Assessing Resilience in Mechanical Systems: A Mining Industry Perspective

Abstract

Resilience is defined as a system's ability to withstand and recover from disruptions such as failures, accidents, or external shocks. In the domain of engineering systems, resilience plays an essential role because it guarantees the system's ability to continue operating despite unexpected events, ultimately maintaining production levels and ensuring customer satisfaction. This paper aims to measure the amount of resilience in the mining industry. In this regard, an approach consisting of reliability, maintainability, supportability, the efficiency of system prognostic and health management (PHM), and organization resilience was introduced. These indexes provide a comprehensive assessment of the system's ability to withstand and recover from disruptions, thereby helping to ensure its continued performance and customer satisfaction. To reduce the uncertainty in the measurement of resilience, operational and environmental variables were used to estimate the values of reliability, maintainability, and supportability. Also, the opinions of experts were used in the estimation of the efficiency of the system (PHM) and indices. Organization resilience. The results of applying this approach are the value of 80% resilience if the variables are considered and 98% if the mentioned variables are ignored. Also, the value of 58% resilience of this organization's management group indicates the weakness of situational awareness and weakness in the vulnerable points of the organization.

keywords: Reliability, Maintainability, Supportability, Organization resilience, Prognostics and health management of the system index

1-Introduction

Over the years, Risk management has been The main approach to increase system safety by developing robust systems. At the same time, disruption indicates that this goal is unachievable. Thus, attention has shifted to developing resilient systems. The term resilience was born (Hosseini et al., 2016). The concept of resilience was expanded from ecology into other fields. (Holling, 1973). Such as social (White et al., 2015), (Yu et al., 2014), economic (Bristow, 2018) (Benito Del Pozo & López-González, 2020), organizational (Aleksić et al., 2013) (Burnard & Bhamra, 2011), and engineering (Cimellaro et al., 2010) (Henry, 2012). Sharma et al. evaluated the Indian transportation system's resilience in 2018. To investigate the relationships between the variables, they created a framework for measuring resilience and employed an analytical model based on the Bayesian belief networks methodology. In their article, Resilience was described as a term that combines the system's capacity to withstand and recover (Sharma & George, 2018). American Society of Mechanical Engineers defined *engineering resilience* as the system's ability to stabilize against internal or external disruptions without reducing the system's performance or quick recovery from disruption and return to its previous and main performance in case of reduction (Ahmed et al., 2019). The European project IMPROPER defines resilience as a system's ability to resist, absorb, adapt, and recover promptly from hazards to maintain and restore essential services. This definition emphasizes the importance of resilience in the context of critical European infrastructures (Petersen et al., 2020). According to the definitions above, the resilience concept can be expressed in Figure 1. As The figure illustrates, resilience changes the system's life cycle. Typically, the performance of the system declines significantly as the system ages. After that, the system can have different reactions to failure events at the time t_e. The flexibility attribute in the resilient system enables it to adapt to new conditions; in other words, this attribute in the system makes it adjust its internal mechanism based on the existing conditions, which can provide service and function even with a decline in operation. While the systems are not resilient at this stage, if the amount of pressure caused by the failure event is higher than the resistance of the mentioned system, it leads to failure and, finally, the system's collapse. In the following, after the end of the disruption at the time t_d, when the system performance reaches its value $Q(t_d)$, the system spends the period $(t_d - t_e)$ in Disrupted conditions. Adequate logistic such as resources, information, components, and timely decision-making will reduce this period. Eventually, the recovery of the system starts over time t_s. The quality of adopted decisions and strategies and using qualified resources will cause the restored system performance level in time t_f to be closer to its initial value. As can be seen resilience is influenced by a lot of factors. Every mining operation must assess the strengths and vulnerabilities of its mechanical systems to guarantee efficient mineral production and customer satisfaction. However, it is impossible to prevent failures and disturbances. Thus, mines need an indicator that, in the first place, has a system resistant to disruption and then, in the event of a disruption, they can be restored as soon as possible. Therefore in This work a formulation is presented to examine the resilience of mechanical systems. Five indicators such as reliability, maintainability, supportability, organizational resilience and efficiency of system (PHM) have been introduced. In this regard Expert judges and operational and environmental variables have been used to quantify these indicators. The remaining parts of the paper are structured as follows: In the section 2 methodology of resilience is describe. In the section 3, the case study and the application of methodology for analyzing the resilience of this system are shown. finally, Section 4 brings our findings.

