The effect of risk factors on the resilience of Industrial Equipment

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ABSTRACT

Recently, to evaluate the response of systems against disruptive events, the application of the resilience concept has been increased. Resilience depicts the system's ability to return to its normal operational status after the disruption. Various studies in the field of engineering and non-engineering systems have only considered systems' performance indicators to estimate resilience. Therefore, the impact of operating and environmental factors (risk factors) has been neglected. In this paper, the influence of the risk factors (rock type), as well as the system's performance indicators, are considered in the resilience estimation of the excavator system of Gol-E-Gohar Iron mine.

Keywords

Resilience; Reliability; Maintainability; Supportability.

1. INTRODUCTION

Keeping the stable operation of systems is a challenge for engineering design. External or internal events like failures or disturbances affect the system operation, negatively. Systems based on their stability have a different reaction against failures. Some systems are vulnerable in case of disruption and lost their functionality. In the engineering domain, the ability of systems to withstand against the failure events and recover their performance in a suitable time is known as resilience [1]. At first, the concept of resilience was introduced by Holling in 1973 in the field of geological systems [2].

According to the necessary role of the resilience concept in the mitigation of the risk of disturbances, it has been used in various fields such as engineering [3], [4], social [5], [6], economic [7], [8], ecological [2], [9], socio-technical [10], [11], and socio-ecological [12], [13]. Newly, it has also been used to COVID-19 pandemic by many researchers [14]–[17]. For example, Barabadi et al. [14] evaluate the resilience of the health infrastructure systems (HIS) in Jajarm and Garme cities before and after the pandemic. Therefore, the resilience concept can be applied in each field.

There is a wide range of definitions for system resilience in the literature. Here are some of these definitions. Allenby and Fink [18] defined resilience as the system's ability to preserve its operations and structure in the presence of internal or external disturbances and to degrade gracefully when it must. Rose [19] defined resilience as the system's ability to maintain its functionally when a disruption occurs. Haimes [20] defined resilience as the system's ability to withstand a major disturbance within acceptable degradation parameters and to recover with a suitable time and reasonable costs and risks. Moreover, the number of resilience definitions have been presented for more specific domains such as engineering, economy, social, ecological, etc. In the engineering domain, resilience is defined as the system's ability to predict, absorb, adapt, and/or quickly recover from a disruptive event [1]. The given definitions highlight the ability of the system to resist against the failures and absorb failures adverse consequences. It should be noted, the pre-failure (preparedness) and post-failure (recovery) activities are both essential in the resilience concept [3]. These activities make the system reliable, supportable, flexible, adaptable, and maintainable.

In Figure 1, the schematic view of the system resilience is shown. As can be seen, the performance level of the system degraded after the disruptive event at t_e. Then, the system performance level reached to lowest value at t_d, and remained at this level until t_s. After commence of the recovery activities, this level increased and reached to the new steady state. It can be either close to or higher than the initial state of the system [21]. It depends on the quality and quantity of the pre- and post-failure activities.

There are many approaches to resilience analysis. Hosseini et al. [1] classified the resilience analysis approach into the qualitative and quantitative groups (see Figure 2). Qualitative approaches, which are divided into the conceptual frameworks and semi-quantitative indices, analysed the resilience of the system without any quantifications. Qualitative approaches are often used in the field of non-engineering systems. Quantification approaches, which are classified into general measures and structural based models, are suitable to apply in the field of engineering systems.

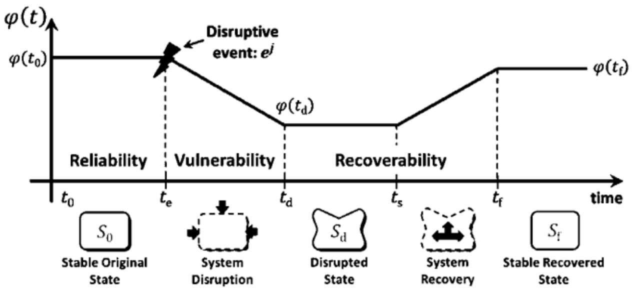

Figure 1. System performance and state transition to describe resilience [1].

