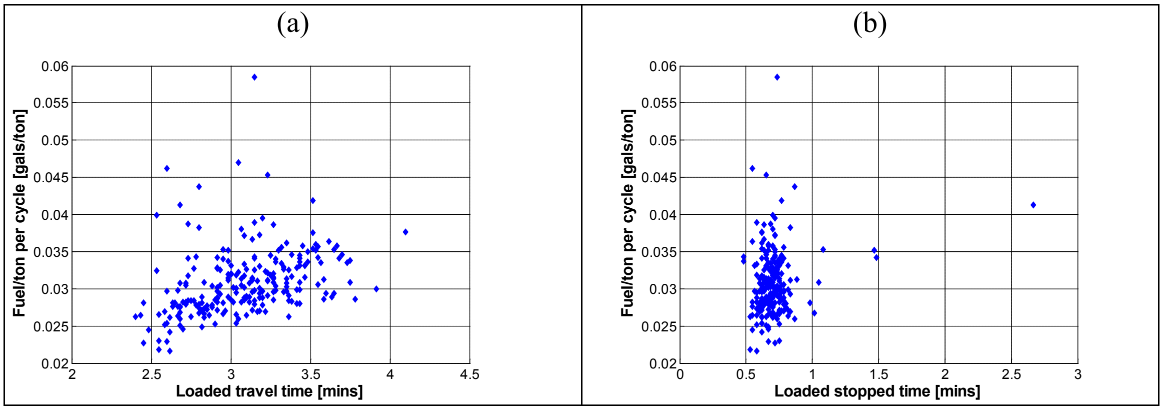

Fig 9. Fuel/cycle/ton against: (a) loaded travel time; (b) loaded stopped time.

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

Fig 10 shows the residuals of the model compared to the actual data. The mean residual for the 158 data points is -8.6857×10^{-18}%. Fig 10 shows only 6 out of 153 data points compared could not be predicted with confidence. The R^2 statistic, the F statistic and its p-value, and the error variance are 0.8356, 139.2678, 0 and 0.0519, respectively.

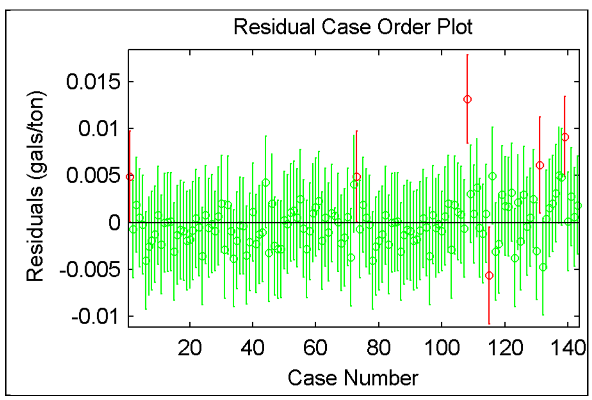

Fig 10. Residuals and 95% confidence intervals of residuals for Equation (3) model. Red data points are residual intervals that do not include zero.

3.3. Simulation model input

Eq. (3) was used, in the simulation model, to predict the amount of fuel consumed by a truck in each cycle. Theoretical statistical distributions were fitted to data to describe the stochastic processes in the simulation model. Chi-squared goodness-of-fit tests were used to fit these distributions to the processes that needed to be modeled this way using the Input Analyzer module in Arena®. Table 5 shows the results of distribution fitting using the data from the time and motion studies and the OEM onboard data logger. The expressions in Table 5 were used to describe the activity times. The average haul distance for the experimental period was surveyed to be 1,207 m (3,960 ft).

Table 5a. Shovel distribution fitting results.

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

Table 5b. Truck distribution fitting results.

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

4. Truck-shovel simulation model

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). 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). A model is therefore an appropriate assembly of blocks to mimic reality as closely as possible.

In modeling energy efficiency of the mine's truck-and-shovel system, drivers/operators were identified as entities. Component cycle times (empty stopped, empty travel, loading, loaded stopped and loaded travel times), arrival and departure time at a station, and payload were defined as attributes which were changed for each cycle by sampling from the distributions in Table 5b or assigning current simulation time. Two stations were defined in the model and transporters (trucks) used to move entities between these stations. The logic at each station is shown in Fig 11. 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. At the end of each cycle, fuel consumed in that cycle is calculated using Eq. (3). 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. Time consuming and instantaneous processes are defined as those that affect the simulation clock and those that do not, respectively.

The main simulation output was energy efficiency, which (in this model) is a function of shovel utilization, truck fuel consumption, and productivity per shift. We, therefore, selected the number of replications to ensure that the half-widths[2] of production, truck fuel consumption per shift, shovel utilization, and energy efficiency were less than 1% of the mean in the base case simulation. It was determined that 100 replications achieved the desired half-widths for these key outputs. Hence, all simulation experiments were set up to run for 100 replications of eleven hours each (equivalent to 100 shifts). The simulation run until it was terminated after eleven hours. All trucks are allowed to dump the last load at the end of the shift.

