Industrial Equipment's Throughput Capacity Analysis

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ABSTRACT
Throughput capacity (TC) is defined as the total amount of material processed or produced by the system in the given time. In practice, full capacity performance for industrial equipment is impossible because the failures are affected and cause a reduction. Therefore, failure interruptions, especially critical ones (bottlenecks), must be detected and considered in production management. From the point of production view, the bottleneck has the lowest production or performance. Most of the previous works used the availability and related importance measures as performance indicators and prioritization of subsystems. However, these measures cannot consider system production in their prioritization. This paper presents a bottleneck detection framework based on system performance and production capacity integration. The integrated approach is used to assess the loading and hauling subsystems of Golgohar Iron Mine, Iran. As a result of the analysis, the hauling subsystem identifies the system's bottleneck.

Keywords
Reliability, Maintainability, Throughput capacity, Mining Fleet.

1. INTRODUCTION
Nowadays, the deliverability of systems is the main challenge of the competitive environment. Production performance analysis is a proposed tool for deliverability assessment in the production plants [1]. Capacity and availability are both important dimensions of the production performance of a production plant and mining equipment [2], [3]. In mining equipment, capacity is a function of equipment utilization and performance [3], [4]. Therefore, the availability and capacity analysis of mining equipment is the first step for assessing system throughput and detecting bottleneck(s) of the production process.

Availability is the function of uptime and downtime, controlled by failures. The failure can be caused by production loss, company reputation, safety, environmental issues, maintenance costs, etc. [2]. In engineering systems, failures cannot be eliminated, but it is possible to mitigate the impact of failures with a better understanding of system behaviour and management.

Availability is defined as “the ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided.” Availability is a function of reliability (uptime), maintainability, and supportability (downtime) [2]. Therefore, calculating the system technical characteristics (RAMS) prerequisite for production performance analysis.

Quantitative Reliability, Maintainability, Availability, and Supportability (RAMS) analysis in mining equipment can be traced to the last 1980s. After that, various studies such as Loud-haul-dump machine in fleet and equipment level [5-7], drum shearer [8], powered supports [9], conveyor system [10], Crushing plant as a part of processing plant [11] had been carried out. Also, open-pit mine equipment’s such as wagon drill [12], shovel [13], and truck [14], [15], have been analyzed in other studies using a statistical approach. Artificial intelligence techniques such as Genetic Algorithm (GA) [16], [17] and Machine Learning (ML) [18], [19] have been used for reliability and maintainability analysis and maintenance management of the mining equipment. In this paper, the statistical method is preferred due to the lack of data and user-friendly statistical procedures for managers and practitioners. In the mining operation, drilling, loading, and hauling equipment should interact with material production. Therefore, fleet or navigation level studies are needed to analyze the real situation. Recently, some studies have focused on RAM-based TC analysis and their equipment's or subsystems interactions in system networks [20], [21]. The studies at this level can reveal the production line bottleneck used for future planning and decision-making process on improving bottleneck and throughput capacity. The reviews present a narrow study carried out in the equipment level of the system in bottleneck recognition. Therefore, the present paper considers loading and hauling a fleet consisting of a shovel and trucks as a system in an open-pit mine. Since the primary purpose of the article is detecting bottleneck in system level, thus, performance characteristics of equipment (RAM) must be analyzed. After that, the TC of each subsystem based on availability, system configuration and capacity is predicted. Finally, subsystems prioritize and critical one is detected. The rest of the paper organized as follow:

Section 2 describes the proposed methodology, which is how to analyze the system's reliability, maintainability, and simulated TC. Section 3 analyzes a case study of Golgohar Iron Mine equipment by the proposed methodology. Finally, in section 4, the conclusions of the paper are provided. This study assumed that:

- Each component, subsystem, and system has two states: working or failed.

- The effect of risk factors (covariates) such as environmental condition, operator skill, etc. not considered in the study.
- The equipment is repairable.
- Due to a lack of supportability data, the indicator is not considered in the study.