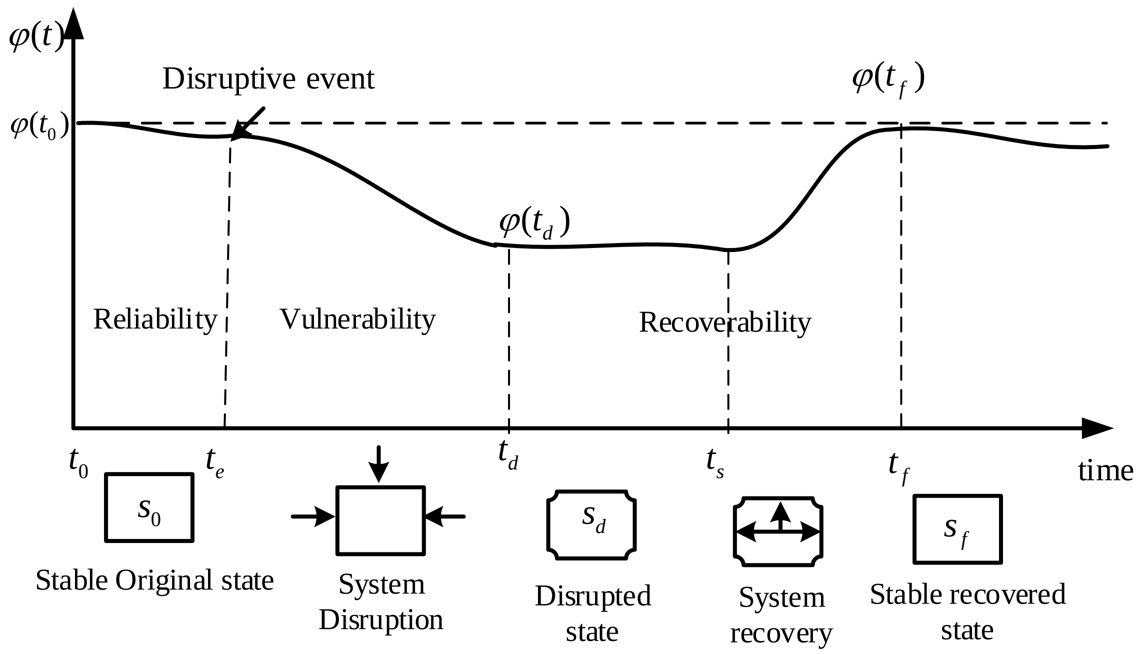

Figure 1: Schematic representation of the concept of resilience (Mottahedi, Sereshki, Ataei, Qarahasanlou, et al., 2021)

2- Methodology of resilience analysis

According to the concept and definitions of resilience, the two main aspects of any resilient system are robustness to disruptive events and recovery in case of disruption. Also, A mechanical system's resilience can be categorized into two parts in broad speaking, including soft resilience and hard resilience. Hard resilience represents the behavior of the technical part of the mechanical system, and soft resilience represents the people and the organization running the mechanical system in the preparedness and recovery phases (before, during, and after disruption).

(Barabadi & Ayele, 2018). In this article, based on the mentioned reasons, a method has been used to quantify and analyze resilience. In the following, this method is quantified using Eq. (1) presented by (Rød et al., 2016a) :

$$\psi(t) = R(t) + \Lambda(t)(1 - R(t)) \tag{1}$$

In Eq. (1) $\Psi(t)$ is resilience at the time of t, R(t) is the reliability of system as robustness aspect of resilience, and $\Lambda(t)$ refer to system restoration. the system restoration can be formulated as Eq. (2):

$$\Lambda(t) = \prod_{i=1}^{4} \beta_i \tag{2}$$

In Eq. (2), β_1 is the system maintainability after disruption, β_2 is supportability, β_3 is the efficiency of the system prognostic and health management (PHM) system before and after disruption, and β_4 is the organizational resilience in case of disruption (Rød et al., 2016a). According to Eq. (1)to Eq. (2), reliability can be defined as "*the ability of the system to maintain its required capacity and performance during a given period under stated conditions"* (Dhillon, 2006a; Ghomghaleh et al., 2020; Komal, 2019; Rød et al., 2016b). Maintainability can be defined as " *the probability that the item will be repaired within a given period using specified resources such as a maintenance crew or spare parts*" (Barabadi & Aalipour, 2015; Rød et al., 2016a). Supportability is "*the maintenance group's ability to meet the demand for sufficient resources to maintain a specific service or devise under certain conditions*" (Ghodrati et al., 2007). PHM system performance is "*failure detection and prediction of defects in engineering systems*" (Omri et al., 2021; Rød et al., 2016a). Investment in the PHM system can increase both of the main resilience capacities. Moreover, finally, Organization resilience is "*the resilience of the team who work on the system*". All managers and people who work in mechanical systems must have high resilience in critical situations(Burnard & Bhamra, 2011; Denyer, 2017).