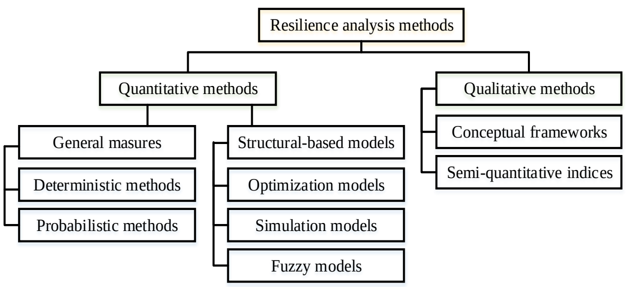

Figure 2. Resilience analysis approaches [1].

The structural based models are divided into optimization, simulation, and fuzzy models. These models examine how the structure of a system affects its resilience. In these models, system behaviour must be observed and the characteristics of the system must be modelled or simulated. General measures are deterministic and probabilistic metrics. In these approaches, the system performances are compared before and after the failure event [1]. Deterministic measures never used uncertainties (like the probability of system repair) in order to analyse the system resilience. While probabilistic measures consider the uncertainties. Here, some of the presented resilience analysis models in the field of engineering are described in Table 1.

Among these models, Rød et al. model has more capability to use. It is probabilistic and time-dependent. It considers the resilience of the owner organization of the system as well as system performance indicators. Therefore, in this paper, this model is used for resilience analysis. However, none of these models considers the impact of operational factors on system resilience. These factors, which have different origins, impact the system reliability, maintainability, and supportability [22]. Therefore, in this study, the impact of these influence factors is considered in the resilience analysis process.

2. RESILIENCE ANALYSIS METHODOLOGY

In the present paper, the resilience analysis is based on the Rød et al. model. Hence, system reliability, maintainability, and supportability (RMS) analysis should be carried out. It must be mentioned these analyses can be conducted considering the effect of risk factors. For this aim, five steps are considered, which are described in the following (see Figure 3).

Table 1. Resilience analysis models.

Author(s)	Model	Model description	
Bruneau et al. [23]	$R=\int_{t_0}^{t_1}[100-Q(t)]dt$	R: Resilience reduction $Q(t)$: System performance function t_0: Disruption initiation time t_1: Recovery actions stoppage time	- It is deterministic - The initial system performance level is considered as 100%
Rose [19]	$\psi=\frac{\%\Delta DY^{max}-\%\Delta DY}{\%\Delta DY^{max}}$	ψ: System resilience $\%\Delta DY$: Difference in non-disrupted and expected disrupted system performance $\%\Delta DY^{max}$: Difference in non-disrupted and worst case disrupted system performance	- It is deterministic - It measures the ratio of the avoided drop in system output and the maximum possible drop in system output
Orwin and Wardle [24]	$\psi=\left[\frac{2\lvert D_0\rvert}{\lvert D_0\rvert+\lvert D_x\rvert}\right]-1$	ψ: System resilience D_0: Refers the maximum intensity of absorbable force without perturbing the system function D_x: Refers to the magnitude of the disturbance effect on safety at time (t_x)	- It is deterministic - Resilience can take the value between 0 and 1 - When the magnitude of the disturbance's effect is equal to zero ($D_x=0$), the maximum resilience can be obtained
Tierney and Bruneau [25]	$R=\frac{\int_{t_0}^{t_1}[Q(t)]dt}{100(t_1-t_0)}$	R: Resilience reduction $Q(t)$: System performance function t_0: Disruption initiation time t_1: Recovery actions stoppage time t_1-t_0: System recovery duration	- It is deterministic - It is time-dependent - The initial system performance level is not considered as 100%
Cimellaro et al. [26]	$\psi=\alpha\int_{T_{LC}}\frac{Q_t(t)}{T_{LC}}dt+(1-\alpha)\int_{T_{LC}}\frac{Q_2(t)}{T_{LC}}dt$	ψ: System resilience $Q_1(t)$: System services quality before the disruption,	- It is deterministic - It considers both pre- and post-failure activities

