

Article

# Stochastic Predictions of Ore Production in an Underground Limestone Mine Using Different Probability Density Functions: A Comparative Study Using Big Data from ICT System

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**Abstract:** This study stochastically predicted ore production through discrete event simulation using four different probability density functions for truck travel times. An underground limestone mine was selected as the study area. The truck travel time was measured by analyzing the big data acquired from information and communications technology (ICT) systems in October 2018, and probability density functions (uniform, triangular, normal, and observed probability distribution of real data) were determined using statistical values. A discrete event simulation model for a truck haulage system was designed, and truck travel times were randomly generated using a Monte Carlo simulation. The ore production that stochastically predicted fifty times for each probability density function was analyzed and represented as a value of lower 10% (P10), 50% (P50), and 90% (P90). Ore production was underestimated when a uniform and triangular distribution was used, as the actual ore production was similar to that of P90. Conversely, the predicted ore production of P50 was relatively consistent with the actual ore production when using the normal and observed probability distribution of real data. The root mean squared error (RMSE) for predicting ore production for ten days in October 2018 was the lowest (24.9 ton/day) when using the observed probability distribution.

**Keywords:** mining; underground mine; truck-loader haulage system; Monte Carlo simulation; stochastic simulation; ore production



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## 1. Introduction

A mine project generally seeks to maximize production profits by using minimum capital and operating costs over the mine's lifetime [1]. Accordingly, mines require optimal operating methods and equipment utilization strategies to increase productivity and minimize operating costs. In particular, efforts are being made to efficiently operate a truck haulage system, which constitutes greater than half of the operating cost [2]. The efficiency of a truck haulage system varies depending on the combination of the equipment used and operating patterns [3]. Therefore, it is necessary to operate an optimal truck haulage system capable of maximizing ore production and minimizing the equipment delay time [4].

An effective method for operating truck haulage systems is to simulate a virtual system model, using various optimization techniques. The input factors of the truck haulage system model include the system operating parameters (e.g., operating time, number of equipment, and load capacity) and truck cycle time. The outputs of the model include the truckload, production rate, equipment utilization, and equipment latency [4]. For the virtual system model, a simulation algorithm can be designed based on discrete events comprising truck haulage operations, such as traveling, spotting, loading, dumping, and queuing. In addition, mathematical optimization techniques can be applied to determine an optimal solution for the truck haulage operations. To date, several algorithms for truck haulage systems have been developed based on linear programming [5–8], genetic algorithms [9], queuing theory [10–15], fuzzy logic [16], and deep neural networks [17,18].

The system operating parameters and truck cycle times are not constant or definitive for each haulage operation cycle and frequently fluctuate according to the working conditions [19]. For instance, the daily working time and number of dispatched trucks can fluctuate according to the ore production schedule. The truck cycle time may vary depending on the equipment breakdown, plant interruption, and haul road conditions. For these reasons, an uncertainty exists in the deterministic simulation method, which predicts the truck haulage system, using constant input values. One method to simulate the system model considering the variability of input parameters is to apply the stochastic simulation technique. This method randomly extracts the input values from the probability distribution of a random variable and predicts the distribution of the output factors through iterative simulations [20].

Until recently, several researchers applied stochastic simulation techniques to analyze optimal equipment combinations and design truck dispatch scenarios in both open-pit and underground mines [1,19,21–34]. In these studies, truck cycle time data were statistically analyzed and a probability density function was selected using probability distribution models, such as Gaussian, triangular, Weibull, gamma, lognormal, exponential, Erlang, and uniform distribution models (Table 1). The optimal probability distribution model was determined by evaluating the goodness-of-fit using the chi-squared test [35], Akaike information criterion (AIC) [36], and Kolmogorov Smirnov tests [37]. The ore production, equipment utilization rate, and equipment downtime corresponding to the truck-shovel combination were analyzed probabilistically [25]. In addition, the ore production was predicted based on the confidence level, using iterative stochastic simulation [30], and the prediction sensitivity was analyzed by alternating the probability distribution models of the truck cycle time data [32]. However, little attention has been paid to analyze and use the probability distribution derived from a large amount of truck cycle time data for stochastic simulations.

**Table 1.** Study cases for the stochastic approach-based truck haulage system simulation.

Reference	Theoretical Model Representing Probability Distribution							
	Gaussian	Triangular	Weibull	Gamma	Lognormal	Exponential	Erlang	Uniform
[1]	X							
[19]	X					X		
[21]	X			X				
[22]	X							
[23]								
[24]	X							X
[25]	X	X	X	X				X
[26]	X							
[27]	X							
[28]						X		
[29]					X			
[30]	X		X	X	X			
[31]	X							
[32]	X						X	X
[33]								
[34]	X							

The truck cycle time data were collected using the stopwatch method while boarding the equipment. For this reason, the theoretical probability distribution model was utilized in the stochastic simulations instead of the real statistical distribution pattern of the truck cycle time data. However, this may reduce the accuracy of the outputs from the truck haulage system simulations. Therefore, to improve the simulation accuracy, it is necessary to analyze and derive the probability distribution from a large amount of truck cycle time data collected over a long period.

