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Resilience estimation of the mining fleet (Case study: Sungun copper mine)

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ABSTRACT

In recent years, the application of the resilience concept has increased in various domains. Resilience depicts the ability of a system to return to its normal operational status after failure events or disruptions. According to the literature survey, there are various studies, which have been done in the field of engineering and non-engineering systems, and there is no study about applying the resilience concept in the field of the mining industry. In this paper, first, the resilience concept is introduced, and the resilience of the mining fleet of Sungun copper mine is estimated later on. For this aim, performance indicators of the system (i.e., reliability, maintainability, and supportability) are used. The results showed that the resilience of the entire system for one hour of its function is equal to 83.1%, and this value decreases to 37.1% after 10 hours. It means if there is a failure in the system, it will have 83.1% and 37.1% probabilities to be resilient against the failure event after 1 hour and 10 hours of system function.

Keywords: *Maintainability, Mining, Reliability, Resilience, Supportability*

1. Introduction

Mining is one of the most significant parts of human industries. This industry is consisted of many complicated processes like ore mining, ore processing, and so on, to supply the primary requirements of other industrial sectors. In the field of ore mining, systems like fan systems, loading and haulage systems, drilling systems, supporting systems, water drainage systems, and so on have worked together to produce the final product of mine and increase productivity. Out of schedule stoppage of these systems due to the failures or disruptions may cause to decreasing both mining safety and productivity.

Resilience has driven from Resilire (a Latin word), which refers to bounce back, flexibility, etc. [1]. In 1625, the resilience concept was used scientifically for the first time [2]. This concept has migrated from the natural and physical sciences into the other sciences [3]. US National Infrastructure Advisory Council (NIAC) defined resilience as the "*system's ability to anticipate, absorb, adapt to, and rapidly recover from a potentially disruptive event*" [4]. The schematic view of resilience is shown in Fig. 1. As can be seen, the system is performing its requested function in an initial stable state (F_1 level) until failure occurring at the time t_2. After the failure event, the performance level of the system decrease (system degradation) until the function level of the system reaches to F_2 at time t_3. The system may stay at the degraded state for a while ($t_2 - t_3$) based on the system supportability. However, by the initiation of recovery actions at time t3, the system return to its desired performance level (F_3) at time t_4.

There are many definitions of system resilience in the literature; most of them are general definitions. Orwin and Wardle [5] defined resilience as the recovery speed of a system to return to its pre-failure status. Allenby and Fink [6] defined resilience as the system's ability to preserve its functions and structure in case of disruptions (internal or external), and to degrade when it must. Haimes [7] defined resilience as the system's ability to withstand a critical disruption within acceptable degradation parameters and to recover with a suitable time and reasonable costs and risks. Youn et al. [8] defined resilience as the sum of the system reliability (passive survival rate) and system restoration (proactive survival rate). Pregenzer [9] defined resilience as the system's ability to absorb continuous and unpredictable change and still maintain its vital functions. Ayyub [10] defined resilience as the ability of the system to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. However, numbers of resilience definitions have been presented for more specific domains as follow (see Fig. 2):

- **(a)** **Engineering resilience:** System's ability to predict, absorb, adapt, and/or quickly recover from a disruptive event [11].
- **(b)** **Ecological resilience:** The ability of an ecosystem to absorb changes of state variables, driving variables, and parameters, that is, to persist after disturbance [12].
- **(c)** **Economic resilience:** Ability and adaptive response that enables firms and regions to avoid maximum potential losses [11].
- **(d)** **Social resilience:** The ability of a society to absorb failures and reorganize while retaining the same function, structure, identity, and feedbacks [13].
- **(e)** **Psychological resilience:** Dynamic process wherein individuals display positive adaptation despite experiences of significant adversity or trauma [14].