		$Q_2(t)$: System services quality after the disruption T_{LC} : Control time of the system α : Weighting factor representing the importance of pre- and post-failure activities qualities	- It considers the importance levels (weights) of the pre- and post-failure activities
Ayyub [27]	$\psi = \frac{T_i + F\Delta T_f + R\Delta T_r}{T_i + \Delta T_f + \Delta T_r}$	ψ: System resilience T_i: Time to incident, T_f: Time to failure T_r: Time to recovery $\Delta T_f = T_f - T_i$: Duration of failure $\Delta T_r = T_f - T_f$: Duration of recovery F: Failure profile R: Recovery profile	- It is probabilistic - It is time-dependent - It considers both pre- and post-failure activities - The failure profile is a measure of robustness and redundancy - the recovery profile measures recoverability
Youn et al. [28]	$\psi = R + \rho = R + \kappa.\Lambda_P.\Lambda_D.(1-R)$	ψ: System resilience R: System reliability ρ: System restoration κ: Probability of successful recovery event Λ_P: Probability of correct Prognosis event Λ_D: Probability of correct diagnosis event	- It is probabilistic - It is time-independent - It considers both pre- and post-failure activities - Resilience can take the value between 0 and 1
Rød et al. [6]	$\psi = R + \Lambda(1-R) = R + \left[\prod_{i=1}^{4} \beta_i\right](1-R)$	ψ: System resilience R: System reliability β_1: System maintainability β_2: Owner organization resilience β_3: Prognostic and health management (PHM) efficiency β_4: System supportability	- It is probabilistic - It is time-dependent - It considers both pre- and post-failure activities - Resilience can take the value between 0 and 1 - It considers the system resilience as a function of system reliability and recoverability
Sarwar et al. [29]	$\psi = R + \mu[V, M]$	ψ: System resilience R: System reliability μ: System recoverability function V: System vulnerability M: System maintainability	- It is probabilistic - It is time-dependent - It considers both pre- and post-failure activities - Resilience can take the value between 0 and 1
Najarian and Lim [30]	$r = r_1\lambda_1 + r_2\lambda_2 + r_3\lambda_3,$ $\sum_{i=1}^{3} \lambda_i = 1 \; and \; \lambda_i \geq 0 \; for \; i = 1,2,3$	r: System resilience r_1: System absorptive component r_2: System adaptability component r_3: System recovery component λ_i: Weight of the i[th] component	- It is time-dependent - It considers both pre- and post-failure activities - Resilience can take the value between 0 and 1

2.1 Database establishment

A database, including time between failure (TBF), time to repair (TTR), and time to delivery (TTD) data should be collected from the accessible sources. Simultaneously, the most critical operational factor should be identified. Afterward, the collected database must be segmentation based on the identified risk factor.

2.2 Selection of the best fit statistical model

After data collection, to pick the best fit model, the assumption of the independent and identically distributed nature (iid) of data should be judged. For this aim, trend tests include Military handbook (MIL), Laplace, Anderson-Darling (A-D), and Mann-Kendall (M-K)) tests should be adopted. Moreover, autocorrelation tests include Graphical method and autocorrelation function (AFC) should be performed. Here, to conduct trend and serial correlation tests, the represented algorithm in Figure 3 is suggested. For more information about trend and autocorrelation tests refer to [31], [32].

2.3 RMS analysis

Here, based on the results of the previous step, if there is any sign of the presence of the trend among the data, then the nonhomogeneous models like the Power Law Process (PLP) should be applied. If there is autocorrelation in data and trend test results do not confirm the potential of the presence of the trend among the data, then the Branching Poisson Process (BPP) models can be utilized. Furthermore, if there is no indication of the existence of trend and autocorrelation among the data, the classical distribution models such as normal or lognormal models can be used (see Figure 3). For more details refer to [8-10].

2.4 Estimation of the management indicators

In this step, the PHM efficiency of the system and the organization's resilience should be estimated.

2.5 Resilience analysis of the system and subsystems

Finally, using the obtained results from the previous steps, the resilience of a subsystem of the series system with n subsystems can be analysed as follow [3]:

$$\psi_i(t)=R_i(t)+\Lambda_i(t)\big(1-R_i(t)\big) \tag{1}$$

The resilience of the series system can be analysed as follow:

$$\psi(t)=\prod_{i=1}^{n}\left[R_i(t)+\Lambda_i(t)(1-R_i(t))\right] \tag{2}$$

3. CASE STUDY

The mining industry is one of the most important sectors among the industries. It is consisted of many complex processes like ore mining, ore processing, and so on, to supply the raw material of other industrial sectors. This field consists of many critical systems like the excavator system. Out of schedule stoppage of this system will lead to mine production reduction and create several problems for the mine management. The application of the resilience concept seems necessary for this sector.