Recently, mine safety management systems with information and communications technology (ICT) have been developed and actively implemented in mine sites worldwide [38–45]. The system recognizes the location of the equipment and workers in real time and monitors the work environment. Equipment location recognition data are transmitted to a web server through a wireless communication network and equipment locations are visualized on a dashboard in an outside office. An outstanding feature of this system is

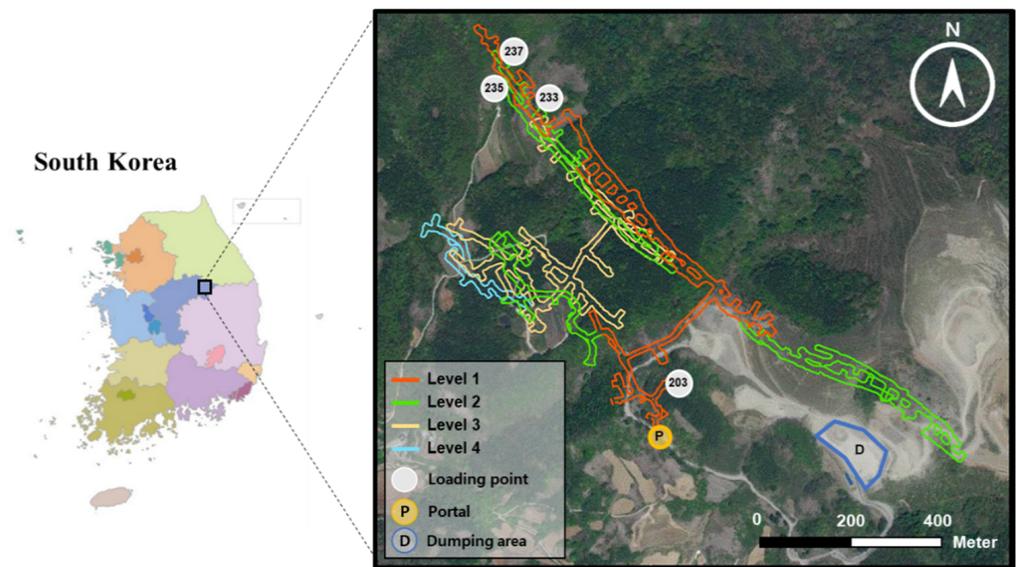
that big data are generated by continuously accumulating equipment location recognition data on the web server. Therefore, it is possible to analyze the long-term truck cycle time by extracting the equipment recognition time from the big data and calculating the difference in the recognition time. Baek and Choi [31] processed the big data acquired from a mine safety management system and statistically analyzed the truck travel time. In addition, the ore production and equipment utilization rates were predicted using a discrete event simulation. However, in this study, the probability distribution of the truck travel time data was assumed to be a normal distribution, as it was impossible to consider the exact variability of the truck travel time data.

The objective of the study was to analyze the probability distribution of the truck travel time using big data acquired from an ICT-based mine safety management system, and stochastically predict ore production through discrete event simulations, using different probability density functions for truck travel times. An underground limestone mine was selected as our study area. The probability distribution of the truck travel time was derived through statistical analysis of the big data acquired from the study area, and the truck travel time was randomly generated using Monte Carlo simulations based on four different probability density functions (uniform distribution, triangular distribution, normal distribution, and observed probability distribution of real data). A comparison between each of the stochastically predicted ore productions was performed to discuss the value of the truck cycle time data collected by the ICT-based mine safety management system.

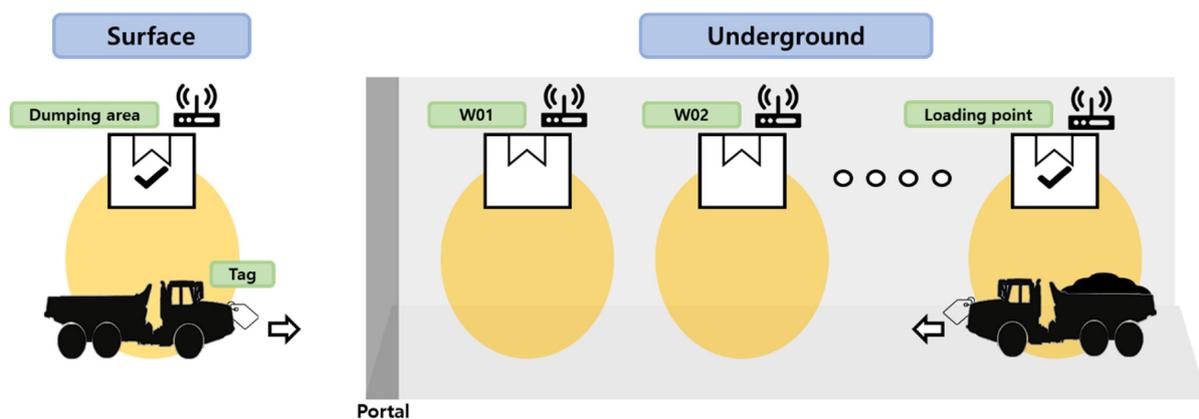
## 2. Study Area

The Yeongcheon underground mine ( $37^{\circ}4'14''$ ,  $128^{\circ}18'46''$ ) of Baek Kwang Mineral Products Co., located in Danyang-si, Chungcheongnam-do, South Korea, was selected as the study area (Figure 1). The mine comprises four levels; the average altitude of Levels 1, 2, 3 were 310, 250, and 280 m, respectively, while the lowest for Level 4 was 220 m. The mining method for room and pillar mining produces approximately 120 tons of limestone ore per year. The mine consists of four loading points underground (the IDs of which are 203, 233, 235 and 237) and a dumping area with a crusher on the surface. The ore was transported, using 30 ton dump trucks. The site's production manager assigns trucks to the loading point daily, accounting for the ore production goals and quality. Next, the truck driver departs to the point to load the ore. The ore is loaded and subsequently moved to the dumping area. The truck driver checks the amount of ore accumulated in the crusher; if the ore quantity does not exceed the crusher capacity, the ore is unloaded into the crusher, and if it exceeds the capacity, the ore is unloaded into the yard. This operation is repeated during the working hours.

The study area was equipped with a mine safety management system based on ICT. Owing to the installation of a wireless communication network, it was possible to implement a digital environment to track the location of equipment in real time, make voice calls, and monitor the working environment at an underground mine site where communication was not possible. Through the wireless communication network, the location of the production equipment in the mine was received in real time on the dashboard in the office. The data acquired through the safety management system were stored in real time. In this study, the location tracking data of the production equipment were used in the mine safety management system. When the production equipment passes by a wireless access point (AP) installed in the study area, its location is tracked and stored as tag-recognition data. Figure 2 shows the process of a truck being recognized by the wireless APs as it passes by them while transporting ore in an underground mine. The tag recognition packet data, stored as the truck passes, includes information regarding the data category, presence of an emergency, tag recognition sequence, ID of the recognized tag, and distance between the wireless APs and the tag. These data are transmitted once every second, and approximately 200,000 packets are stored in the web server per month; the size of the data packet is 20 bytes each.