All of these definitions have emphasized that a resilient system should be able to withstand the failures and absorb failures' impacts. These abilities are about preparedness activities or pre-failure features of the

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system. These are activities that make the system reliable, robust, flexible, and adaptable. However, the post-failure features of system or recovery activities are also significant for having a resilience system. These activities help the system to return to its normal performance status. System supportability and maintainability levels have a critical effect on the system recovery process. Haimes [7] and Ayyub's [10] definitions have considered both pre-and post-failure features of the system. Preparedness and recovery activities are both vital for having a resilience system [15].

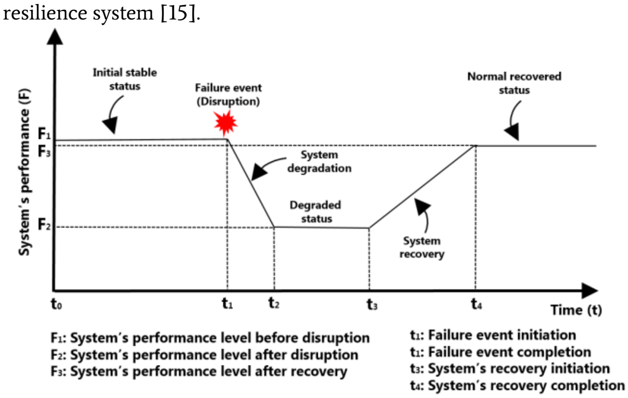

Fig. 1. System's performance transition in resilience.

Fig. 2. Different resilience definitions domains.

In the last years, numerous researchers have worked on the philosophy of resilience concept and also have attempted to apply this concept in the field of engineering and non-engineering systems. They introduced many qualitative and quantitative methods for systems resilience estimation. However, in this paper, the resilience concept has been applied in the field of the mining industry.

2. Resilience estimation methods

In the last years, many methods have been introduced for the estimation of the system's resilience. Hosseini et al. [11] classified resilience estimation methods into two groups include qualitative and quantitative. Qualitative methods are usually used in non-engineering systems domains. Nevertheless, in the field of engineering systems, quantitative methods have more enthusiasts. In the following, some of the presented resilience estimation methods are depicted.

Bruneau et al. [16] introduced four dimensions include robustness, redundancy, resourcefulness, and rapidity for civil infrastructure (such as power generation systems, transportation systems, etc.) resilience against natural disasters such as an earthquake. They have presented a deterministic metric (Equation 1) for measuring the resilience reduction of the civil infrastructures. In this metric, R is the infrastructure resilience reduction, $Q(t)$ is the system's performance function, t_0 is the disruption event time and t_1 is the system recovery completion time. In this metric, the initial system's performance level has been considered as 100% (see Fig. 3). They assumed that recovery actions commence immediately after the disruption completion. Moreover, they supposed the infrastructure is a brittle system that has not any flexibility against disruptive events. Hence, its quality falls dramatically after the disruption. These assumptions may be unrealistic.

$$R = \int_{t_0}^{t_1} [100 - Q(t)]dt \tag{1}$$

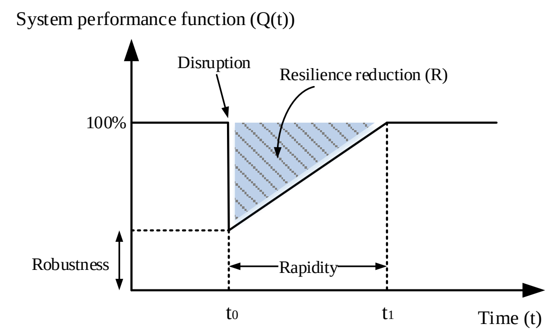

Fig. 3. The measure of the resilience reduction (adapted from [16]).

Orwin and Wardle [5] presented a deterministic quantitative metric for measuring the resilience of soil's biota against exogenous disruptions. They have introduced Equation (2) as follow:

$$\text{Rsilience} = \frac{2|D_0|}{(|D_0| + |D_x|)} - 1 \tag{2}$$

As can be seen in Fig. 4, D_0 is the difference between the control (C_0) and the disturbed soil (P_0) at the end of the disturbance (t_0), and D_x is the difference between the control (C_x) and the disturbed soil (P_x) at the time point (t_x) chosen to measure resilience.