[2] Half-width, h, is defined, using central limit theorem, as $h = s_x \times t_{\nu,\left(1-\alpha/2\right)}$, where s_x is the standard deviation of x, and $t_{\nu,\left(1-\alpha/2\right)}$ is the t-statistic for ν degrees of freedom and (1-α) confidence level.

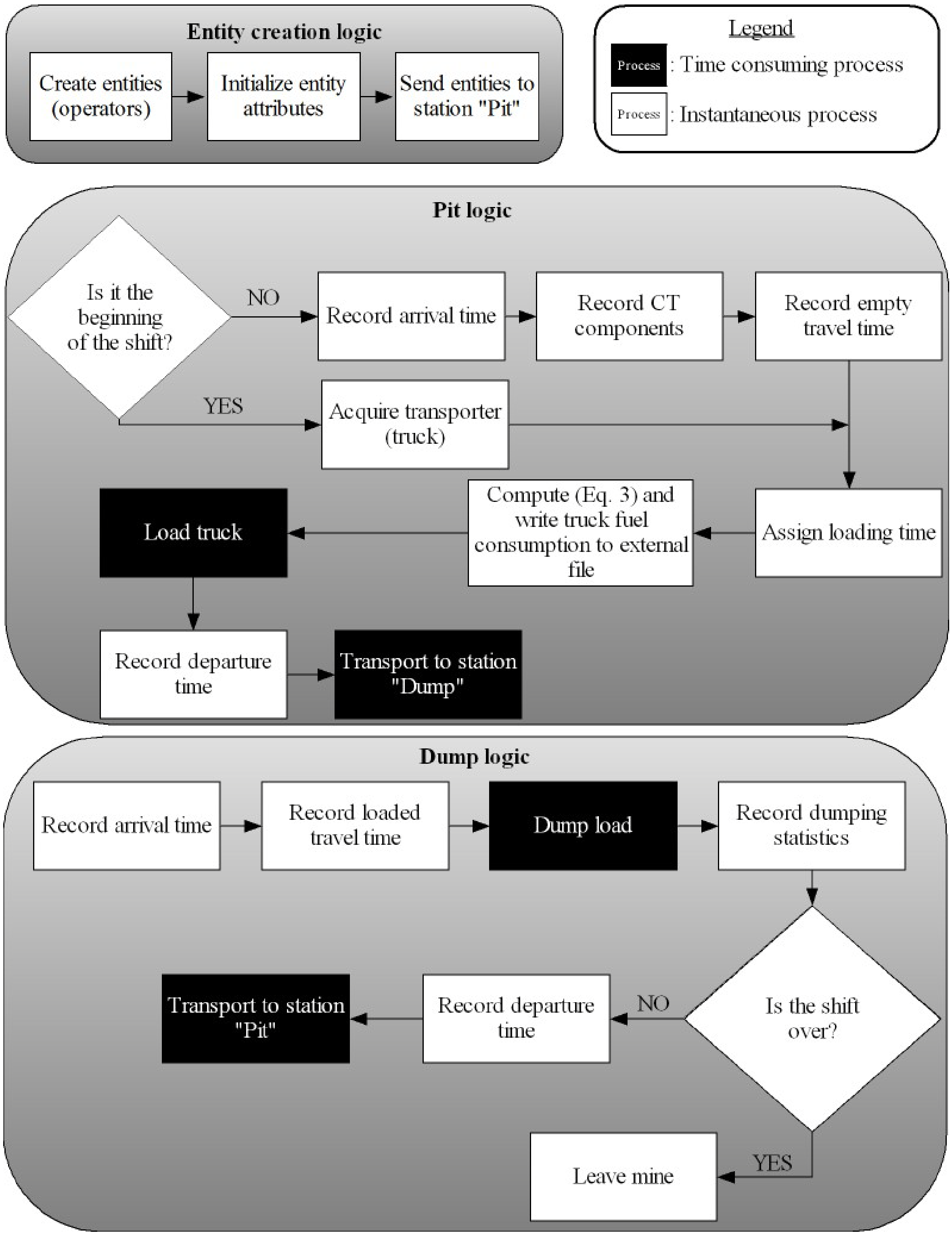

Fig 11. Flowchart of Arena® model logic.

The model was verified and validated with animation and comparing with the field data, respectively. Table 6 shows comparison of the actual truck data for the experimental period and the average values after the 100 replications. The model was validated based on the truck data because the VIMS data was more detailed and useful for validation. Average shovel shift front end utilization and load factor from the MIC data is 80.31% and 66.78%, respectively. Since the 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 shift shovel utilization to be 67.43% (less than the front end utilization, as expected). Given, the similarity between the shovel utilization and the load factor, it was assumed that the shovel utilization is a good predictor of the engine load factor for subsequent analysis. On the basis of the truck predictions, the model was deemed validated as it predicts fuel efficiency and fuel consumed per cycle to within 5%.