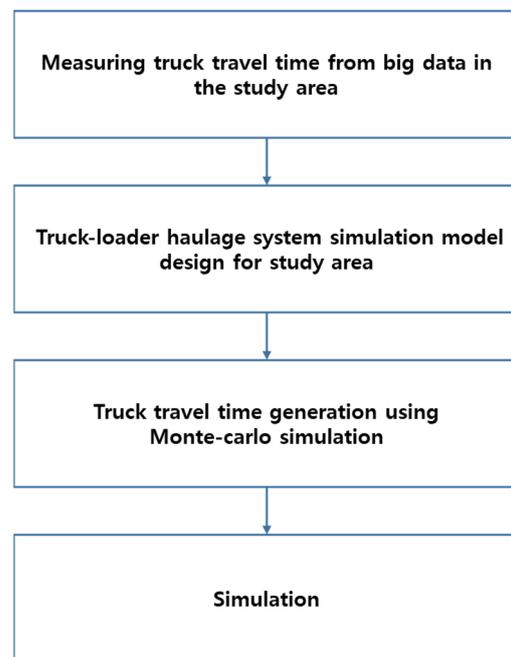
**Figure 1.** Aerial view of the study area displaying the various facilities. (Image source: National Geographic Information Institute of South Korea).



**Figure 2.** Diagram showing the sequence of wireless APs in the underground mine; W01 (W02): 1st (2nd) wireless access point (AP) installed underground.

### 3. Methods

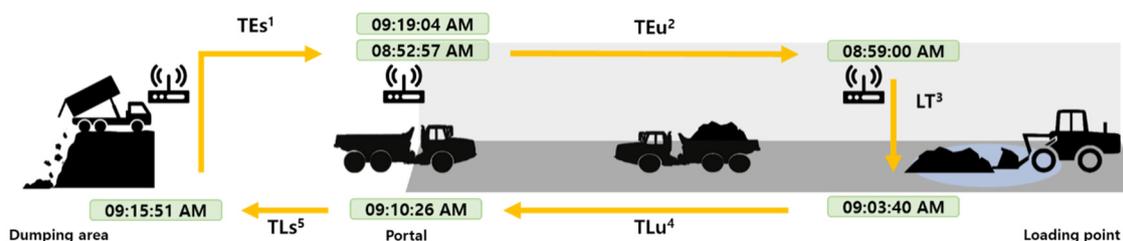
Big data collected for the location tracking of production equipment in the mining safety management systems were analyzed to compare and predict the ore production based on probability density functions. For the simulation, time and simulation parameters were received as input variables, and ore production was obtained as a probability distribution. Through big data analysis, the truck cycle time (TCT), which is the time parameter, was acquired. We designed a stochastic simulation model to fit the truck haulage system of the underground mine selected as the study area. Uniform, triangular, normal, and observed probability distributions were generated by measuring the truck travel time. Travel times and ore production rates were predicted by the Monte Carlo simulation (by applying the probability density functions) and stochastic simulation model, respectively (Figure 3).



**Figure 3.** Study process of truck-haulage system stochastic simulation using the proposed method.

### 3.1. Measuring Truck Travel Times from Big Data

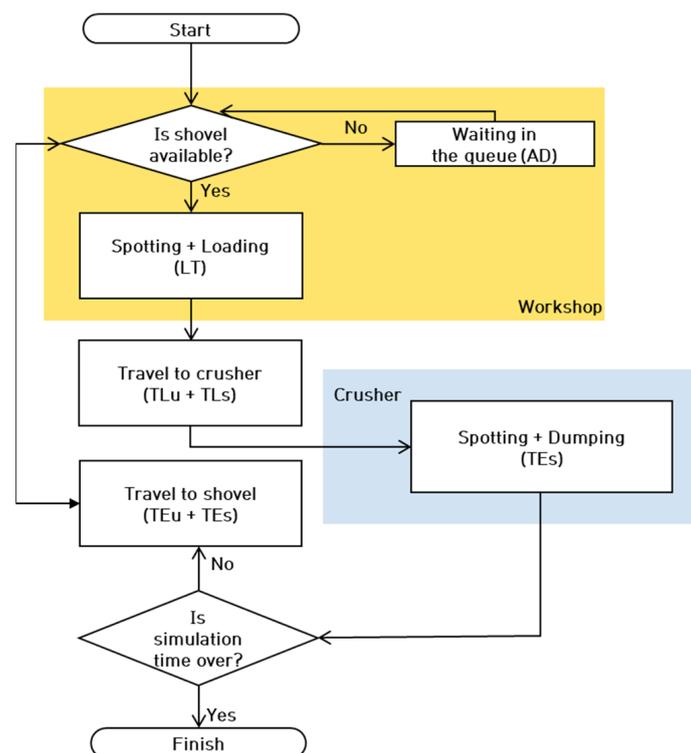
The truck travel time was measured through the following process using big data. In this study, truck tag recognition packet data were extracted from big data for October 2018. The truck tag recognition packet data store approximately 200,000 packets per month. Among the packet data properties, tag recognition time, the IP address of wireless APs, and distance packet information were considered and classified according to the truck workplace. The study area consists of four loading points and four routes were identified. If all the wireless AP recognition data of the identified route do not exist and there are missing data, the data are deleted. By calculating the difference in the recognition time of the wireless APs, we obtained the truck travel time between each wireless AP. If the trucks remained in the recognized range for a considerable amount of time, the distance packet information was used to extract the tag recognition time, which is the minimum distance between the wireless APs and the truck. The difference in tag recognition time of the APs was calculated to measure the truck travel time. The types of truck travel times are as follows: the time lapsed when the truck moves from the portal to the loading point in an empty state (TEu); the time needed to load ore into the truck (LT); the time needed to transport the ore from the loading point to the portal with the ore loaded (TLu); the transport time from the portal to the dumping area and the unloading time in the dumping area (TLs); and the time to return to the portal (TEs) (Figure 4).