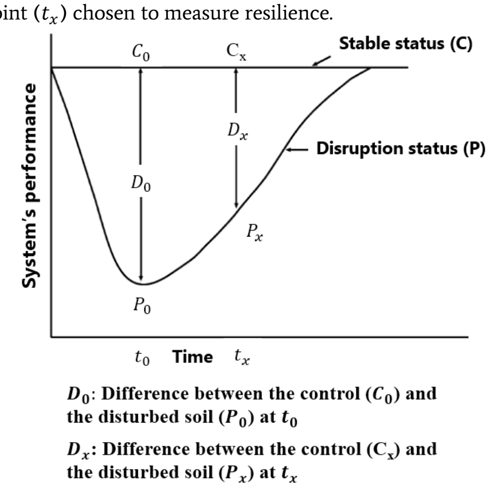

Fig. 4. A schematic view of the soil's biota resilience in case of disruption [5].

As said, in Bruneau et al. [16] metric, the initial system performance level was assumed equal to 100%, but this hypothesis may not be right in reality. For this reason, Tierney and Bruneau [17] proposed Equation (3) as a new resilience reduction metric to overcome the issues of Equation 1. They have claimed resilience can reduce the infrastructure system's failure.

$$R = \frac{\int_{t_0}^{t_1} [Q(t)]dt}{100(t_1 - t_0)} \tag{3}$$

Where $Q(t)$ is the system's performance function, t_0 is the disruption event time, and t_1 is the system recovery completion time. In Equation 3, recovery duration has been also considered using the $(t_1 - t_2)$ term.

Cimellaro et al. [18] presented a deterministic metric (Equation 4) for measuring the resilience of six hospitals in Memphis against seismic disruption using four resilience dimension that introduced by Bruneau et al. [16]. In this equation, Q_1 and Q_2 are the system's services quality before and after the disruption, T_{LC} is the control time of the system, and α is the weighting factor representing the importance of pre- and post-failure activates qualities. This weight can be obtained using expert judgment.

$$R = \alpha \int_{T_{LC}} \frac{Q_t(t)}{T_{LC}} dt + (1 - \alpha) \int_{T_{LC}} \frac{Q_2(t)}{T_{LC}} dt \tag{4}$$

Due to the opinions of experts, the weighting factor may obtain differently. Then, using Equation 4, different resilience values can be calculated. Moreover, it is not clear how four resilience dimensions are used in this metric.

Youn et al. [8] introduced a metric for resilience estimation using system reliability and restoration, as represented by Equation (5). Their metric is probabilistic and considering the uncertainties, but it is not time-dependent.

$$\psi = R + \rho = R + \kappa.\Lambda_P.\Lambda_D(1 - R) \quad (5)$$

Where ψ, R, and ρ represent system resilience, reliability, and restoration. Reliability is the ability of the system to maintain its required capacity and performance during a given period under stated conditions. Restoration is the system's ability to recover permanently from a disruptive event. It is the recovery degree of the system reliability and depends on the probability of the correct diagnosis event (Λ_D), correct prognosis event (Λ_P), and successful recovery event (κ) [8]. Based on Youn et al. [8], the system with restoration has more resilience.