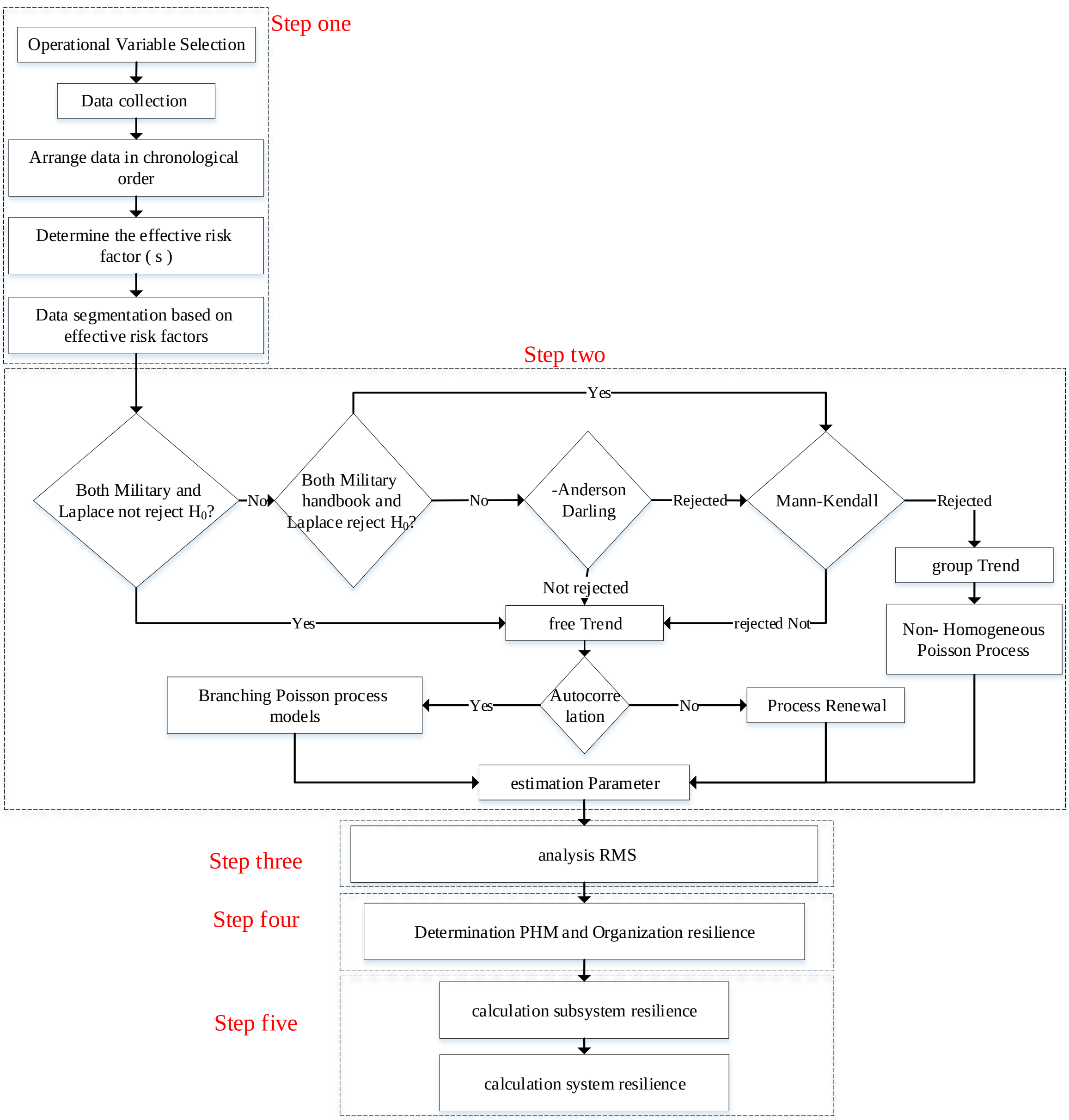

Figure 3. Resilience analysis algorithm.

In this work, Gol-E-Gohar Iron mine is selected as a case study. This mine, with six mining sites, is one of the largest producers of Iron with and supplies the raw material of some industries like automobile manufacturing. The estimated deposit of this mine is about 1135 million tons. It is situated 55 km southwest of Sirjan between 551150E and 551240E longitudes and 29,130 N and 29,170 N latitudes at an altitude of 1750 m above sea level (see Figure 4), and surrounded by 2500 m height Mountains [34]. The excavator system of the mining site No.1 is selected for resilience analysis. The excavator system consists of six series subsystems. The characteristics of this system and its flowchart are presented in Table 2 and Figure 5, respectively.