2. Methodology

Figure 1 illustrates the proposed approach flowchart. The methodology consists of four main steps that represent in detail as follows:

1. The identifying system, subsystem, and component boundaries and collecting required data in defined boundaries.
2. The identical and independent (iid) assumptions validation. Then select the best model for reliability and maintainability.
3. The estimation of reliability, maintainability, and availability characteristics.
4. Merging RAM characteristic and capacity at equipment level and simulating considering by system configuration, finally, predicting system and subsystem's TC.

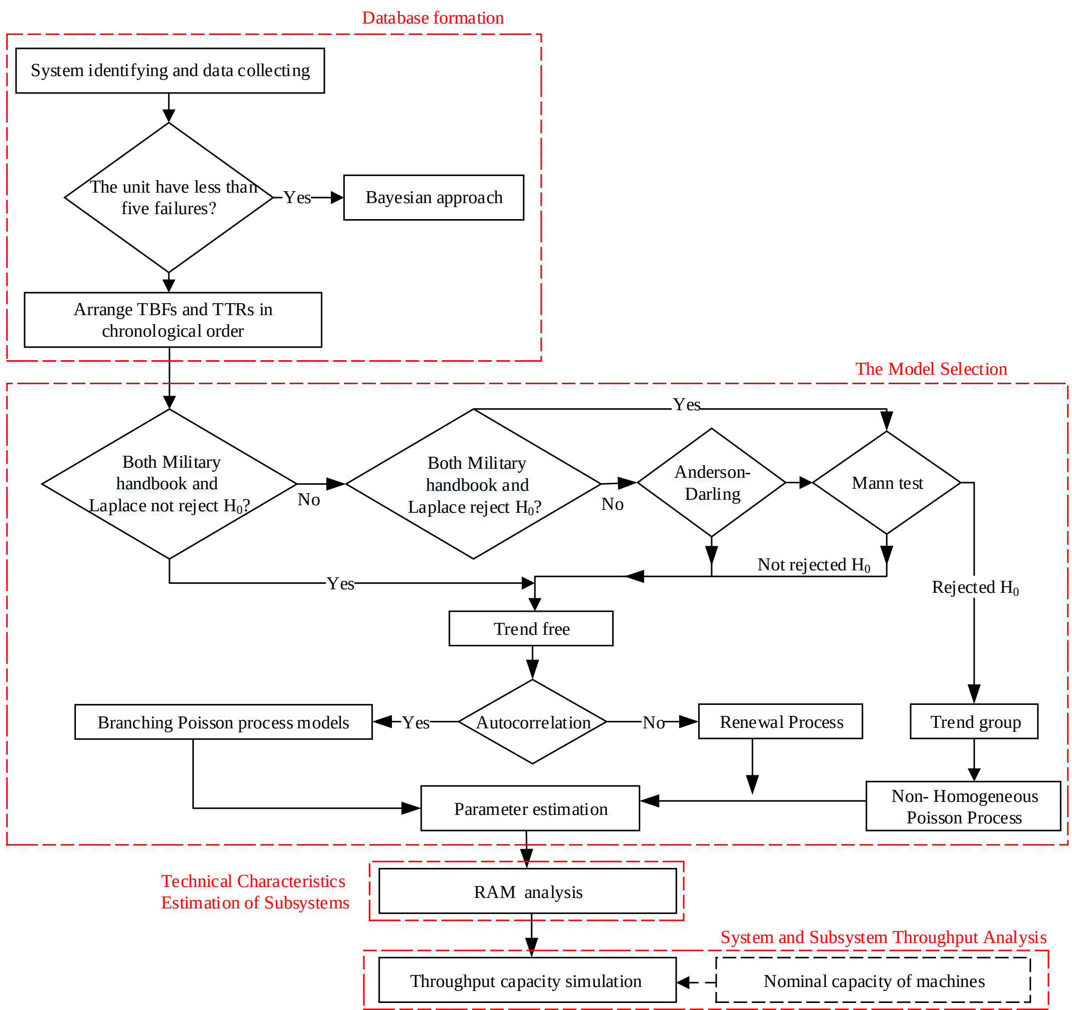

Figure 1- TC analysis methodology

2.1 Boundary identification and data collection

Preceding of data collection, system, subsystem, and component boundaries should be defined. These boundaries depend on the importance of the studied system, expert opinions, system configuration, management comments, data sources, and data collection process. Also, it must be preventing overlap in adjoining systems, subsystems, and components [20]. Sometimes, the study level (fleer or equipment) can be a useful factor in defining these boundaries [22].