Ayyub [10] proposed a metric for the system's resilience estimation as Equation 6. In this formula, R_e is the system resilience, T_i is the time to the incident, T_f is the time to failure, T_r is the time to recovery, ΔT_f is the duration of failure ($T_f - T_i$), ΔT_r is the duration of recovery ($T_f - T_f$), and F is the failure profile (ratio of the robustness to redundancy). Moreover, R is the recovery profile (proportion of the resourcefulness to rapidity).

$$R_e = \frac{T_i + F\Delta T_f + R\Delta T_r}{T_i + \Delta T_f + \Delta T_r} \quad (6)$$

Rφd et al. [19] inspired by Equation (5) and presented a new metric for resilience estimation of Arctic region infrastructures (Equation 7). They have considered resilience as a function of system reliability and recoverability. Rφd et al. defined recoverability as the system's ability to restore its capacity and performance by recovering from the effects of disruption during a period, under a given condition using the available resources. Recoverability is a combination of [19]:

- Disrupted system maintainability and supportability
- PHM system efficiency before the disruption (This item takes into account the system anticipation ability)
- The resilience of the system owner in case of disruption (Because the organizations with low resiliency cannot accurately use the material and human resources in critical situations)

$$\psi = R + \Lambda_r(1 - R) \quad (7)$$

In Equation (7), Λ_r refers to the system recovery efficiency and can be formulated as following [19]:

$$\Lambda_r = \prod_{i=1}^{4} \beta_i \quad (8)$$

Where β_1 is the organization resilience, β_2 is the system maintainability, β_3 is the PHM efficiency, and β_4 is the system supportability. As can be seen, recoverability is the function of reliability, and its performance is affected by the health condition of the system.

Cai et al. [20] have introduced a probabilistic metric for the system resilience estimation based on system availability (Equation 9). They have believed that resilience is an intrinsic system ability, and it is composed of two features known as performance and time-related features. The system structure determines the performance-based features (e.g., robustness and adaptability). But maintenance resource determines the time-related features (e.g., recoverability and resourcefulness). Based on Cai et al. [20], similar to the reliability, failure events (external factors) are not intrinsic properties of the system resilience. Then, they have not involved the failure events properties in their resilience metric.

$$\rho = \frac{A_1}{n\ln(t_1)} \sum_{i=1}^{n} \frac{A_2^i A_3^i}{\ln(t_3^i - t_2^i)} \quad (9)$$

In Equation (9), n is the number of failures or shocks, A_1 is the steady-state availability, A_2 is the post-failure transient state availability, A_3 is the post-failure steady-state availability, and t_1 is the steady-state time. Moreover, $(t_3 - t_2)$ is the post-failure steady-state time (see Fig. 5). These parameters can be determined by the structure of the engineering system and maintenance resources, such as redundant structure, failure rate, and repair rate [20].

According to the investigated metrics, in Equation (7), uncertainties have been considered, and this metric is time-dependent (considering system maintainability). Moreover, pre-and post-failure system features are also embedded in this metric. Accordingly, this metric has been applied in this paper.

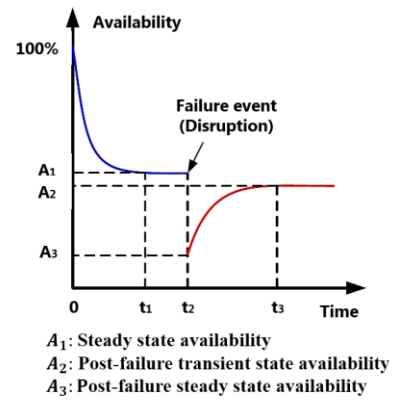

Fig. 5. Availability of the system subject to degradation and failure [20].

3. Resilience estimation approach

According to Equation (7), reliability, maintainability, and supportability (RMS) estimation are required for resilience estimation. The RMS estimation using time data has consisted of the below steps:

1) Database establishment
2) Selection of the best fit statistical model
3) Estimation of the system's performance indicators

In this study, a database that was consisted of the failure, repair, and delivery has been established firstly. After data collection, the hypothesis of the independent and identically distributed nature (iid) of data should be evaluated to select the best fit model. For this aim, trend and autocorrelation tests are usually used. For example, if collected data has a trend, then the nonhomogeneous models like the power law process (PLP) should be used. If there is no autocorrelation in data, and also the trend test results show the potential of the presence of a trend in the data, then the PLP model can be used. Moreover, if there is no evidence about the presence of trend and autocorrelation in the data, the classical distribution models such as normal or lognormal models can be used [21–23]. However, in the present paper, to perform trend and serial correlation tests, the illustrated algorithm in Fig. 6 has been used.