Table 6. Simulation model validation.

	Actual	**Simulated**		**Error**
		Mean	*Half-width*	
Production [tons]	15,887	16,590	57	4%
Number of loads	114	120	0.4	5%
Total fuel consumption [gals]	488.87	502.60	1.54	3%
Average fuel consumption per cycle [gals]	4.24	4.27	0.01	1%
Overall fuel efficiency [tons/gal]	17.81[1]	18.51	0.03	4%

[1] Based on calculated shovel fuel efficiency of 39.29 tons/gal from average engine load factor of 66.78% and hourly production from truck production data.

The half-width is a good measure of the uncertainty surrounding each of the estimates from the model. At (1-α) confidence, the estimate (predicted by the expected value, $\overline{x}$) will be between $\overline{x}-h$ and $\overline{x}+h$. All half-widths in Table 6 are less than 1% of the mean, which indicates the 100 replications are adequate. The ability to quantify that uncertainty is a key advantage of stochastic process simulation over deterministic methods such as those found in OEM haulage software.

5. Evaluating energy-saving strategies

The validated simulation model was then used to evaluate the 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 matching. In an alternate scenario, additional Caterpillar 777 (100-ton) trucks were added to the fleet since the mine has two of 777 trucks available already. The mine is more likely to add these 777 trucks than purchase new 785 trucks. It is estimated that the EX1900 shovel is able to load the 777 trucks in five passes.
- **Strategy 2:** Increase shovel capacity. This scenario involved simulating the use of an EX2500 (20.4 yd^3 dipper), which is the next size up in Hitachi's fleet, instead of the EX1900 shovel currently in use. In order to do this, it was assumed (after consultation with Hitachi dealer staff) that the cycle times for the EX2500 shovel were the same as those for the EX1900 shovel. This shovel will load the 785 trucks in 5 passes.
- **Strategy 3:** Shorten haul roads. This can be achieved by reducing the size of the pit. This involved varying the haul distance from 0.2 to 1.0 miles in steps of 0.2 miles while keeping everything else constant.

6. Results and discussions

6.1. Strategy 1: increase shovel utilization through optimal truck matching

Fig 12 shows there are potential gains in production and shovel utilization from adding trucks as expected (for each box, the central mark is the median, the notches represent the 95% confidence interval, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points the MATLAB boxplot algorithm does not consider to be outliers, and the outliers are plotted individually in red). The largest gain comes when the number of trucks is increased from two to three – mean production increases by 4,400 and 5,700 tons/shift (Fig 12a and Fig 13a), and shovel utilization increases by 19.53 and 23.26% (Fig 12b and Fig 13b) for adding 777 (100-ton) and 785 (150-ton) trucks, respectively. However, increasing the number of trucks increases queue lengths or time spent waiting at the shovel (Fig 12c and Fig 13c) and longer queue lengths causes total fuel consumed by trucks in a shift to increase, even when shovel fuel consumption is constant (Fig 12b & d and Fig 13b & d). The overall effect is that fuel efficiency declines in spite of the increased productivity. Adding one 777 or 785 truck decreases fuel efficiency by 1.06 and 0.89%, respectively. The reduction is significant at 95% confidence, as shown by the non-overlapping notches in Fig 12e and Fig 13e.