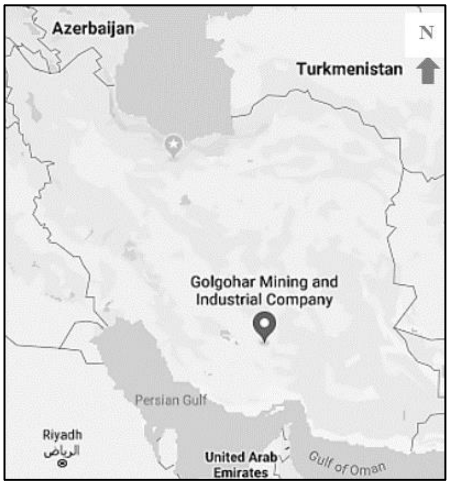

Figure 4. Gol-E-Gohar Iron mine location.

Table 2. Excavator system characteristics.

System model	Series subsystems	Codes
Caterpillar 390DL	Boom	Bo
	Cabin	Ca
	Engine	En
	Electric	El
	Hydraulic	Hy
	Undercarriage	Un

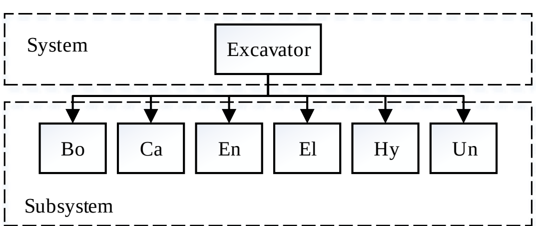

Figure 5. Flowchart of the excavator system.

4. RESULTS AND DISCUSSION

According to section 2, a database of TBFs, TTRs, and TTDs of the excavator system and its subsystems were collected. These data belonged to a period of 24 months from January 2016 to December 2018. Moreover, rock type was recognized as the most important factor that impacts the failure of the excavator system. In the field of mining engineering, rock type is such operational factors. This factor can be divided into ore and waste rocks, based on the hardness and specific gravity variations. For example, high hardness of rock can damage the teeth of the bucket, and the high specific gravity of rock can put excessive pressure on the engine. The collected database (only TBFs) was segmented based on the rock type. Some parts of the collected data are displayed in Table 3. Afterward, the iid assumption was evaluated for TBFs, TTRs, and TTDs. For checking the data autocorrelation, the Graphical method is used. In the graphical method, the autocorrelation test was carried out graphically by plotting the ith TBF (TTR) against (i-1)th TBF (TTR). If the plotted points do not follow a special trend and randomly scattered without any clear pattern, it can be inferred that the data are free from serial correlation or independent [35]. For example, the results of the autocorrelation test for the TBFs data of the Bo subsystem is shown in Figure 6. As can be seen, the TBFs data of the Bo subsystem has no autocorrelation.

The results of the trend tests for failure, repair, and delivery data are illustrated in Tables 4 and 5, respectively. Based on the results, in the ore segment, TBFs of El, En, Hy, Ca, and Bo subsystems had not trend and autocorrelation. Then classical distribution models were used for their modelling. As there were signs of the trend in TBFs of the Un subsystem, the PLP model was used for it. Moreover, based on the obtained results in the waste segment, there was no evidence of the trend, and autocorrelation in the TBFs of El, En, and Bo subsystems, thus classical distribution models were used for them. While the TBFs of Ca, Hy, and Un subsystems had trend, then the PLP model was used for these subsystems. According to the TTRs data, Bo, Ca, Hy, and El subsystems had no trend and autocorrelation. Then classical distribution models were used for their modelling. While the TTRs of En and Un subsystems had trend, then the PLP model was used for these subsystems. It must be mentioned, because of the same model, repair and, spare parts for the excavator subsystems, the supportability analysis was performed only for the entire excavator system. In Figures 7-9 and Table 6, the best-selected models for the subsystems are presented.

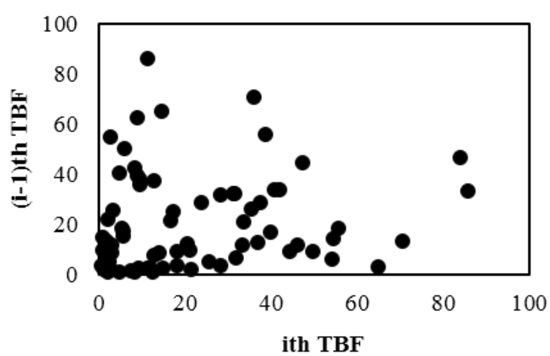

Figure 6. Autocorrelation test for the TBFs data of the Bo subsystem.