Finally, the resilience of the system can be estimated using Equation (7). Hence, for a series-parallel system with n series and m parallel subsystems, the resilience of the subsystem ($\psi_{ij}(t)$) can be obtained using Equation (10), and the resilience of the entire system can be estimated using Equation (11).

$$\psi_{ij}(t) = R_{ij}(t) + \Lambda_{ij}(t).\left(1 - R_{ij}(t)\right) = 1 - (1 - R_{ij}(t)).(1 - \Lambda_{ij}(t)) \quad (10)$$

$$\psi(t) = \prod_{i=1}^{n}\left[1 - \left[\prod_{j=1}^{m}\left(1 - R_{ij}(t)\right).\left(1 - \Lambda_{ij}(t)\right)\right]\right] \quad (11)$$

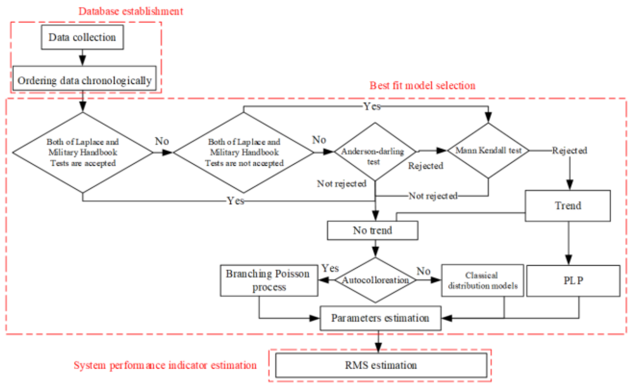

Fig. 6. Reliability, Maintainability, and Supportability (RMS) estimation algorithm using time data [25, 26]

4. Case study

In this section, the mining fleet of Sungun Copper mine, the second-largest copper mine in Iran, is considered as a case study. The estimated deposit of the mine is about 828 million tons, with an average copper grade of 0.62%. As can be seen in Fig. 7, the Sungun Copper mine is located 75km northwest of the provincial town of Ahar, East Azarbaijan, Varzaqan County, Iran. This region is regarded as one of the coldest zones in Iran. Furthermore, heavy precipitation and heavy fog are common atmospheric phenomena all year round. The mining operation is managed in the mine site by employing a fleet of dump trucks, loaders, shovels, excavators, bulldozers, and drilling rigs [24]. The characteristics of the mining fleet and its block diagram are illustrated in Table 1 and Fig. 8.

Fig. 7. Sungun Copper mine location [27].

Table 1. Sungun mine's fleet characteristics.

Subsystem name	Model	Code
Drill wagon	Hasher	Wa.
Bulldozer	Caterpillar-d11n	Bl.
Loader	Caterpillar-988b	Lo.
Dump truck	Komatsu-785-5	DT.1
Dump truck	Komatsu-785-5	DT.2
Dump truck	Komatsu-785-5	DT.3
Dump truck	Komatsu-785-5	DT.4
Dump truck	Komatsu-785-5	DT.5
Dump truck	Komatsu-785-5	DT.6