When boundaries are defined, required data should be collected. Data can be gathered from many sources such as sensors, operator interfaces onboard equipment, historical operational and maintenance reports [23]. In addition, data collecting time intervals is a crucial issue. The data collecting time interval must be at least ten months [24]. The reliability and maintainability data is sorted as Time between Failures (TBFs) and Time to Repairs (TTRs) in chronological order. This data can be categorized into censored and complete groups. Failure occurring time is precisely not known in the censored data, but it is correctly known in the complete data [25].

2.2 Validation of assumption of identical and independent distribution (IID)

After the data collection, these data should be sorted into the required formatting, and the assumption of the Identical and Independent (iid) nature of data must be validated. Independency means that the data are free of trends and that each failure (repair) is independent of the preceding or succeeding failure (repair). Identically distributed data mean that all the data in the sample are obtained from the same probability distribution. In the non-repairable component, a failed component is replaced by the new one; therefore, the new component failure is independent of the previous component failure [26]. But in the repairable component, verification of the assumption that the data are iid should be done. Otherwise, completely wrong conclusions can be drawn [27].

Two common methods for validating the assumption of independent and identically distribution of sample are trend and autocorrelation test, respectively. If the assumption that the data are identical and independent is valid, the homogeneous Poisson Process (HPP) and Renewal Process (RP) must be fitted. Otherwise, the Non-Homogeneous Poisson Process (NHPP) is an appropriate model. For more information, see ref [25], [28], [29].

2.2.1 Trend test

Trend tests can be categorized into two main groups; graphical and analytical. The graphical method is simple and does not require any calculations. The cumulative failures are plotted against the cumulative time in this kind of test. The straight line indicates trend free and convex or concave shows the trend in the data. The graphical method is strong when there are definite trends in the data. This solution may not be enough when slight trends are present and analytical tests should be performed [28].

In the analytical methods, the null hypothesis (H_0) is trend-free, and the alternative hypothesis (H_1) is a monotonic or non-monotonic (or both of them) trend. Four communal tests to trend analysis are the Laplace test, Military handbook test, Mann-Kendall test, and Anderson–Darling test. Depending on the nature of data, two or more tests must be performed. The null hypothesis in the military handbook and Laplace test is HPP. However, in the Mann-Kendall test is RP. Therefore, the Mann test must be performed after the rejection null hypothesis by both the Military handbook and Laplace test [25]. For more information about the tests as mentioned earlier, see [29]:

2.2.2 Autocorrelation

According to the proposed framework in Figure 1, if there is no apparent trend, then the autocorrelation test needs to be carried out to check the independence between the TBF and TTR data. After sorting data in chronological order, ith failure against (i-1)’th failure is plotted. If all plot points generate a single cluster, then the data are independent, whereas the multi-clusters (two or more clusters) or a straight line lead to data dependency [28].

2.3 Reliability and Maintainability characteristics estimation

After selecting the best analysis model for the system's technical characteristics, parameter estimation and the goodness of fit test should be carried out. Weibull is the most popular distribution in the field of reliability engineering. Weibull distribution can model the early phase (decreasing failure rate), useful life (constant failure rate), and wear-out phase (increasing failure rate) of the system [7]. However, the lognormal distribution is suitable for mechanical component maintainability modeling [30]. The goodness of fit tests such as Anderson Darling (A-D), Kolmogorov-Smirnov (K-S), etc., can be used for best distribution selection through candidate distributions.