**Figure 4.** An illustration of the process of classifying the truck tag recognition packet data and measuring the five types of truck travel time: TEs<sup>1</sup>—empty truck surface travel time; TEu<sup>2</sup>—empty truck underground travel time; LT<sup>3</sup>—loading time; TLu<sup>4</sup>—loaded truck underground travel time; TLs<sup>5</sup>—loaded truck surface travel time.

### 3.2. Design of a Truck Haulage System Model for Stochastic Discrete Event Simulation

A simulation model of a truck haulage system was designed to fit the study area (Figure 5). When the truck moves to the loading point, it determines whether a loader is available. If a loader is available, the truck loads the ore and proceeds to the dumping area. If another truck is loading, the truck waits for the job to be completed, loads the ore, and subsequently, proceeds to the dumping area. The trucks move to the dumping area and unload at the crusher or loading dock. If the simulation is not completed, the truck returns to the underground loading point. At the end of the simulation, the rate of ore production is predicted.



**Figure 5.** Flow chart displaying procedures for implementing the truck haulage simulation algorithm.

The truck haulage system simulation algorithm was modified for the measured truck travel time based on the TCT theory proposed by Suboleski [46]. TCT consists of the time a truck requires to travel from the portal to the loading point (TEu), the time a truck requires to load the ore at the loading point (LT), the time a truck needs to move to the portal from the loading point (TLu), the time taken by a truck to move to the dumping area (TLs), the time the truck needs to remain at the dumping area for the ore unloading process and the time needed to return to the portal (TEs) (see Equation (1)).

$$\text{TCT} = \text{TEu} + \text{LT} + \text{TLu} + \text{TLs} + \text{TEs} \quad (1)$$

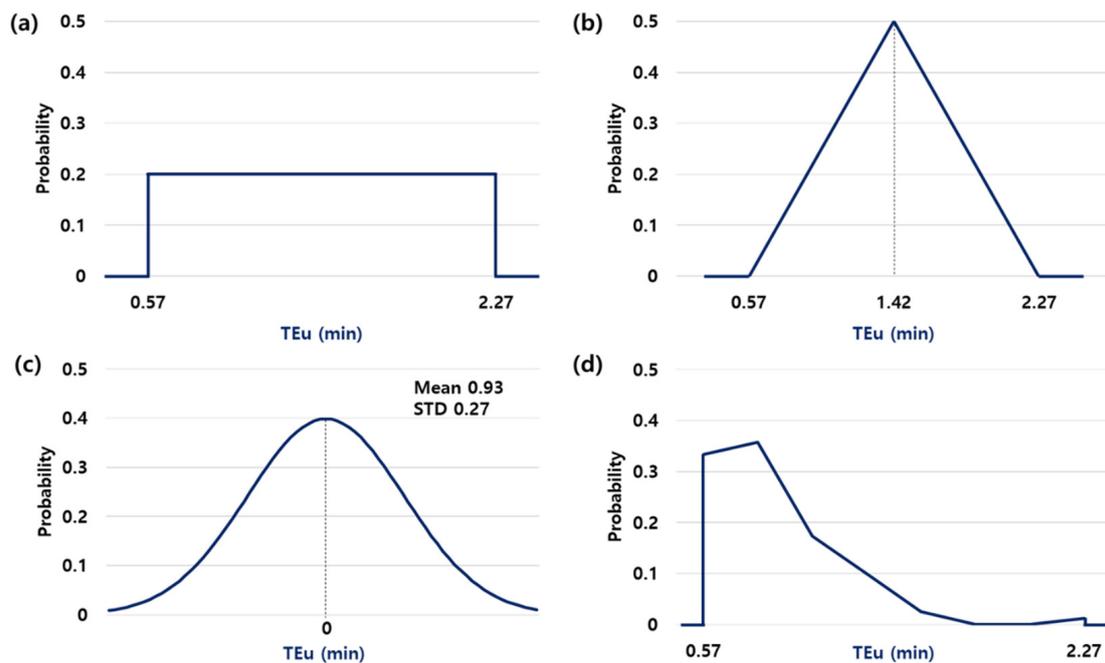
Table 2 lists the input and output values of the truck haulage system simulations. The input data include time parameters that control the TCT (which can control the truck operating time) and simulation parameters (which can control the operating facility or operating time). Time parameters were generated through Monte Carlo simulations and used as the input for the simulation model. The simulation parameters can be set as the conditions to be simulated. The simulation result is the rate of ore production.

**Table 2.** Description of the input and output parameters of the truck haulage system simulation.

Type	Data	Unit	
Input	Time parameters	Travel time of the empty truck	TEu Minutes
		Travel time of the loaded truck	TLu TEu Minutes Minutes
	Working time	LT Minutes	
	Simulation parameters	Daily working time	Minutes
		Number of trucks	Numbers
Capacity of a truck		Tons	
Number of simulations	Numbers		
Output	Total amount of the loaded ore	Tons	

### 3.3. Generation of Truck Travel Times

In this study, we compared the simulation results of instances wherein different probability density functions of the measured truck travel time were used as the input variables. The simulation results were compared by creating five temporal elements of the TCT with the Monte Carlo simulation, using the uniform, triangular, normal, and observed probability distributions derived from actual truck travel time data. The uniform, triangular, normal, and observed probability distributions were used in this study because they are widely used as probability density functions and can be defined using the big data of an ICT system. It should be noted that the uniform, triangular and normal distributions are theoretical probability density functions defined mathematically; however, the observed probability distribution is an empirical one. The uniform and triangular distributions were generated by considering the maximum and minimum values. The normal distribution was generated by considering the mean and standard deviation (STD), and the observed probability distribution was obtained using actual accumulated data (Figure 6).