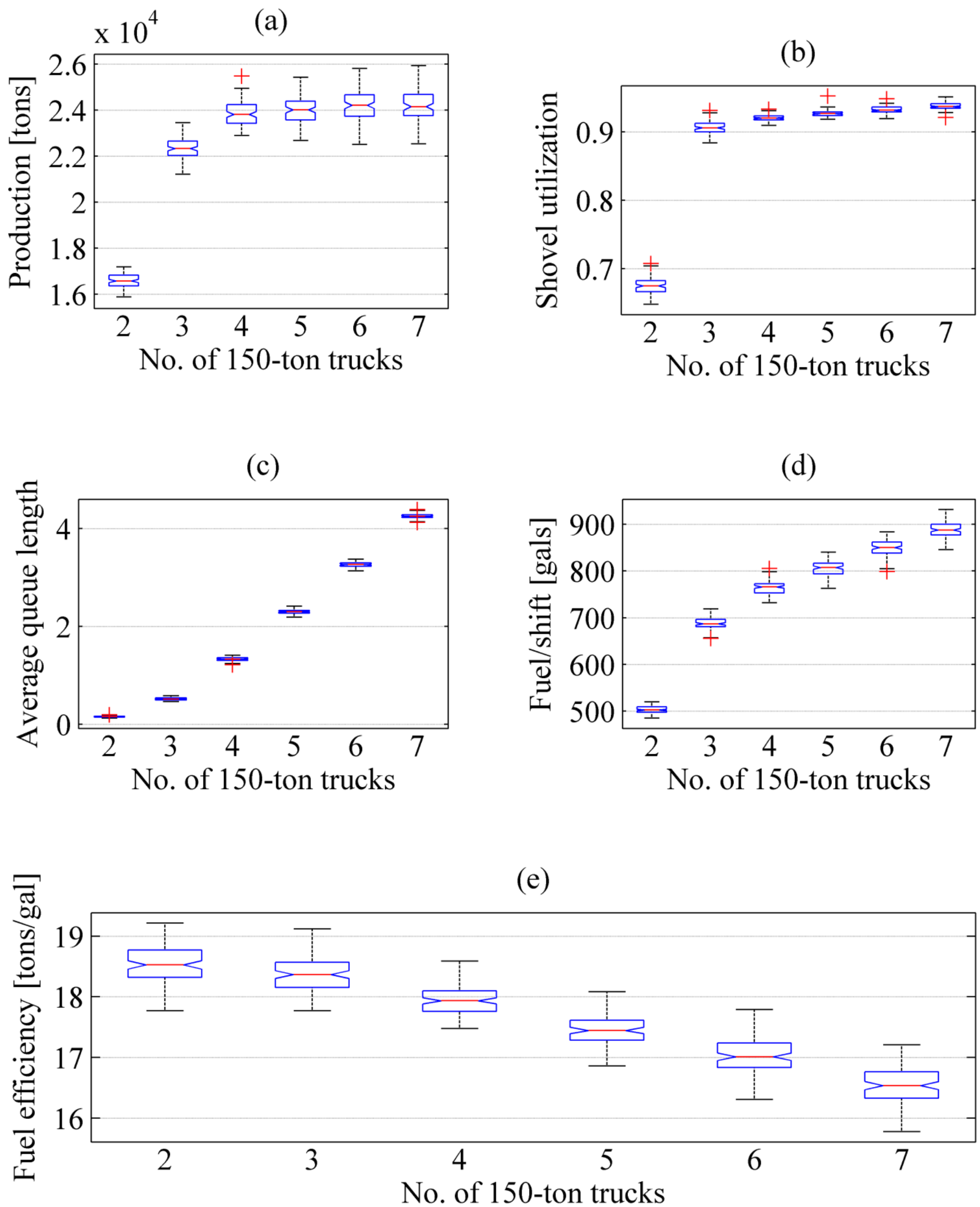

Fig 12. Simulation Results for Strategy 1 – Adding 150-ton Trucks.