2.4 Throughput capacity

TC is defined as; the amount of material that each system can process. When output at the system level is analyzed, the interaction between components must be considered [20]. For this purpose, the reliability block diagram (RBD) [26] and Fault tree (FT) [31] are two conventional methods. TC can be calculated using analytical and simulation techniques. The analytical approach is cheaper; on the other hand, the simulation method is more realistic [32].

To measure the product's availability, its component's availability must be calculated. However, to deal with this issue, the Norwegian oil and gas industry (Norwegian Technology Standards Institution, 1998) developed the Norsok Z-016 standard to assess the production availability of the system based on Figure 2. This standard shows that system availability is the function of item availability and product availability is the function of system availability [1].

However, capacity performance must be considered an essential parameter to assess production performance. For instance, one has a production plant availability of 90 percent, the plant throughput capacity, and production rate may be less than desired due to the low capacity of items. Therefore, capacity performance at the item level must be considered. Figure 3 illustrates the production performance that consists of availability and capacity performance. It is noteworthy that throughput capacity can be described by production performance and production availability [2]

3. Case study

Here we present a case study describing the proposed methodology. Golgohar complex is the first-largest iron mine in Iran. This complex is located in Sirjan, southeast of Iran. The complex consists of six mines, named by numbers, from one to six. Mine 1 is the largest and oldest mine in this complex and is operated by Arman Gohar Sirjan (AGS) Co. Golgohar mines are open-pit, so the shovel-truck fleet is used for raw material production.

This mine uses Liebherr shovels and three trucks: Terex, Caterpillar, and Komatsu. Dispatching priority in this mine has led to choosing Terex trucks for top levels and a combination of Komatsu and Caterpillar trucks for lower levels. The top-level (bench 10 to 12) using expert opinion and dispatching data shovel-truck fleet illustrated in figure 4 is selected as a case study.

This shovel-truck fleet is defined as a system. Each series and machine is defined as a subsystem and component. As previously noted, the illustrated system is working in the pre-stripping phase

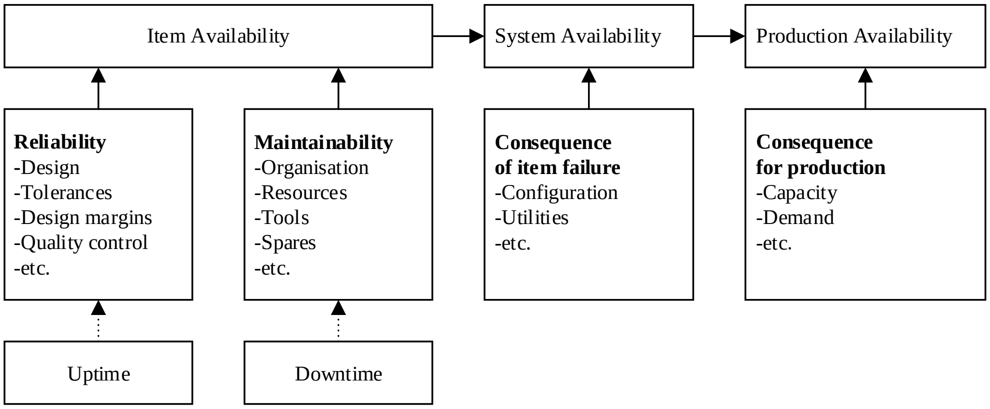

Figure 2- Relationship between the availability of component and production availability [1]

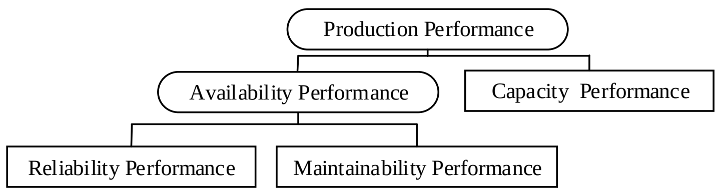

Figure 3- Production performance concept, Adapted from [2]

and on the top-level (bench 10 to 12) (Figure 5). According to the mine production plan, this system will work about 500 hours on the mentioned level. Therefore, analysis of this system during 500 hours operation time is interesting. Table 1 depicts the production line corresponding codes as well as their functional capacity