Table 3. Samples of the collected database.

Reliability database				Maintainability database		Supportability database	
Ore section		West section					
TBF (Hr)	system	TBF (Hr)	system	TTR (Hr)	system	TTD (Hr)	system
160.45	1	6.56	1	0.33	1	0.80	1
54.17	1	40.85	1	1.20	1	31.11	1
5.86	1	203.00	1	0.61	1	0.33	1
143.31	1	29.78	1	0.22	1	1.20	1

Table 4. The result of the trend test for TBFs data.

Index	subsystem	Data		MIL	Laplace	A-N	M-K	Result
Reliability	Bo	TBF of ore	Test statistic	920.53	0	6.13	–	No Trend
			P-value	0.409	0.709	0.001	–	
		TBF of west	Test statistic	418.24	0.99	-	–	No trend
			P-value	0.97	0.321	-	–	
	Ca	TBF of ore	Test statistic	47.98	1.02	-	–	No trend
			P-value	0.354	0.307	-	–	
		TBF of west	Test statistic	31.86	1.99	-	-2.084	trend
			P-value	0.025	0.046	-	0.018	
	En	TBF of ore	Test statistic	126.86	3.59	-	-4.238	No trend
			P-value	0.001	0	-	0.13	
		TBF of west	Test statistic	208.19	0.07	-	–	No trend
			P-value	0.811	0.946	-	–	
	Hy	TBF of ore	Test statistic	179.18	-0.34	-	–	No trend
			P-value	0.839	0.733	-	–	
		TBF of west	Test statistic	242.48	-3.03	-	3.55	trend
			P-value	0	0.002	-	0.019	
	El	TBF of ore	Test statistic	86.41	1.01	-	–	No trend
			P-value	0.504	0.314	-	–	
		TBF of west	Test statistic	71.99	1.18	-	–	No trend
			P-value	0.66	0.24	-	–	
	Un	TBF of ore	Test statistic	135.94	4.33	-	-4.48	Trend
			P-value	0	0	-	0.036	
		TBF of west	Test statistic	158.58	5.71	2.68	-4.162	trend
			P-value	0	0	0.04	0.0157	

Table 5. The result of trend test for the TTRs and TTDs data.

Index	System or Subsystems		MIL	Laplace	A-N	M-K	Result
Maintainability	Bo	Test statistic	1295.05	-0.64	-	-	No Trend
		P-value	0.19	0.523	-	-	
	Ca	Test statistic	119.06	0.64	-	-	No trend
		P-value	0.986	0.52	-	-	
	En	Test statistic	238.65	3.12	-	-3.73	trend
		P-value	0.07	0.002	-	0.0092	
	Hy	Test statistic	343.43	-1.29	-	-	No trend
		P-value	0.161	0.199	-	-	
	El	Test statistic	186.16	1.34	6.77	-	No trend
		P-value	0.566	0.179	-	-	
	Un	Test statistic	455.59	2.8	-	-3.129	trend
		P-value	0.024	0.005	-	0.009	
Supportability	Excavator	Test statistic	2680.97	-0.65	-	-	No trend
		P-value	0.446	0.516	-	-	

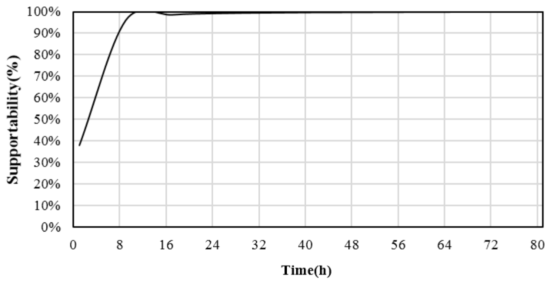

Figure 7. Excavator system supportability analysis results for 81 hours of activities.

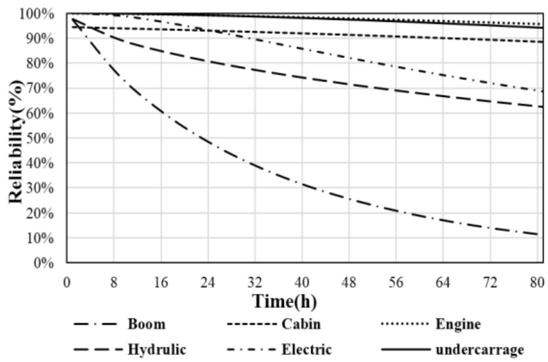

Figure 8. Excavator subsystem reliability analysis results for Ore section for 81 hours of activities.