Mechanical systems are always in conflict with various factors during their useful life. Ignoring these important factors leads to errors in identifying the strengths and weaknesses of the system. It is clear that in Eq. (1) to estimate the system's resilience, the effect of these factors has been neglected. Therefore, in 2021, Mottahedi et al. presented Eq. (3) to estimate the system's resilience by considering the effects of environmental and operational factors that are known as Risk factors which are used in reliability, maintainability, and supportability (RMS) analysis (Mottahedi, Sereshki, Ataei, Nouri Qarahasanlou, et al., 2021).

$$\psi(t;c,c(t)) = R(t;c,c(t)) + \Lambda(t;c,c(t))(1 - R(t;c,c(t))) \tag{3}$$

In Eq. (3), $\psi(t;\ c,c(t))$ refer to the system resilience, considering the environmental and operational factors, $R(t;c,c(t))$ and $\Lambda(t;c,c(t))$ are reliability and the rate of system restoration, respectively. Using the presented method in Figure 2, Eq. (3) indexes will be evaluated.

- Part 1: Estimation of the organization's resilience
- Part 2: Estimation of the system's RMS
- Part 3: Estimation of the efficiency of the system (PHM)

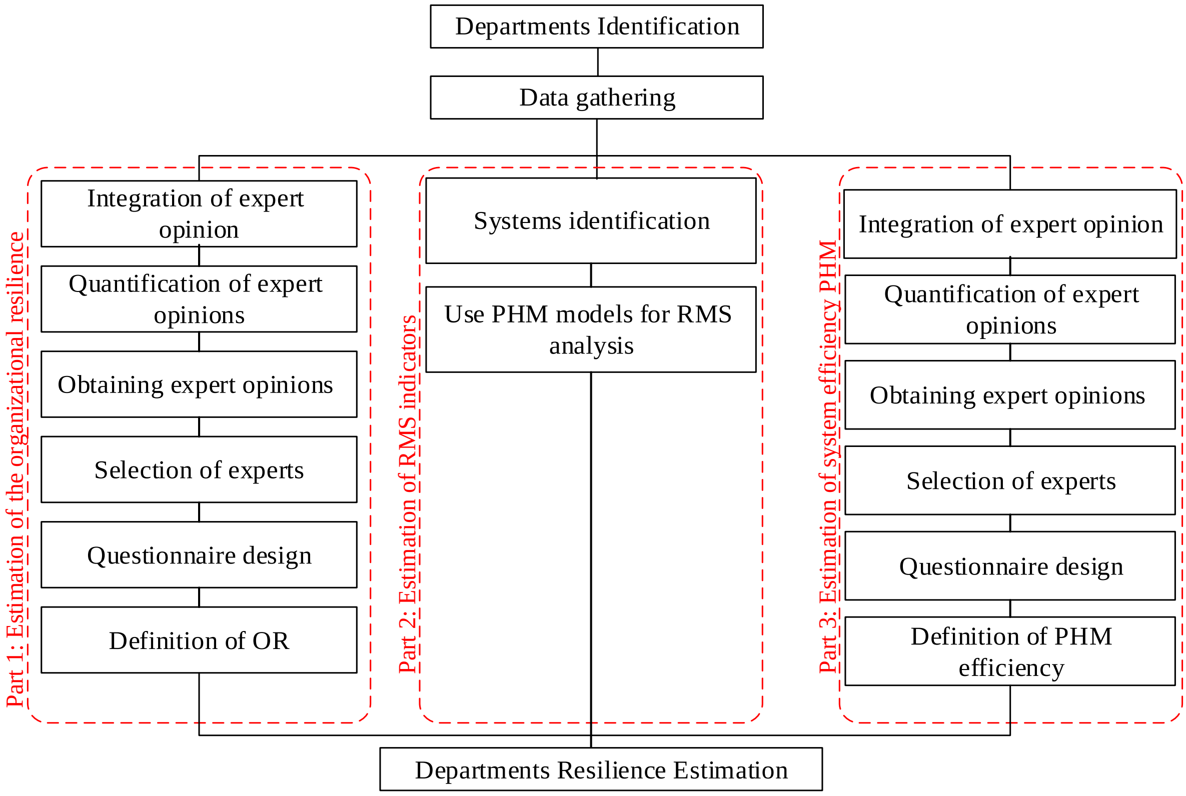

Figure 2. Resilience estimation method [***Author's own creation***]