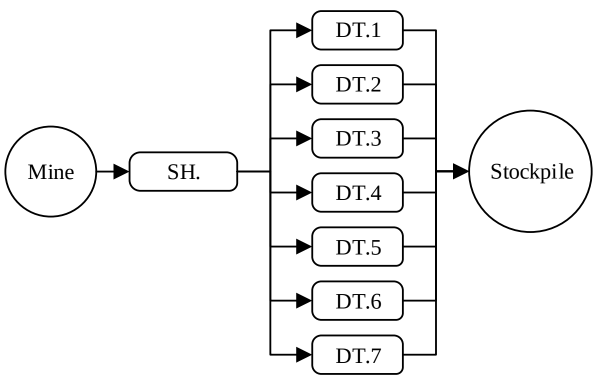

Figure 4- Block diagram for shovel-truck fleet

After boundary identification, required data were collected, sorted, and classified in the form required for the analysis (i.e., TBF and TTR). This mine uses the SmartMine system, so every moment equipment state (working or failed) automatically is recorded. Therefore, archived data in this data bank is a reliable data source. Data is used in this study were collected over 18 months.

The next step after collecting, sorting, and classifying the data is to validate the iid assumption of the nature of the data. As mentioned in Figure 1, trend tests should be performed using two or more tests, according to trend behavior. Table 2 shows the p-value statistic of tests. The null hypothesis is considered in the confidence level of 95%. Thus, this assumption is rejected for less than 5% P-value.

Table 1- Mine equipment model and functional capacity

Row	Equipment	Model	Code	Mean capacity (m^3/h)
1	Shovel	Liebherr R9350	SH.	420
2	Dump Truck	Terex-TR100	DT.1	53.8
3	Dump Truck	Terex-TR100	DT.2	53.3
4	Dump Truck	Terex-TR100	DT.3	54.5
5	Dump Truck	Terex-TR100	DT.4	53.4
6	Dump Truck	Terex-TR100	DT.5	53.7
7	Dump Truck	Caterpillar-777D	DT.6	57.7
8	Dump Truck	Caterpillar-777D	DT.7	60

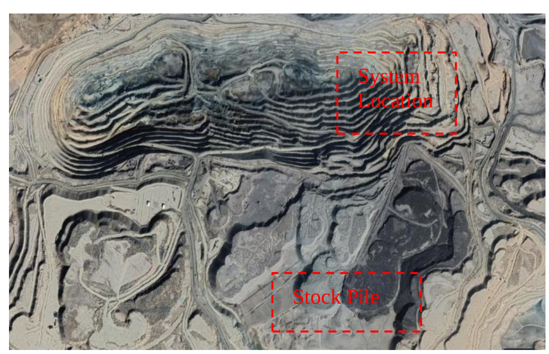

Figure 5- Location of the selected system

NHPP (PLP) must be fitted for components that have a trend. Trend-free groups are subject to dependency analysis. Due to the scarcity of space, the DT.7 TTR autocorrelation test is illustrated in Figure 6.

Table 2- Computed p-value of trend tests

Eq.	Data	MIL.	Laplace	A-D	M-K	Result
SH.	TBF	0.002	0	-	0.02	R*
	TTR	0.05	0.017	-	0.035	R
DT.1	TBF	0.2	0.042	0.029	0.078	NR**
	TTR	0.059	0.004	0.003	0.04	R
DT.2	TBF	0.076	0.38	-	-	NR
	TTR	0	0	-	0.007	R
DT.3	TBF	0.18	0.62	-	-	NR
	TTR	0	0	-	0.22	NR
DT.4	TBF	0.015	0.033	-	0.03	R
	TTR	0.67	0.74	-	-	NR
DT.5	TBF	0	0	-	0	R
	TTR	0	0.001	-	0.15	NR
DT.6	TBF	0.54	0.82	-	-	NR
	TTR	0.87	0.49	-	-	NR
DT.7	TBF	0.16	0.021	0.019	0.04	R
	TTR	0.22	0.42	-	-	NR

*R: Rejected
**NR: Not Rejected

As can be seen, the first lag in the ACF graph is in the confidence level (95%), and the data has no evidence of any trend in the scatter plot. For all trend-free components, the dependency test shows the same result.