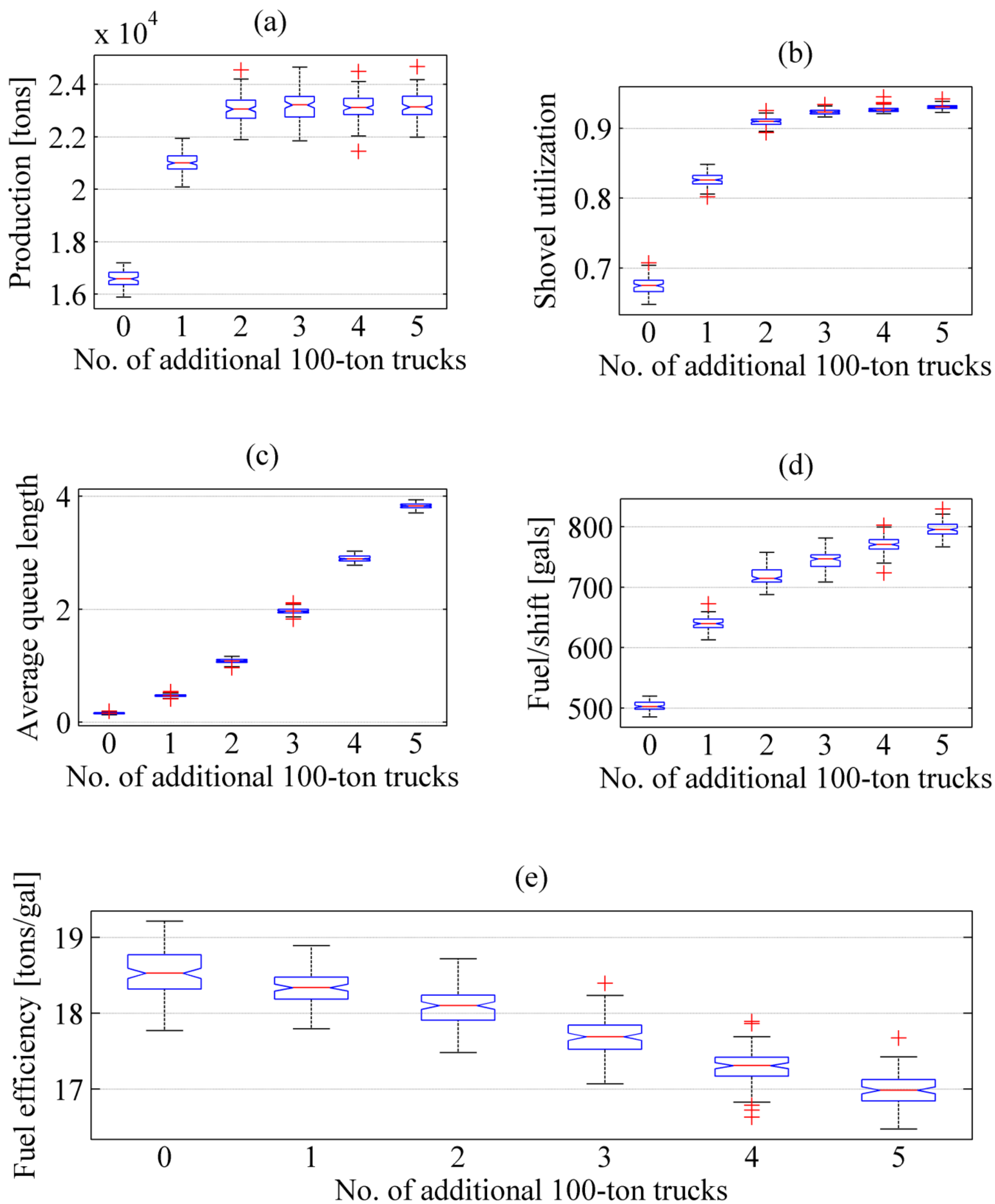

Fig 13. Simulation Results For Strategy 1 – Adding 100-ton Trucks.

This phenomenon is described more clearly in Fig 14, 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 this mine, having more than three trucks in the system is sub-optimal.

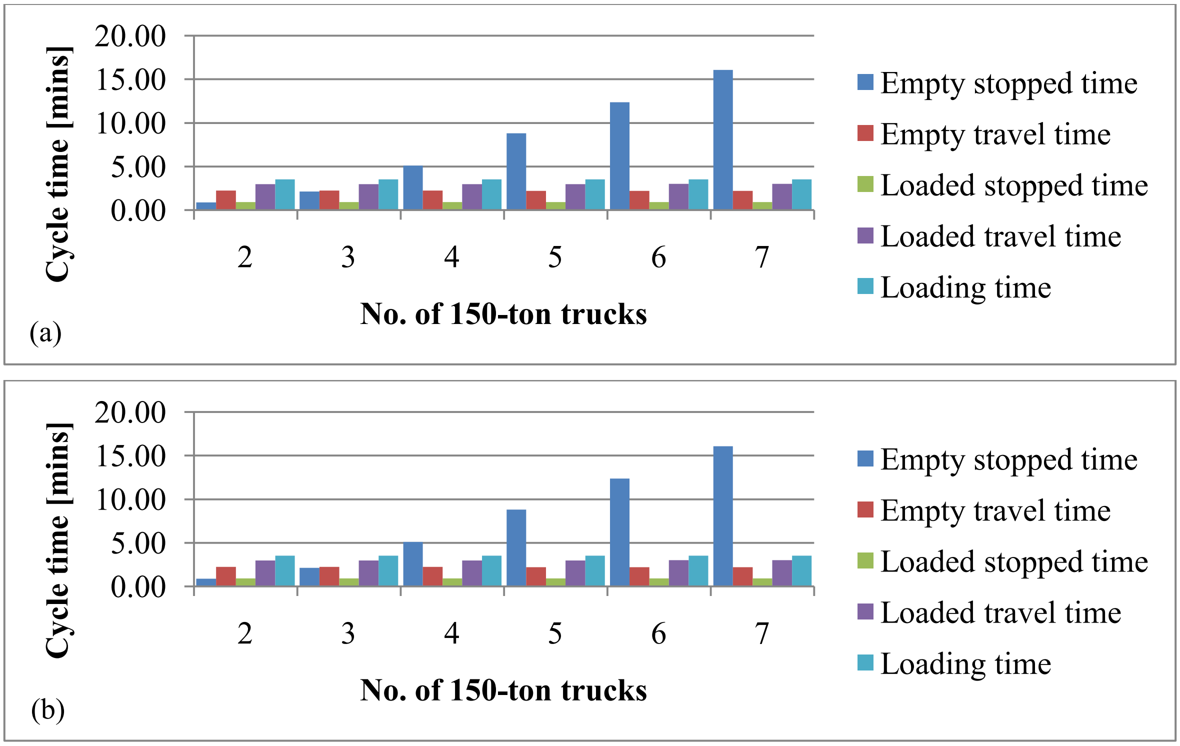

Fig 14. Simulated Cycle Time Components for Trucks: (a) 100-ton; (b) 150-ton.

The uncertainty surrounding the estimates in Figs 12 and 13 are relatively low, which builds confidence in the estimates and the conclusions drawn from them.

6.2. Strategy 2: increase shovel capacity

Fig 15 gives results when use of the larger EX2500 shovel, instead of the currently used EX1900, was evaluated. It shows a statistically significant increase in production and fuel consumed by the trucks (Fig 15a & d) and decreases in shovel utilization (Fig 15b) and average queue length (Fig 15c), which lead to a 3.3% increase in fuel efficiency (Fig 15e). 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.

Fig 16 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.