5. Results and Discussion

Based on the previous section, using the time between failure (TBF), time to repair (TTR), and time to delivery (TTD) data of the mining fleet subsystems of Sungun Copper mine, RMS estimation of subsystems for 10 hours of the operation have been performed. According to the obtained results, For example, the TBFs data of BI, Wa, Lo, DT.2, and DT.3 subsystems had no trend and autocorrelation. Therefore, classical distribution models have been used for modeling the failure data of these subsystems. While, the TBFs of DT.1, DT.4, DT.5, and DT.6 have trend and autocorrelation. Therefore, the PLP model has been used for these subsystems. For instance, the results of iid assumption evaluation for TBFs data of Wa and DT.5 subsystems are shown in Table 2. As can be seen, all performed trend tests have shown that the TBFs data of the Wa subsystem have no trend. The statistical and graphical tests have indicated that this subsystem has no autocorrelation. Therefore, the Weibull-3P distribution model (a classical model) has been used for modeling the TBFs data of the Wa subsystem. The results have also shown that TBFs data of the DT.5 subsystem have a trend but no autocorrelation. Hence, the PLP model should be used for this subsystem. Finally, in Table 3, the best-fitted models for the subsystems of the mining fleet based on their TBFs, TTRs, and TTDs are presented.

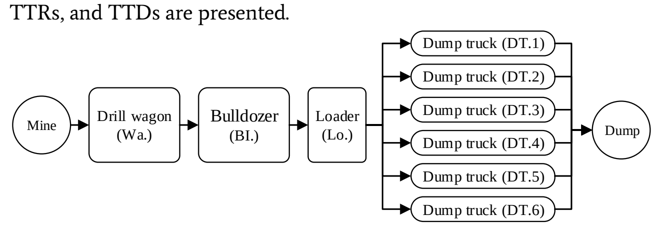

Fig. 8. Block diagram of Sungun mine's fleet.

The results of the mining fleet subsystems RMS estimation are shown in Fig. 9-11. It must be mentioned, because of the same model, repair, and spare parts for the dump truck subsystems, these subsystems have the same supportability. According to Fig. 9-11, at a determined time, DT.2 and DT.1 will have the lowest and highest reliability, respectively; DT.3 and Wa will have the lowest and highest maintainability, respectively. Furthermore, BI will have the highest supportability. Through time, the supportability of Wa will have improved and get better than Lo and DT.1 supportability. As an example, according to Fig. 9, after 4 hours of operation of the mining fleet, the reliability of DT.5 will reach 40%. It means this subsystem has a 40% failure probability after 4 hours of functionality.

Table 2. The results of iid assumption evaluation for TBFs data of Wa and DT.5 subsystems.

Subsystem	Trend Tests					Autocorrelation Tests				iid Assumption	Model		
	Test & Result	MIL-Hdbk-189	Laplace's	Anderson-Darling	Mann-Kendall	Test & Result	ACF	TSTA	LBQ				
Wa.	Statistic	393.6	0.100	1.410	0.486	Statistic-Log 1	-0.08	-1.15	1.34	Accept	Weibull-3P		
	P-Value	0.308	0.920	0.200	0.313	Statistic-Log 2	0.11	1.48	3.61				
	Analytic	No Trend				Analytic	No Autocorrelation				Parameters		
	Graphical	No Trend				Graphical	No Autocorrelation				β	η (hr)	γ (hr)
	Trend	No Trend				Autocorrelation	No Autocorrelation				1.062	3.824	0.375
DT.5	Statistic	331.0	2.680	4.530	-1.57	Statistic-Log 1	0.01	0.12	0.01	Reject	PLP		
	P-Value	0.015	0.007	0.005	0.941	Statistic-Log 2	0.06	0.80	0.66				
	Analytic	Trend			No trend	Analytic	No Autocorrelation				Parameters		
	Graphical	Trend				Graphical	No Autocorrelation				β	η (hr)	γ (hr)
	Trend	Trend				Autocorrelation	No Autocorrelation				0.937	5.627	

Table 3. Best fitted models for mining fleet subsystems.