The next step is selecting the best distribution through candidate distributions. For this purpose, the Anderson-Darling goodness of fit test is used. The distribution that has the lowest AD is chosen as the best distribution. The reliability and maintainability characteristics of the equipment have been calculated and presented in Table 3 and Figure 7 using the software Minitab 18. As can be seen, Weibull and lognormal distributions are appropriate for reliability and maintainability modeling, respectively.

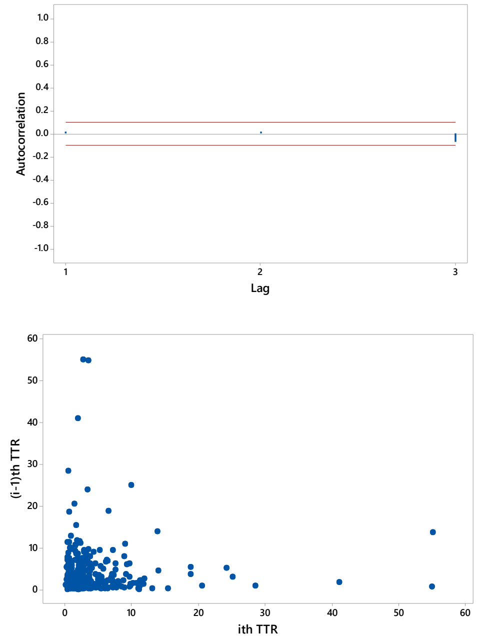

Figure 6- Autocorrelation test for the DT.7 TTR

The logical relationship between components and components capacity is calculated for the TC analysis component technical characteristic. After that, the TC of the fleet is predicted using BlockSim 9 software for 500 hours.

In the “Blocksim software” at the first step, simulate failure and repair characteristics of components, then incorporate the component's capacity into simulated times [33]. The failure and repair characteristics simulation technique works as the following; the first simulation yields first a random time to first failure, then a random time to first repair, then a random time to second failure, then a random time to second repair, and so on, until the chosen mission time ends. This sequence is repeated based on the number of simulations, yielding a different sequence. All the different sequences are stored each time. The number of simulations represents the number of different times to the first failure, the number of different times to first repair, and so on. The average of all times to the first failure is used as the time to the first failure. Similarly, the average of all times to first repair is used as the repair time for the first repair. The same process applies for the rest of the failures and repairs until the mission end time is reached [34].

Table 3- Best-fit distribution for TBF and TTR data

Eq.	Reliability		Maintainability	
	Best-fit	**Parameters**	**Best-fit**	**Parameters**
Sh.	PLP	Beta=1.3; Eta=140.4	PLP	Beta=1.18; Eta=18.36
DT.1	Weibull 3P.	Beta=0.88; Eta=12.08, Gamma=0.44	PLP	Beta=1.09; Eta=10.31
DT.2	Weibull 3P.	Beta=0.803; Eta=9.8; Gamma=0.437	PLP	Beta=1.19; Eta=16.93
DT.3	Weibull 2P.	Beta=0.99; Eta=19.9	Lognormal	LMean=1.16; LStd=1.31
DT.4	PLP	Beta=0.89; Eta=7.53	Lognormal 3P.	LMean=1.08; LStd=1.45; Location= 0.12
DT.5	PLP	Beta=0.75; Eta=2.27	Lognormal	LMean=1.08; LStd=1.48
DT.6	Weibull 2P.	Beta=0.88; Eta=27.94	Lognormal 3P.	LMean=0.347; LStd=1.25; Location=0.028
DT.7	PLP	Beta=1.08; Eta=41.75	Lognormal	LMean=0.68; LStd=1.14