2-1 Estimation of the organizational resilience

Organizational resilience is the capacity of a company or organization in predictive, absorptive, adaptive, and restorative. Madani et al. considered the concept of resilience as an organization's capacity in predictive, absorptive, adaptive, and restorative. In this regard, they presented an integrated model that examines the quality perspective and how resilience and innovation are related (Madani & Parast, 2023). In this article, the Macknemus model, as extended by Seville, is used to estimate organizational resilience(McManus et al., 2007). Maknemus defines organizational resilience as an organization's ability to plan in order to be flexible in the face of a catastrophe. Crisis (McManus, 2007). In Maknemos' model, the resilient organization has indicators in three main principles:

- *The indicators measure the organization's situational awareness level*
- *The indicators measure the level of the management keystone vulnerability of the organization*
- *The indicators measure the organization's Adaptive capacity*

In this article, expert judgment is used to quantify the Makenmuns model. Furthermore, fuzzy set theory is applied to reduce uncertainty in the expert's viewpoint. Table 1 shows the components and indicators of organizational resilience.

Table 1.Organization Resilience Indicators(Seville, 2009)

Adaptive Capacity	Symbol	Management of keystone	Symbol	Situation Awareness	Symbol
Silo Mentality	AC_1	Quality of Planning Strategies	KV_1	Roles & Responsibilities	SA_1
Communications	AC_2	Exercises	KV_2	Hazard & Consequences	SA_2
Strategic Vision	AC_3	Internal Resources	KV_3	Awareness of Connectivity	SA_3
Management Information and Knowledge	AC_4	External Resources	KV_4	Insurance	SA_4
Leadership, Management Structures	AC_5	Connectivity	KV_5	Recovery Priorities	SA_5
Innovation & Creativity	AC_6	Staff Engagement	KV_6	Informed decision making	SA_6
Devolved and responsive Decision-making	AC_7	Robust Processes	KV_7	Situation Monitoring	SA_7

The article uses a questionnaire to obtain expert opinions on fuzzy set theory in Table 2 (Mottahedi & Ataei, 2019). Then, the quantified opinions are integrated to fuzzify the organization's resilience indicators. When the number of experts who participated in the survey process is equal to z and the fuzzy number obtained from the opinion of the zth expert about the influential component is equal to $\tilde{s}_{iz} = (a_{iz} b_{iz} c_{iz})$, the output of the experts' judgment is in the form of Eq. (4) (Chen, 2000).

$$(\tilde{s}_i)_k = (a_i, b_i, c_i) = \left(min_z\{a_{iz}\}, \frac{\sum_{z=1}^{n} b_{iz}}{Z}, max_z\{c_{iz}\} \right) (z = 1,2,3,.,z) \tag{4}$$

Table 2. Linguistic terms and their corresponding fuzzy components

No.	Linguistic Terms	Symbol	Corresponding fuzzy components
1	Very low-very weak-very bad-completely contrary	VL	(0,0,0.1)
2	Low-weak-bad-contrary	L	(0,0.1,0.3)
3	Relatively low-relatively weak- relatively bad- relatively contrary	RL	(0.1,0.3,0.5)
4	Moderate-medium-mediocre-unbiassed	M	(0.3,0.5,0.7)
5	Relatively high-relatively strong-relatively good-relatively agreeable	RH	(0.5,0.7,0.9)
6	High-good-strong-agreeable	H	(0.7,0.9,1)
7	Very high-very strong-very good-very agreeable	VH	(0.9,1,1.1)

In Eq. (4), $c_i. b_i. a_i$ are the lower, average, and upper limits, respectively, of the expert's opinion about the effective component of organizational resilience. This number is fuzzy, and it must be de-fuzzified to obtain the value of organizational resilience. In this case, if the resulting output of the experts' opinions about the mentioned components is equal to $\left(\tilde{S}_i\right)_k = (a_i. b_i. c_i)$, the non-fuzzified output is obtained using Eq. (5). The following equation's output is considered the non-fuzzy final score of each component (Carlsson & Fullér, 2001).

$$(\tilde{s}_i)_k = \frac{(a_i + 4b_i + c_i)}{6}, (0 \leq s_i \leq 1) \tag{5}$$

After determining the score of each component, the score of three indicators or the main principle of organizational resilience is determined using the average score of the components related to each principle. Finally, the value of organizational resilience is obtained by averaging the scores of all three main principles.