Sub systems	Reliability				Maintainability				Supportability			
	Model	Model parameters			Model	Model parameters			Model	Model parameters		
		β	η (hr)	γ (hr)		β	η (hr)	γ (hr)		β	η (hr)	γ (hr)
Wa.	Weibull-3P	1.06	3.82	0.37	Weibull-3P	1.31	0.43	0.78	Weibull-2P	1.86	6.41	0.00
Bl.	Weibull- 3P	1.06	26.84	0.37	Weibull-3P	1.04	1.76	0.37	Weibull-3P	0.49	34.57	0.83
Lo.	Weibull- 3P	1.16	10.52	0.59	Weibull-3P	1.23	3.11	0.37	Loglogistic-2P	2.05	0.48	0.00
D.T.1	PLP	1.21	94.63	0.00	PLP	1.41	2.72	0.00	Weibull-3P	0.64	15.59	0.92
D.T.2	Weibull-3P	0.91	23.44	0.18	Weibull-3P	1.02	3.01	0.23	Weibull-3P	0.64	15.59	0.92
D.T.3	Weibull-3P	0.91	28.11	0.21	Weibull-3P	0.74	5.26	0.24	Weibull-3P	0.64	15.59	0.92
D.T.4	PLP	0.99	12.70	0.00	PLP	1.51	2.52	0.00	Weibull-3P	0.64	15.59	0.92
D.T.5	PLP	0.99	12.70	0.00	Weibull-3P	1.36	2.52	0.00	Weibull-3P	0.64	15.59	0.92
D.T.6	PLP	0.99	0.99	0.99	PLP	0.99	0.99	0.99	Weibull-3P	0.64	15.59	0.92

In this study, the values of PHM efficiency and organization resilience are determined as constant values. In this paper, the used values of PHM efficiency and organization resilience are adapted from Rød et al. [19] (Table 4).

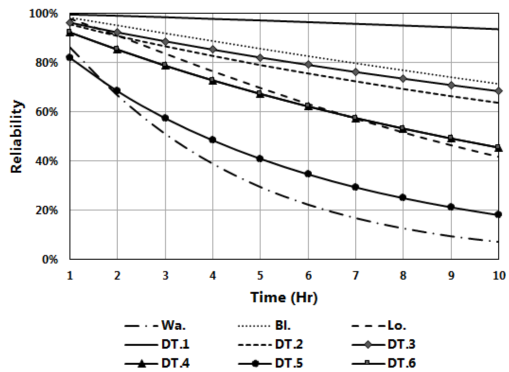

Fig. 9. Mining fleet subsystems reliability for 10 hours of function.

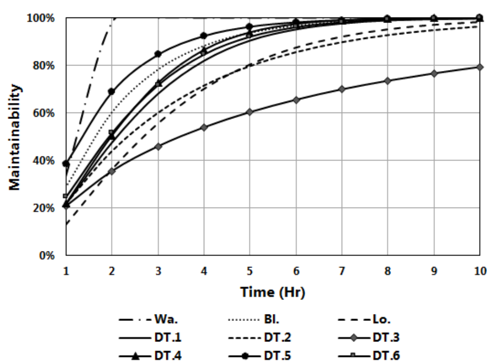

Fig. 10. Mining fleet subsystems maintainability for 10 hours of function.

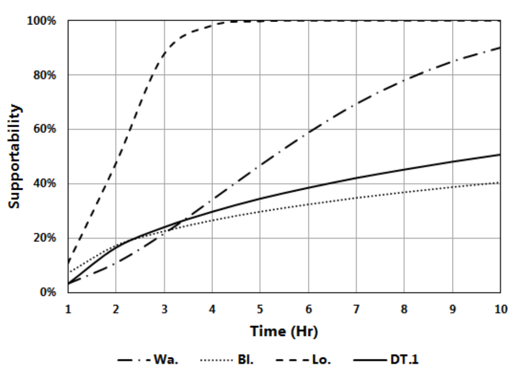

Fig. 11. Mining fleet subsystems supportability for 10 hours of function.

Table 4. The considered values for β_1 and β_3 [19].