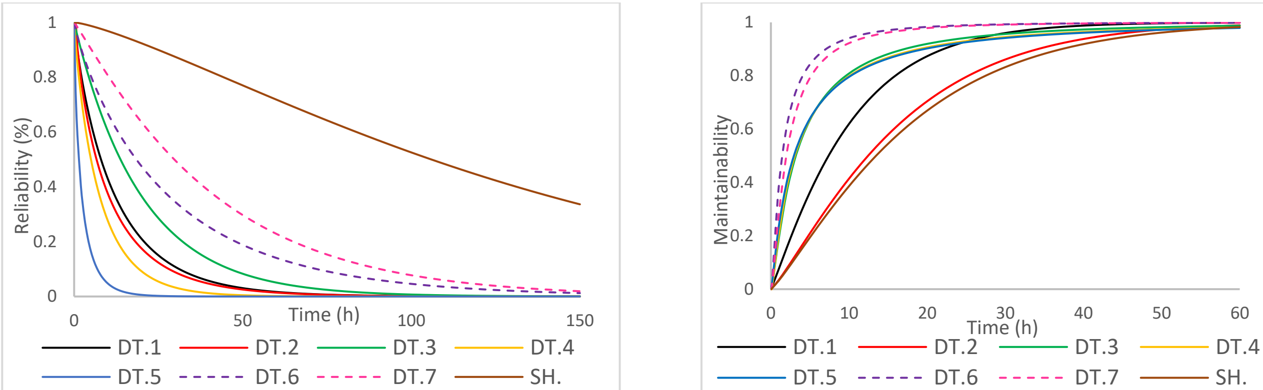

Figure 7- Reliability and Maintainability characteristics of the trucks and shovel.

The result of the simulation is shown in Table 4; the following are revealed:

- FCI is the contribution of equipment failure to system failure. Because of existing only one shovel in the system, shovel failure has the greatest influence on the system failure.
- Excess Capacity is the additional amount a component could have produced while up and running.
- The utility is a proportion of time that available components can produce without blockage.

Because of low reliability and maintainability, Terex trucks have a weak performance (Table 4), while based on the result, Caterpillar trucks have higher strength and reliability. Therefore, a detailed study should be performed on Terex trucks at the equipment level. According to the simulation result, system throughput will be the sum of the truck's mean capacity (110039). Due to the high gap between loading and hauling subsystems, the hauling subsystem was identified as a bottleneck from the throughput capacity perspective. In other words, improving the truck's performance or increasing the number of trucks is needed.

Table 4- Throughput analysis result for individual equipment

Eq.	FCI (%)	MA* (%)	MC** (m3/h)	EC*** (m3)	Utility (%)
DT.1	0.21	69	15960	2617	85.92
DT.2	0.12	47	10399	2122	83.05
DT.3	0.5	76	18018	2700	86.97
DT.4	0.44	54.46	12279	2256	84.48
DT.5	0.35	30.2	6176	1920	76.28
DT.6	0.65	91.7	23294	3145	88.1
DT.7	0.36	90.32	23913	3182	88.25
SH.	95.76	88.81	186457	49	99.97

MA*: Mean Availability, MC**: Mean Capacity, EC***: Exceed Capacity

4. Conclusion

The fleet level is more effective for the mining production system than the equipment level assessment for weakness point detection. Therefore, the right decision can be made for system improvement at the right time. In this paper, the reliability and maintainability characteristics of equipment were analyzed. After that, the system's throughput capacity using RM characteristics predicted the logical relationship between components and components capacity. The result shows that Terex trucks are tangibly weaker than Caterpillar trucks. Caterpillar truck's high performance is due to high reliability and maintainability (dashed lines in Figure 7). The shovel is the newest equipment in the system, so; this equipment represents high reliability. In addition, poor maintainability of the shovel can result in in-site maintenance. Therefore, a detailed study should be performed on the feasibility of Terex trucks. From the bottleneck point of view, the high gap between loading and hauling subsystems (76418 m^3) demonstrated that improving trucks' performance or increasing trucks' number is necessary for throughput capacity improvement.

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