**Figure 6.** Probability density functions of the truck travel time for loading point 203. (a) Uniform distribution, (b) triangular distribution, (c) normal distribution, (d) observed probability distribution.

Considering the measured truck travel time, a random variable for truck travel time was created based on a Monte Carlo simulation. A Monte Carlo simulation is a numerical, experimental method to obtain the output variable value of the system calculation model by considering the statistical value of the input variable. The values of the input random variable were sampled based on the statistical distribution, and the output variable was calculated using a computational model [47]. To use the Monte Carlo simulation, a cumulative relative frequency graph of the TCT was created.

The class width and relative frequency are required to generate the cumulative relative frequency graph of the TCT. Using the statistical analysis results, the class width required to create a cumulative relative frequency graph was calculated (Equation (2)). The frequency of each class was calculated according to the data, and the relative frequency of each class was calculated by dividing the total data recorded (Equation (3)). The cumulative relative frequency was calculated using the relative power of each class, as shown in Equation (4):

$$\text{Class width} = \frac{\text{Maximum value} - \text{Minimum value}}{\text{Number of classes}} \quad (2)$$

$$F_i^r = \frac{f_i}{N} \quad (3)$$

$$F_n^c = \sum_{i=1}^n F_i^r \quad (4)$$

Using the cumulative relative frequency graph based on the probability function distribution, a random variable for truck travel time was created by Monte Carlo simulation, as follows: the cumulative relative frequency graph  $F(x)$  represents the probability  $P$  that the truck travel time  $X$  is less than or equal to  $x$  (Equation (5)). Because  $F(x)$  is a probability, it possesses a value from 0 to 1. Thus, we can determine the inverse function of  $F(x)$ , where  $G(F(x))$  is the inverse function of  $F(x)$ , and  $r$  is any real number between 0 and 1. In this study, we generated the actual number between 0 and 1 and subsequently assumed each generated actual number as the  $y$  value of the cumulative relative frequency graph and predicted the trucking time by determining the  $x$  value corresponding to the  $y$  value (Equation (6)).

$$F(x) = P(X \leq x) \quad (5)$$

$$G(F(x)) = G(r) = x \quad (6)$$

### 3.4. Setting Simulation Parameters

To perform the simulation, we set the simulation parameters, which consisted of the daily working time, number of trucks, capacity of a truck, and number of simulations. The simulation parameters were set using the operational parameters analyzed from the big data. On the morning of 16 October in the study area, two 30 ton trucks were used at the loading point 237 from 7:00 a.m. to 12:50 p.m. The simulation was performed by setting the following parameters: operating time as 350 min, two trucks, a truck capacity of 30 tons, and simulation iterations as fifty times (Table 3).

**Table 3.** The value of the simulation parameters used for truck haulage system simulation.

Simulation Parameters	Value
Daily working time (min)	350
Number of trucks	2
Capacity of a truck (ton)	30
Number of simulations	50

## 4. Results

### 4.1. Statistical Characteristics of Truck Travel Times Measured from Big Data

In the study area, the TCT was analyzed using big data recorded in October 2018 (Table 4). Figure 7 shows the cumulative relative distributions of TEu, TEs, TLu, TLs, and LT at each of the four loading points. Loading point 203 required the least time with an average of approximately 22.74 min for a single haulage cycle; loading point 235 required the most time with an average of approximately 34.07 min. Loading point 203 was located closest to the portal, resulting in an average difference of approximately 11.33 min in TCT.

**Table 4.** Results of the statistical analysis of the truck travel time measured using the big data.

Loading Point	Statistics	Truck Travel Time				
		TEu	TLu	TLs	TEs	LT
203	Mean (min)	0.93	1.10	5.55	7.58	7.58
	Min (min)	0.57	0.75	4.02	2.72	3.58
	Max (min)	2.27	1.95	8.98	44.37	21.95
	STD (min)	0.27	0.23	0.92	9.82	3.73
	Kurtosis	7.14	4.33	3.70	7.09	3.19
233	Mean (min)	9.47	10.17	5.48	3.75	4.25
	Min (min)	5.52	8.05	4.03	2.43	2.08
	Max (min)	23.08	11.85	8.18	6.55	20.55
	STD (min)	3.32	0.73	0.77	0.92	2.57
	Kurtosis	4.46	0.23	4.01	2.18	26.67
235	Mean (min)	7.20	10.97	5.52	4.63	5.75
	Min (min)	5.77	9.57	4.78	3.07	0.63
	Max (min)	13.62	14.25	8.00	11.32	19.17
	STD (min)	1.85	1.32	0.63	2.07	3.95
	Kurtosis	28.00	28.00	27.00	23.00	28.00
237	Mean (min)	6.52	7.98	5.30	3.50	5.52
	Min (min)	4.72	6.42	4.72	2.70	3.53
	Max (min)	11.30	9.23	6.43	6.23	16.57
	STD (min)	1.27	0.62	0.42	0.68	3.38
	Kurtosis	7.90	0.23	0.90	10.47	4.18

The uniform and triangular distributions of the truck travel time were set using the minimum and maximum values of the measured TCT. A normal distribution was simulated using the mean and standard deviation of the TCT. The cumulative distribution was simulated by calculating Equations (3)–(5), using actual data. For loading point 203, the difference between the maximum and minimum classes of TEu, TLu, and TLs, which are truck travel time elements, was 1.52, 1.10 and 4.40 min, respectively, whereas LT and TEs, which are the time required to load or unload ore, were 18.10 and 34.53 min, respectively, and exhibited additional differences than other factors. Loading point 233 exhibited significant differences in class at 17.30 and 18.40 min, respectively, for TEu and LT. Loading point 235 displayed a difference between the maximum and minimum classes at 7.80 min and 14.25 min for TEs and LT, and for loading point 237, at 11.65 min for LT. The comparison proved the existence of a significant time lag when working with ores. The TCTs were predicted using a Monte Carlo simulation. The generated times were used for simulations to predict ore production rates.