2-2 estimation of RMS indicators based on covariates

Engineering systems are often impacted by various environmental and operational factors that can affect their performance. These factors are commonly referred to as "covariates," and it is important to consider them in the analysis of the system to understand its behavior and potential weaknesses. (Kumar & Klefsjö, 1994). In this article, the models based on the proposed covariates by Cox are used to estimate the behavioral indicators of the system. The analysis requires two types of data: time series data and information about covariates. This information can be gathered from various sources, such as reports from the control room, daily reports, reports from the spare parts warehouse, reports from the repair shop, data from the meteorological unit, as well as interviews and meetings with the operators and maintenance personnel (Dhillon, 2006b, 2008). To use the models based on the covariates proposed by Cox, it is necessary to evaluate the time dependence of the covariates(Cox, 1972). This article used the proportional hazard rate (PH) (shown in Eq. (6)) assumption to investigate the interdependence between covariates and time. The stratified Cox regression models (SCRM)(is shown in Eq. (7)) are used if the covariates depend on time. The proportional hazard rate models (PHM) or Cox proportional repair rate models are used instead if they are independent. Table 3 demonstrates the mentioned models for reliability (Barabadi et al., 2011b). Regarding maintainability, "$M_0 = 1 - R_0$" is used.

Table 3. Cox models for performance analysis (Barabadi et al., 2011a)

Model	Formula	Model Description
PHM	$R(t,z) = (R_0(t))^{exp\sum_{i=1}^{n}(\alpha_i z_i)}$ (6)	$R(t,z)$: Reliability rate function, $R_0(t)$: Baseline Reliability rate function, z: Covariates, α: Impact coefficient of covariates, $exp\sum_{i=1}^{n}(\alpha_i z_i)$: Link function in exponential function mode
SCRM	$R_s(t,z) = (R_{0s}(t))^{exp\sum_{i=1}^{n} z_i \alpha_i}$ (7) $s = 1,2,3,.,r$	$R_s(t,z)$: Reliability rate function in the "s" layer, $R_{0s}(t)$: Baseline Reliability rate function in the "s" layer, z: Covariates, α: Impact coefficient of covariates, $exp\sum_{i=1}^{n}(\alpha_i z_i)$: Link function in exponential function mode

The paper used statistical software such as SPSS, Stata, and Minitab to apply risk factors in the risk rate (PHM) and proportional repair rate models (PRM). The Backward Stepwise Method was used to determine the effective risk factors in the linking function model. The Akaike and

Bayesian information criteria were used to evaluate the basic functions of the models. (Javed et al., 2014; Rahimdel et al., 2016). The research determined the reliability, maintainability, and supportability of the basic functions and identified effective risk factors in the linking function of each indicator. This information was then used to calculate the system behavior over time based on the effective risk factors.

2-3 Estimation of the efficiency of system PHM

Recently, proactive maintenance decisions have been enabled by developing prognostics and health management (PHM) methods that detect, diagnose, and predict the effects of adverse events. Capitalizing on PHM technology at an early design stage can transform passively reliable (or vulnerable) systems into adaptively reliable (or resilient) systems while considerably reducing their life cycle cost (LCC). Based on the research, PHM efficiency is mainly determined by the probability of the correct failure diagnosis event and the probability of the correct failure prognosis event (Youn et al., 2011). The probability of correct diagnosis can be measured using sensors in the design stages. Also, the probability of correct prognostics van measured by prognostic algorithm design to meet the required prognostic accuracy level(Youn et al., 2011).