6.3. Strategy 3: shorten haul roads

The variation in truck fuel consumption and average haul distance over a shift is evident in the VIMS (‘Actual’) data shown in Fig 17. However, the observed variation 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 Fig 17).

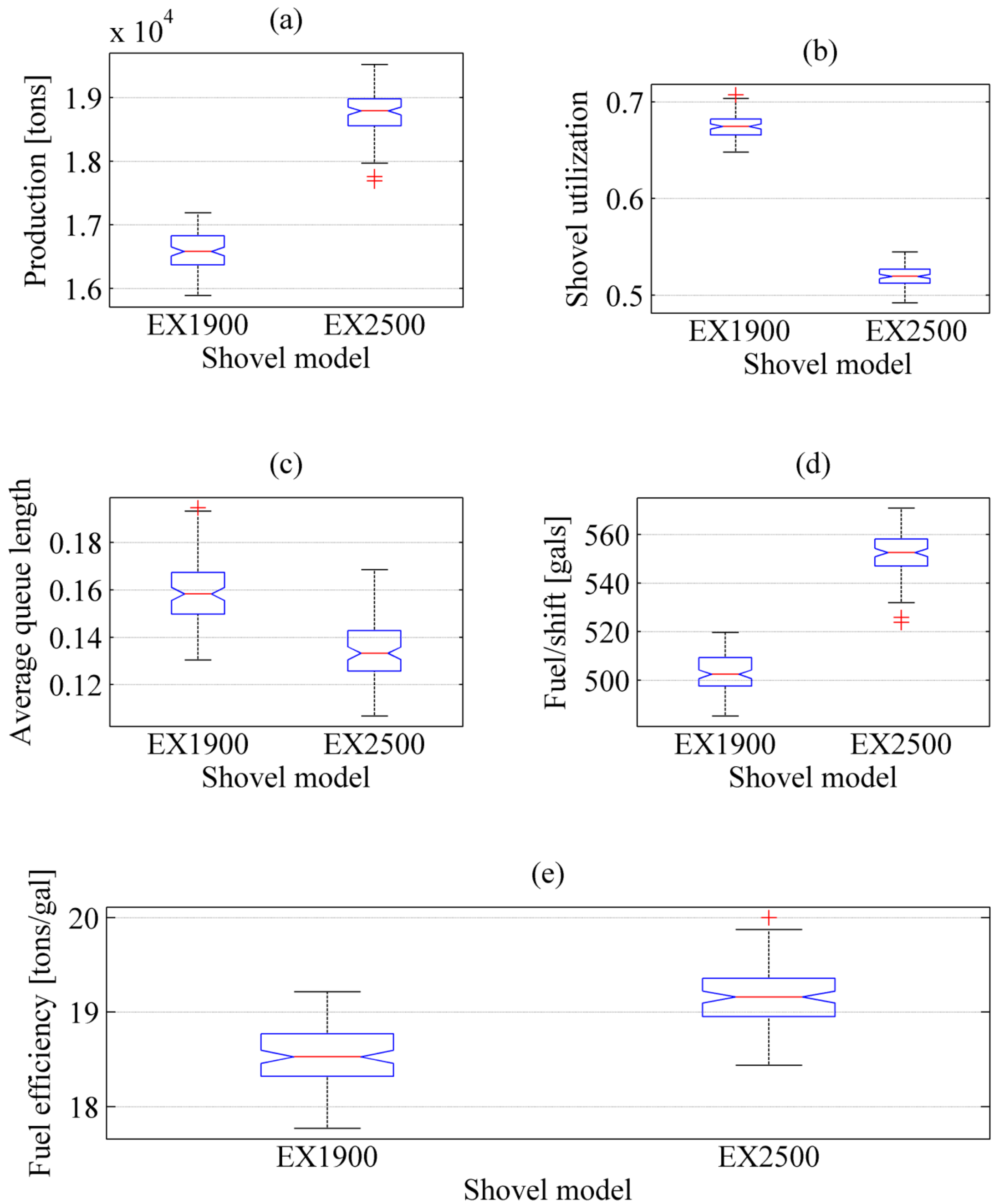

Fig 15. Simulation Results for Strategy 2 – Larger Shovel.

Fig 18 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 Fig 19, such that beyond approximately 0.8 miles, empty stopped time is not dependent on haul distance. Fig 19 shows both travel times increasing with longer haul distances. This predictably increases the overall cycle time.