### 4.2. Predictions of Ore Productions by Stochastic Discrete Event Simulation

The actual production in the field and the simulation results were compared. In the designated study area, the simulation parameters were set and simulations with two 30 ton trucks and an operating time of 350 min were conducted, as shown in the data for 16 October. The TCT was used as the input in the Monte Carlo simulation as the

time obtained for each uniform distribution, that is, triangular, normal, and observed probability distribution.

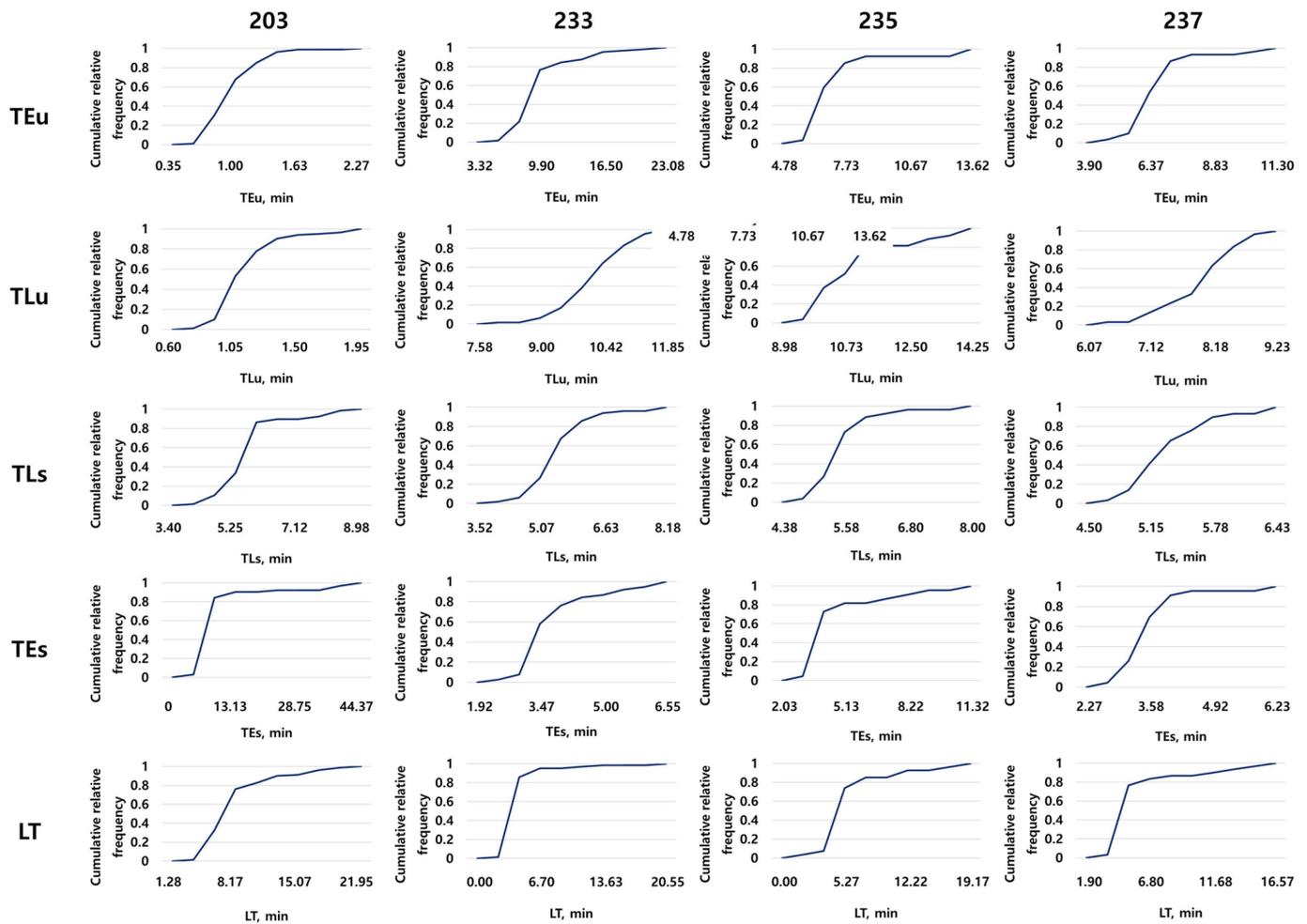
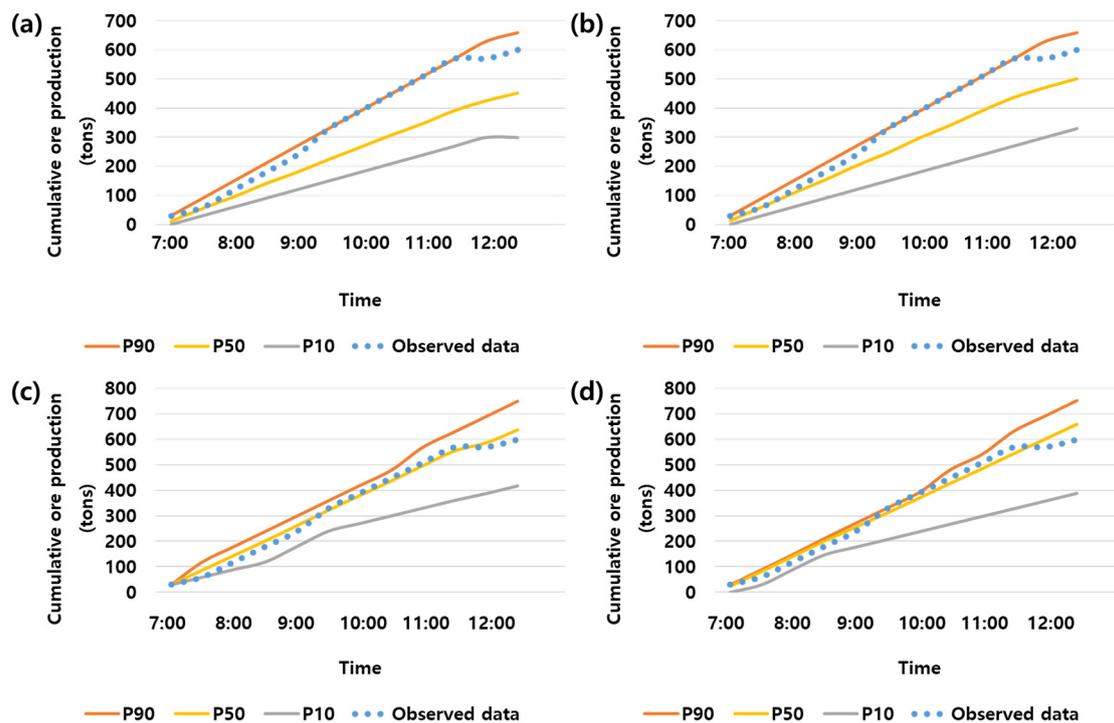