In some cases, the efficiency of the system PHM in mechanical systems may not match the standard duty cycle. This is because the information provided by the sensors may not be recorded or analyzed correctly by operators or maintenance personnel. In such cases, the efficiency of system PHM depends on the accuracy of defect detection and failure prediction by the operators and maintenance personnel. This efficiency is usually determined by evaluating the probability of correct defect detection and the probability of correct failure prediction (Ahmed et al., 2019). The article uses the probability of accurately detecting the defect and correctly predicting the failure to determine the efficiency of the system PHM by applying Fuzzy Fault Tree Analysis (FFTA) (Mottahedi & Ataei, 2019).

The experts' opinions must be used using the linguistic expressions in Table 4 to estimate the basic events. The obtained opinions must be merged after quantifying the experts' opinions using Eq. (8). In this equation, W_j is the weight of each expert, which is calculated according to the educational, occupational, and such characteristics. Also, A_{ij} is the *j* th expert's opinion about *i* th basic event. After merging opinions, using Eq. (9), the fuzzy numbers resulting from combining opinions are deterministic, and each basic event's failure probability (FP) is estimated.

$$\mathrm{M_i} = \sum_{j=1}^{n} \mathrm{w_j A_{ij}}\,,, \mathrm{M_i} = (\mathrm{a_i}, \mathrm{b_i}, \mathrm{d_i}) \tag{8}$$

$$\mathrm{FP} = \frac{1}{3}\frac{(a_4 + a_3)^2 - a_4 a_3 - (a_1 + a_2)^2 + a_1 a_2}{(a_4 + a_3 - a_2 - a_1)},, \tilde{a} = (a_1, a_2, a_3, a_4) \tag{9}$$

Table 4. Linguistic terms and their corresponding fuzzy components (used in the FFTA method)

No.	Linguistic Terms	symbol	Corresponding fuzzy Components
1	Very low	VL	(0,0,1.0,25.0)
2	Low	L	(0,25.0,25.0,4.0)
3	Medium	M	(3.0,5.0,5.0,7.0)
4	High	H	(6.0,75.0,75.0,9.0)
5	Very High	VH	(8.0,9.0,1,1)

The probability of failure of the PHM system efficiency, which consists of correctly detecting the defect and the probability of accurately predicting the failure, is estimated using Eq. (10). Since the events of efficiency and the absence of the PHMs system are both related to the same sample space and are complementary at the same time, in this equation, $FP(BE_i)$ is equal to the failure possibility of i'th basic event, and m is equal to the number of basic events. The possibility of the efficiency of the system ($P(\Lambda_{PHM})$) or the efficiency index of the PHM system is equal to the complement of the failure possibility of this system through Eq. (11) (Mottahedi & Ataei, 2019).

$$FP(\Lambda_{PHM}) = \prod_{i=1}^{m} FP(BE_i) \tag{10}$$

$$P(\Lambda_{PHM}) = 1 - FP(\Lambda_{PHM}) \tag{11}$$

3- Case study

The Chadormalu Iron Ore mine was used as the case study for applying the proposed approach. The mine is located in the central desert of Iran, near Yazd City, with a geological reserve of 400 million tons and an average iron grade of 55.2%. The extraction ratio is 2 to 1 ton. The equipment at the mine is divided into two parts: machinery in the extraction unit and equipment and systems in the processing unit. The mill system, located at the entrance of production line 2 and responsible for milling minerals, was chosen for the study as it is considered a bottleneck in the production line. The mill system includes an electric motor, gearboxes, a lubrication system, and a mill body. Due to the increase in mineral grade at the mine, the mill system has changed from semi-autogenous grinding mills (SAG MILL) to autogenous mills (AG MILL). Figure 3 demonstrates a view of the mill system.