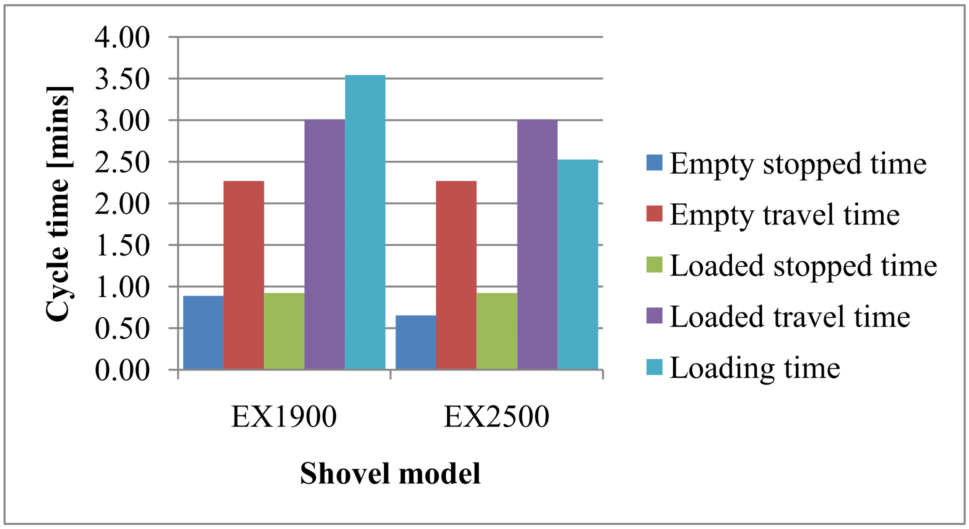

Fig 16. Truck Cycle Time Components When Different Shovels Are Used.

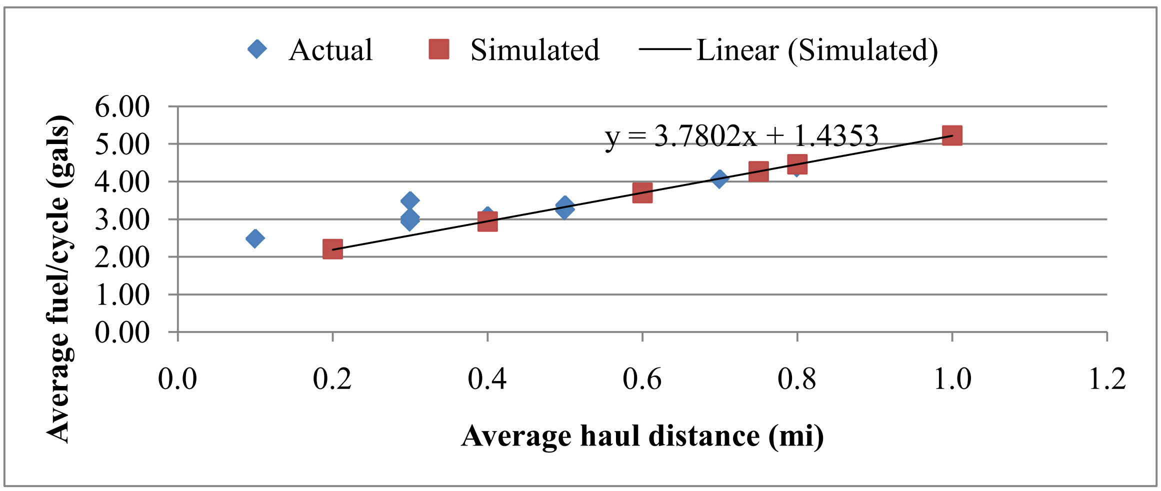

Fig 17. Variation in Truck Fuel/cycle with Average Haul Distance.

While significant gains can be achieved 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.

7. Conclusions

The objective of this work was to apply stochastic process simulation to model the energy efficiency of a typical truck and shovel mining system and use the model to evaluate production strategies to improve energy efficiency. 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.