Figure 7. Histogram and cumulative relative frequency graphs of the truck travel time for each loading point.

The simulation results indicated the production volumes of P10, P50 and P90. P10 represents the value of the lower 10% ore production, P50 represents a production rate lower than 50%, and P90 represents a simulated rate lower than 90%. If we cross-check the results with the P10 values, we can conclude that the ore production is low, while P50 and P90 are the average and high production volumes, respectively. In all four probability density functions, we confirmed that the actual field data are located within the range of the simulation results. The uniform and the triangular distribution models exhibited similar results for the actual and simulated results of P90. The overall prediction result was lower than that of the actual data. It was determined that the truck cycle time was generated longer than the actual truck cycle time owing to the distribution of the probability density function when the truck cycle time was generated. Conversely, the normal distribution and observed probability distribution models displayed results similar to that of the actual values and P50 as a result of the simulation (Figure 8).



**Figure 8.** Comparison of the simulation and haulage operations results (observed) obtained on 16 October 2018 for (a) uniform distribution, (b) triangular distribution, (c) normal distribution, and (d) observed probability distribution.

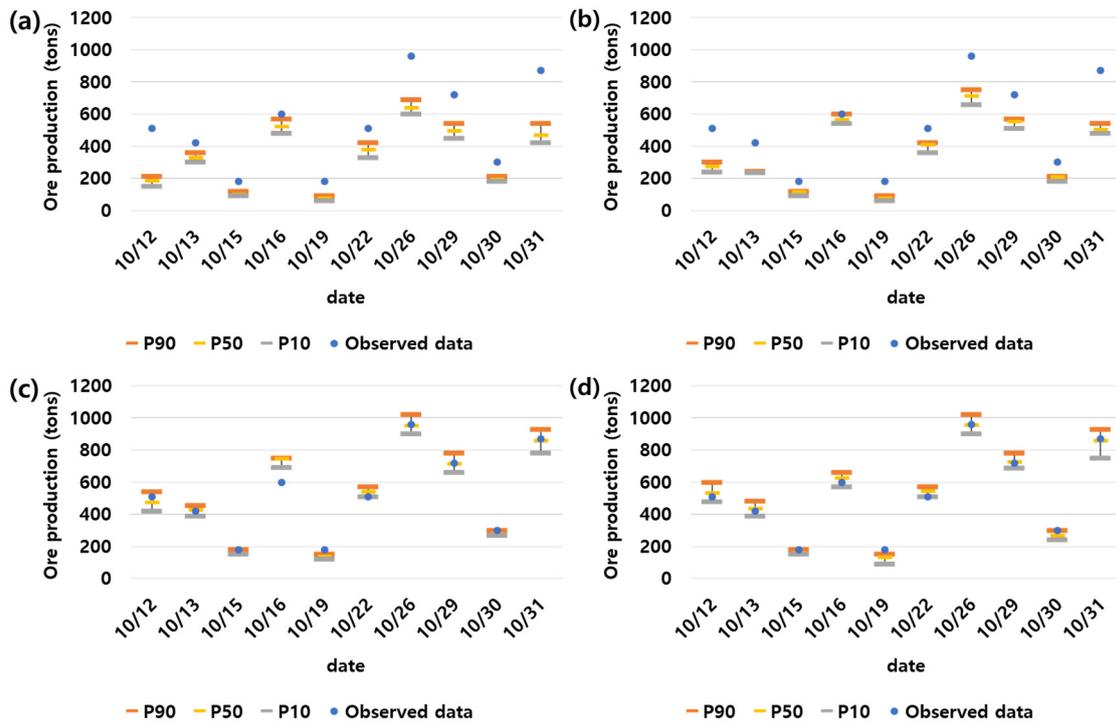
## 5. Discussion

The truck haulage operations in the mine are not constant at each loading and unloading cycle and vary from time to time depending on the working conditions [19]. Therefore, the simulation results for each day were compared using data from October 2018 for long-term simulations. Time parameters were created by the Monte Carlo simulation for each loading point and the simulation parameters were set according to the date (Table 5). The truck capacity was set to 30 tons, and fifty iterations of the simulation were run. The ore production predictions achieved as a result of the simulation were expressed as P10, P50, and P90.