Parameters	Symbols	Values
Organization resilience	β_1	0.85
PHM efficiency	β_3	0.75

Finally, using Table 4, the results of RMS estimation, and also Equation (9) and Equation (10), the resilience of mining fleet subsystems and the entire system for 10 hours of function have been estimated. The results are shown in Fig. 12 and 13. As can be seen, DT.1 and DT.5 will have the highest and lowest resilience, respectively. According to the figures, DT.1 and DT.5 have the same supportability and maintainability, approximately. But the higher reliability of DT.1 is the reason for its higher resiliency compares to DT.5. Additionally, the resilience of the mining fleet system at the first hour of function will be about 83.1% and will reduce through time. It means if there is a failure in the first hour of mining fleet operation, it will have an 83.1% probability to predict, absorb, adapt, and quickly recover from the failure event. Moreover, after 10 hours of operation, the resilience value of the mining fleet will be reached to 37.1%. It means the system will have a 37.1% probability to be resilient against the failure event after 10 hours of function. Generally, to increase or maintain the mining fleet resilience against the failure events, the mine's management should be more focused on the subsystems that their RMS are in an unsuitable condition (i.e., wagon drill, dump trucks, and bulldozer subsystems). Hence, the reliability of Wa and DT.5 should be increased by some measures. For instance, improvement of the preventive maintenance activates and increment of training programs for staff are such measures that mine's management can implement. Furthermore, the supportability of the bulldozer and dump trucks should be increased using proper spare parts logistics, fast and secure coordination of the demand for spare parts, providing enough workforces, and enhancing spare parts transportation speed to the workstation, etc.

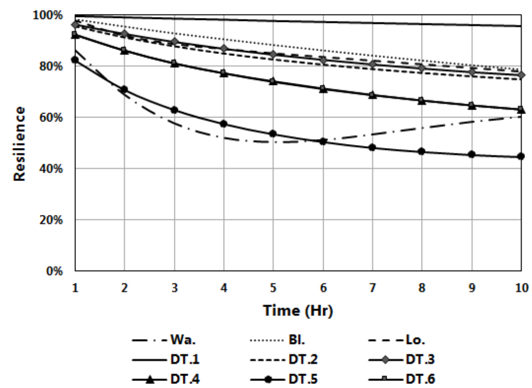

Fig. 12. Mining fleet subsystems resilience for 10 hours of function.

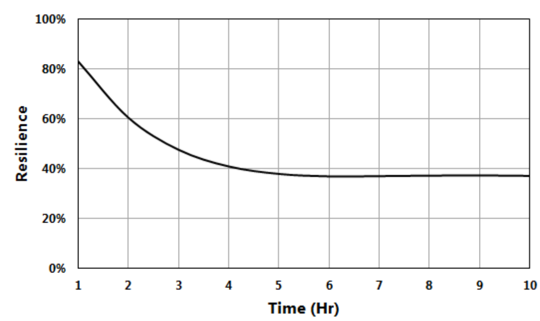

Fig. 13. Mining fleet resilience for 10 hours of function.

6. Conclusion

Resilience is defined as the ability of the system to anticipate, absorb, adapt to, and rapidly recover from a potentially disruptive event. Each system may act differently in the face of failure events. Some of them may entirely fail in the face of failure, while some of them may show resistance, adaptation, and then recover their initial status. In this work, the resilience concept was applied to a case study from the mining industry. For this aim, the system's RMS, PHM efficiency, and organization resilience were estimated. Based on the results, at the fixed time, DT.2 and DT.1 will have the lowest and highest reliability, respectively. Moreover, DT.3 and Wa will have the lowest and highest maintainability, respectively. The results also showed that BI has the highest supportability. Through time, the supportability of Wa will improve and get better than Lo and DT.1 supportability. As shown, the resilience of the mining fleet at the first hour of function will be about 83.1%. However, to increase and maintain the system resilience, the RMS state of the critical subsystems that are not in a suitable condition should be increased. For instance, improvement of the preventive maintenance activates, the increment of training programs for staff, proper spare parts logistics, fast and secure coordination of the demand for spare parts, and providing enough workforces, etc. are such measures that mine's management can implement.

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