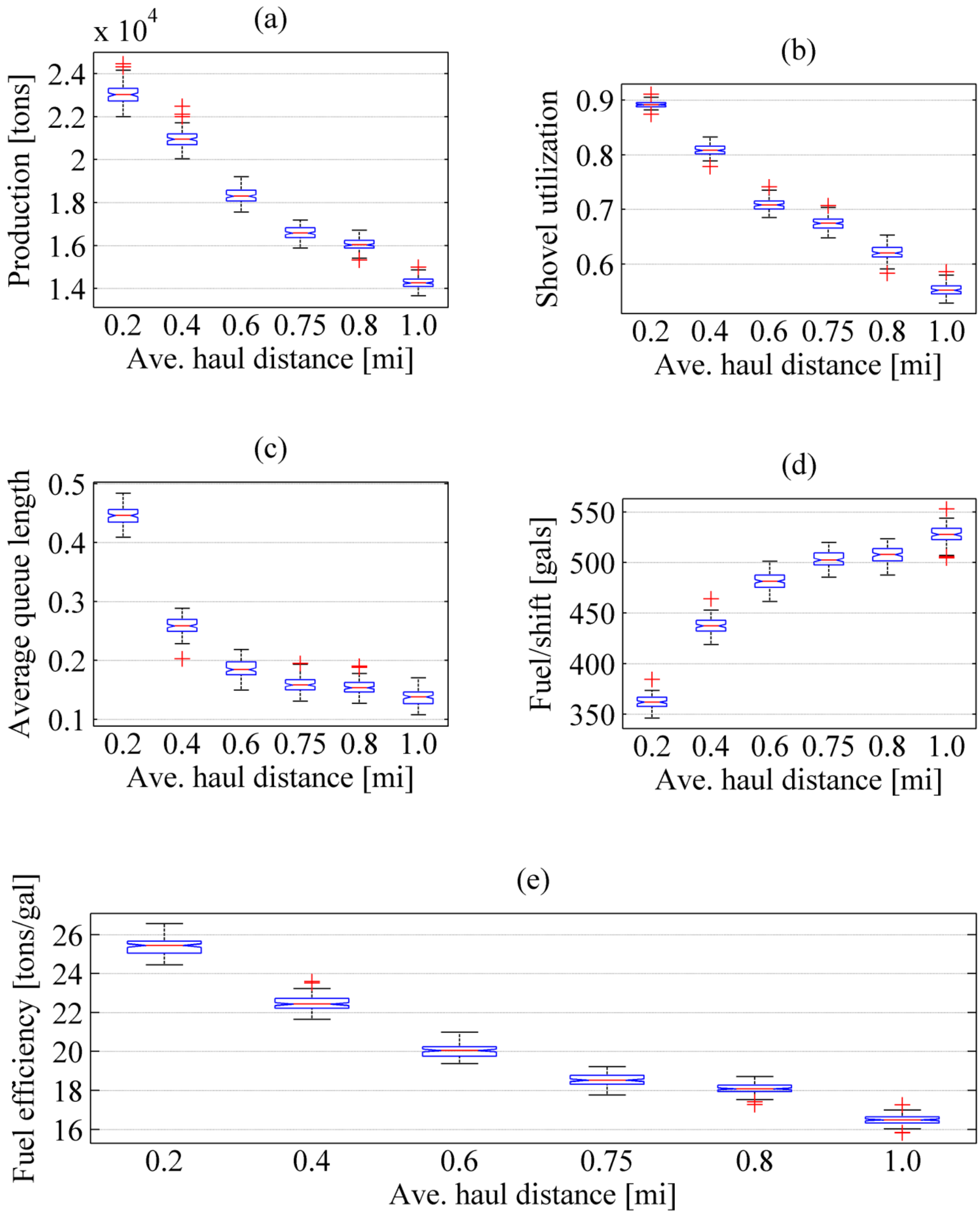

Fig 18. Simulation Results for Strategy 3 – Shorten Haul Distance.

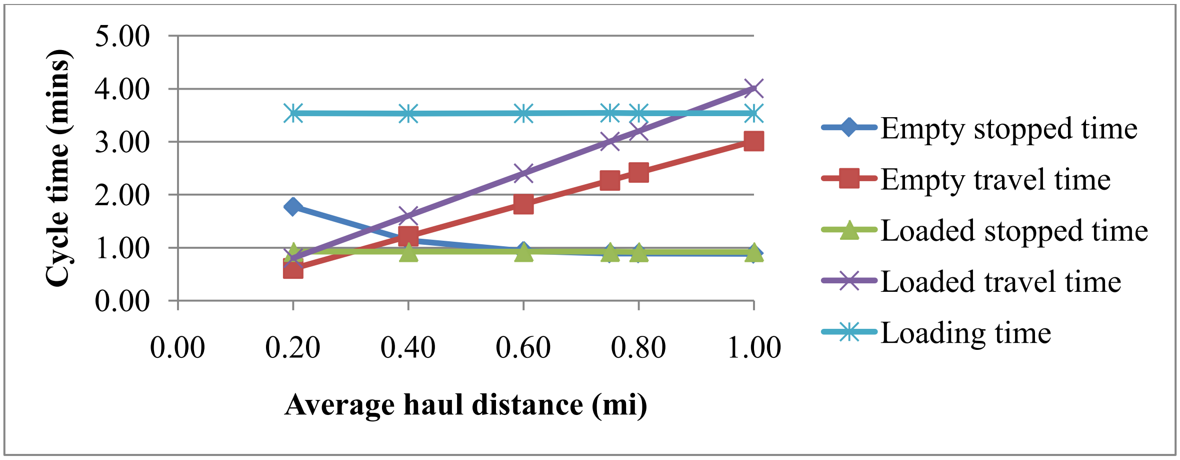

Fig 19. Variation in Truck Cycle Time Components with Haul Distance

- Eqs. (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 the study mine, the following strategies, in decreasing order of impact, provide the most improvement in energy efficiency for truck-and-shovel overburden removal: (i) shorten haul road lengths while maintaining similar haul road grades and dozer push distances; (ii) increase shovel capacity by using next size model (Hitachi EX2500); and (iii) 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 777 and 785 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.

8. Acknowledgements

The authors are grateful for the financial support provided by the Illinois Clean Coal Institute (www.icci.org) through grant # 10/ER9. We are also grateful for the support of Hitachi dealers, Rudd Equipment Company (St. Louis, MO), and technical support staff as well as the support of Caterpillar Inc. and staff.

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