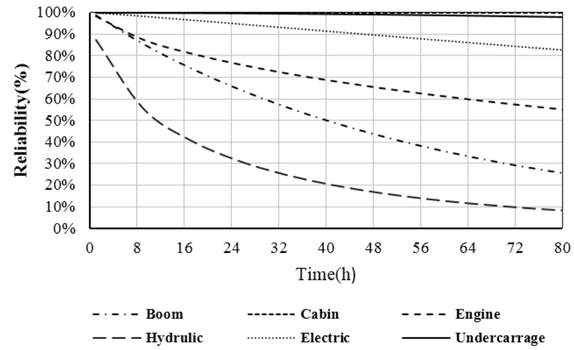

Figure 9. Excavator subsystem reliability analysis results for waste section for 81 hours of activities.

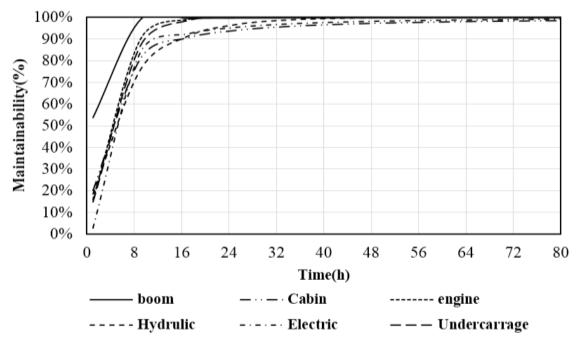

Figure 10. Excavator subsystem maintainability analysis results for 81 hours of activities.

Table 6. Best-fitted models for the subsystems reliability, maintainability, and supportability.

Subsystems		Reliability				Maintainability	
		ore		West			
Bo	Model	weibull-3P		weibull-3P		loglogistic-3P	
	parameter	β	0.905	β	0.975	β	- 0.20717
		η(hr)	33.69	η(hr)	57.77	η(hr)	0.51
		ɤ(hr)	0.3706	ɤ(hr)	0.315	ɤ(hr)	0.121
Ca	Model	Normal		PLP		Log logistic	
	parameter	mean	333.72	β	1.633	β	1.069
		Std	209.66	η(hr)	3170	η(hr)	0.778
		-	-	ɤ(hr)	-	ɤ(hr)	-
En	Model	PLP		weibull-3P		PLP	
	parameter	β	1.448	β	0.664	β	1.173
		η(hr)	692.35	η(hr)	172.2	η(hr)	4.4146
		ɤ(hr)	-	ɤ(hr)	0.633	ɤ(hr)	-
Hy	Model	wiebull-3P		PLP		weibull-3P	
	parameter	β	0.6437	β	0.66	β	0.8423
		η(hr)	260.61	η(hr)	19.93	η(hr)	5.887
		ɤ(hr)	0.154	ɤ(hr)	-	ɤ(hr)	0.10132
El	Model	lognormal		weibull-2P		Lognormal-3P	
	parameter	LMe	4.977	β	1.078	β	0.555
		LSt	1.207	η(hr)	371.5	η(hr)	1.542
		-	-	ɤ(hr)	-	ɤ(hr)	0.912
Un	Model	PLP		PLP		PLP	
	parameter	β	1.588	β	1.778	β	1.154
		η(hr)	469.69	η(hr)	652.4	η(hr)	4.866
		ɤ(hr)	-	ɤ(hr)	-	ɤ(hr)	-
System	Supportability						
Excavator	Model	Loglogistic-3P					
	parameter	β			0.275		
		η(hr)			0.603		
		ɤ(hr)			0.018		

Based on Figure 3, After RMS analysis, management indicators should be determined. According to Rød et al. [3], the values of PHM efficiency and organization resilience can be considered as the constant values. In this study, the adopted values by Rød et al. were considered for PHM efficiency and organization resilience (see Table 7).