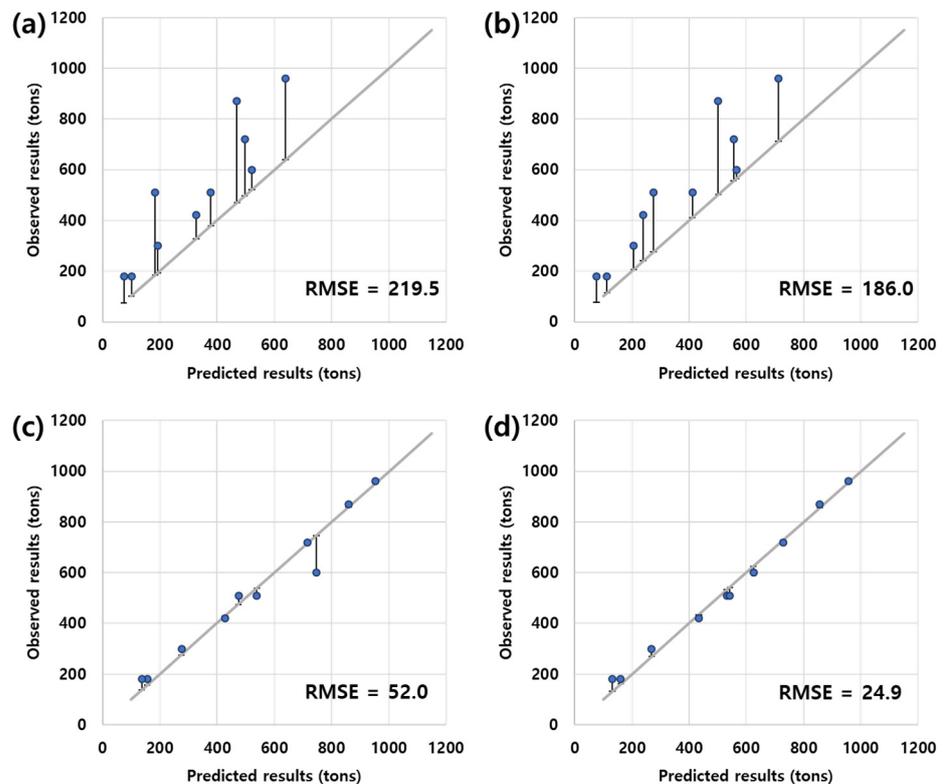
The observed probability distribution model was used to predict the actual field data in the distribution of the simulation results (Figure 9); the TCT generated was higher than the actual TCT. The actual field data were not included in the distribution of the results of the simulation model that generated the TCT by providing a uniform distribution as the input to the Monte Carlo simulation. In the triangular distribution model, only one day—that is, 16 October—was included. In the simulation model that used the normal distribution, the results for three days were not included in the ore production simulation distribution. To quantify the simulation results, we calculated the root mean square error (RMSE, ton/day) of the P50 results of each simulation result and the actual data (Figure 10). The observed probability distribution model achieved the lowest value at 24.9 ton/day.

**Table 5.** Description of the input data of the truck haulage system simulation for ten days in October 2018.

Simulation Parameters		Date										
		12 October	13 October	15 October	16 October	19 October	22 October	24 October	26 October	29 October	30 October	31 October
Loading point 203	Daily working times (min)	400				100		355		55		385
	Number of trucks	1				1		2		1		2
Loading point 233	Daily working times (min)		330	80	40		445		290		280	
	Number of trucks		2	2	2		1		2		1	
Loading point 235	Daily working times (min)								245	370		
	Number of trucks								2	2		
Loading point 237	Daily working times (min)				270		40			115		
	Number of trucks				2		1			3		



**Figure 9.** Comparison of the simulation and haulage operation results (observed) for ten days (Month/Day) in October 2018 for (a) uniform distribution, (b) triangular distribution, (c) normal distribution, and (d) observed probability distribution.



**Figure 10.** Results of the correlation analysis between the predicted and observed ore productions for ten days in October 2018 for (a) uniform distribution, (b) triangular distribution, (c) normal distribution, and (d) observed probability distribution.

The results indicate that the case using observed probability distribution based on the big data of an ICT system showed the best performance for ore prediction. This demonstrates the value and importance of the data collected by an ICT system in the mining site from a practical point of view.

## 6. Conclusions

This study stochastically predicted ore production through discrete event simulation, using four different probability density functions for truck travel times, and compared the simulation results for the four cases. The TCT was measured by dividing it based on the four loading points, using the truck tag recognition time record big data obtained through the mine safety management system based on a wireless communication network for an underground limestone mine. The discrete simulation model was designed to stochastically predict ore production in the designated study area. The uniform, triangular, normal, and observed probability distribution obtained using the measured truck driving time were fed into the Monte Carlo simulation to generate the respective TCTs. The generated TCTs were input into a discrete simulation model. The results of the ore production prediction were validated using field data of the morning of 16 October. As a result of the verification, the data on 16 October 2018 included all four models in the distribution of the simulation results. The uniform and triangular distribution models predicted relatively lower ore production than the actual production because the results of P90 and the field data were similar. The normal distribution and observed probability distribution models were similar to the P50 results and the field data.

Because the working conditions at the mine site changed regularly, the stochastic simulation model was used in the short term as well as in the long term in various ways. Therefore, we performed a simulation with ten days of valid data for October 2018. Simulated with data for the month of October, the RMSE of the observed probability distribution model was the lowest at 24.9 ton/day. The comparison results prove that the developed observed probability distribution model can predict the rate of total ore production within the range of actual values.

To use the observed probability distribution, the truck travel time data must be recorded. Simulation results of higher accuracy can be derived, such as that of the simulation of the observed probability distribution models used, by processing stored data. If the ICT-based mine safety management systems are introduced at various sites, simulations of higher accuracy can be achieved. It was possible to consider time through a Monte Carlo simulation using the data stored in the field without excluding various events occurring in the field. Thus, it is possible to obtain the resulting distribution of various ore productions. Because the stochastic simulation result is displayed as a distribution rather than a single value, various statistical values, such as the maximum and minimum, were confirmed in the field. It will be helpful for managers to use simulation results to set up or modify work plans according to desired production goals or perspectives.

Delay time is an important indicator for evaluating the performance of mining operation. This study did not use the delay time as an input or output parameter of the simulator; however, the delay time was considered during the simulation process. In future work, it would be interesting to stochastically estimate the delay time with simulation output to make decisions for maximizing ore production.

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