Table 7. The considered values for PHM efficiency and organization resilience [3]**.**

Parameters	Values
Organization resilience	0.85
PHM efficiency	0.75

Finally, using Equations 1 and 2, the resilience of the excavator system and its subsystems (in the ore and waste rocks) for 81 hours of activities were analysed. The results are shown in Figures 11-13. For example, the resilience of the Hy subsystem (see Figures 11 and 12) in the waste rocks will be notably lower than its resilience in the ore rocks. After 81 hours of activities, the Hy subsystem resilience in the ore rocks will be reached to 86%, but it will be 66% in the waste rocks. Because the hardness and specific gravity of waste rocks are more than ore rocks, which can damage the excavator subsystems like the Bo subsystem. These differences indicate the influence of rock type on system resilience. Moreover, as can be seen, the impact degree of this factor depends on its direct contact with the subsystem. For example, the impact of rock type on the Ca subsystem is lower than the impact on the Hy subsystem.

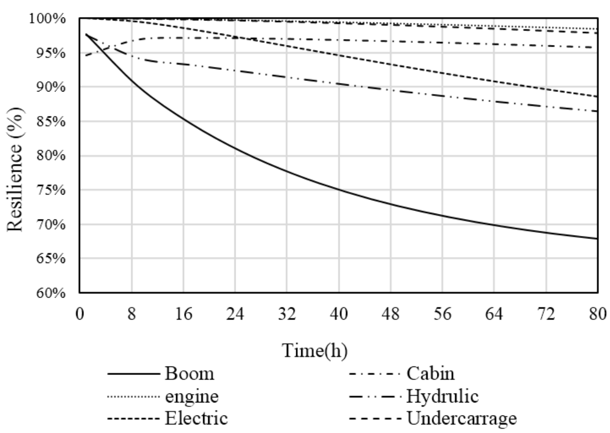

Figure 11. Excavator subsystem resilience analysis results for ore section for 81 hours of activities.

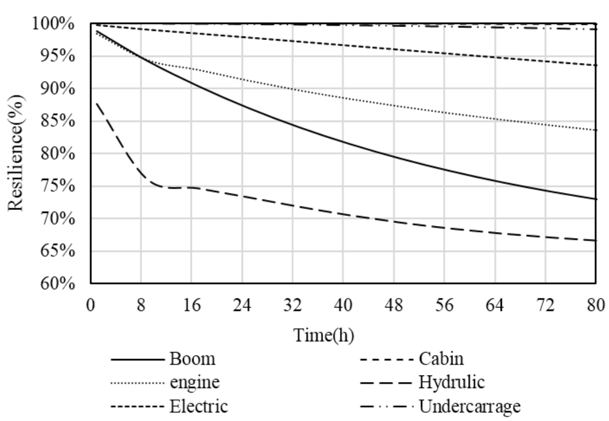

Figure 12. Excavator subsystem resilience analysis results for waste section for 81 hours of activities.

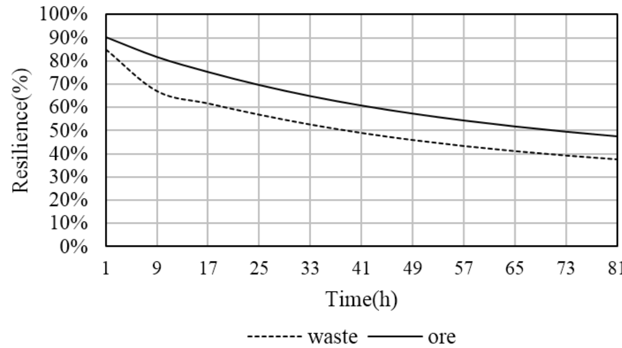

Figure 13. Excavator system resilience analysis results for ore and waste sections for 81 hours of activities.

5. CONCLUSION

Systems based on their stability have a different reaction against failures. Some systems are vulnerable in case of disruption and lost their functionality. In the engineering domain, the ability of systems to withstand against the failure events and recover their performance in a suitable time is known as resilience. In this work, the resilience concept was used in the field of mining industry, and the excavator system of Gol-E-Gohar Iron mine was considered as a specific case study. In this paper, the influence of the risk factors on the system resilience was considered. The rock type was identified as the risk factor that affects the resilience of the excavator. Therefore, by segmentation of the collected database into the ore and waste rocks groups, the impact of rock type on the excavator resilience were evaluated. This factor affects the reliability indicator. The results emerge the importance of consideration of the risk factors in the resilience estimation process. As shown, the resilience of the excavator system can be varied based on the rock type. It can be due to the high hardness and density of the waste rock compared to the ore rock. It must be mentioned that the mining industry is an essential industry that supplies the raw material of other sectors. Thus, the application of the resilience concept with consideration of risk factors will improve its overall functionality.

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