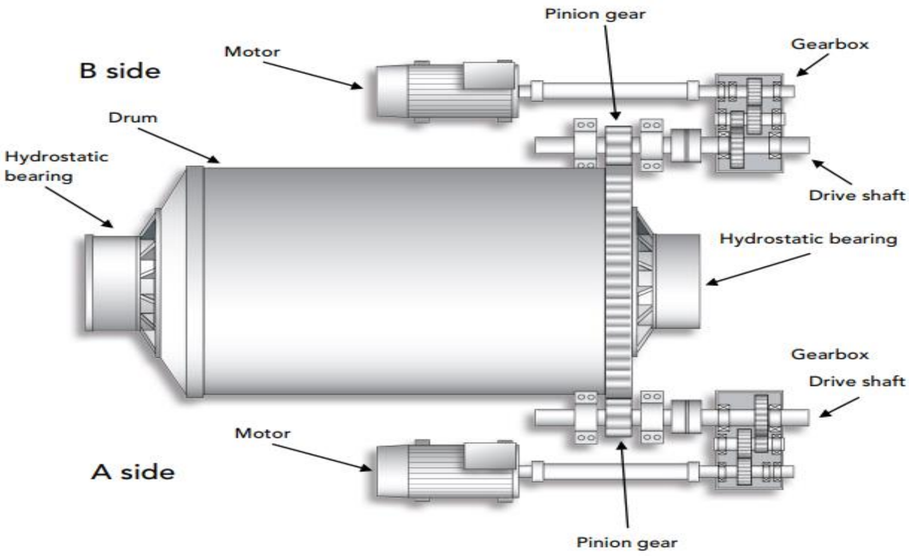

Figure 3. Diagram of AG MILL department [***Author's own creation***]

3-1 Organizational Resilience analysis of the mill department

The methodology shown in Figure 2 was used to evaluate the organizational resilience of the management team of the Chadormalu mine processing plant. A questionnaire with key components for measuring resilience was used. The questionnaire was carefully designed to be clear for better understanding and accurate answers. The questionnaire was used to collect the perspectives of fifteen experts who were selected as representatives of the relevant domain. The Likert rating technique was then used to quantify the gathered expert opinions, as shown in Table 2. Subsequently, following the quantification of expert opinions, the quantified opinions were integrated using Eq. (4) to obtain the fuzzy values of each factor influencing the mentioned organization's resilience. Due to the factor scores being fuzzy, these scores cannot be used to calculate the resilience of the intended organization. According to Eq. (5), these numbers became non-fuzzy. Finally, the resilience of the Chadormalu set was calculated using the average of the main influential factors. Table 5 shows the results of the above calculations. A fixed and equal weight for experts is a crucial consideration when assessing this rating. This is the result of getting input from a group whose members all possess the same amount of education and expertise.

Table 5. The results of the estimated scores for major influence factors on the organization's resilience

Symbol of Factors	Final Score of Factors	Organization Resilience Attributes	Final Score of Organization Resilience Attributes	Organization Resilience Score
SA1	0.567	Situation Awareness (AS)	0.53	0.53
SA2	0.560			
SA3	0.463			
SA4	0.466			
SA5	0.543			
SA6	0.631			
SA7	0.507			
KV1	0.492	Management of keystone Vulnerabilities (KV)	0.51	
KV2	0.501			
KV3	0.567			

KV4	0.464			
KV5	0.641			
KV6	0.415			
KV7	0.493			
AC1	0.559	Adaptive Capacity (AC)	0.54	
AC2	0.548			
AC3	0.500			
AC4	0.653			
AC5	0.550			
AC6	0.495			
AC7	0.448			

3-2 Estimation of RMS indicators in the mill department

Following delimitation and the system selection based on the suggested methodology in Figure 2, data was gathered over 24 months from various departments, such as the production line, control room unit, and the repair shop unit. The collected data was categorized into the time between failure (TBF), time to repair (TTR), and time to delivery (TTD). Table 6 provides an example of failure data (TBF) extracted from the collected mine data.

Table 6. TBF data of AG mill system

Failures No.	TBF	Status	Covariates				
			Field Data			Monitoring data	
			Shift	Team	Environment Temp	System Temp	Gearbox Vibration
1	21.7	0	3	3	20.15	58.99	2.15
2	342.3	1	3	3	11.79	58.28	2.3
3	48.5	1	3	1	10.79	61.64	2.75
4	13.5	1	1	1	7.84	55.63	2

The article emphasizes the importance of keeping high supportability, set at 90%, for mineral processing operations to ensure continuous production. The AG mill system is a critical component in the production line, highlighting the need for a quick response in case of failures. The mine's policy dictates zero downtime, and the spare parts warehouse is designed to minimize response time. Also, time to repair (TTR) data are demonstrated in Table 7 to analyze the AG system's maintainability and the influential risk factors.

Table 7. TTR data of AG mill system

NO.of Repairs	TTR	Status	Shift	Environment Temp (C°)
1	0.72	0	1	16.39
2	0.75	0	2	10.79
3	0.75	0	1	9.93
4	125.78	1	1	11.02

The article utilized both graphical and analytical methods to determine the most suitable model from Table 3. The analytical method was specifically employed to overcome the limitations associated with the graphical method, particularly when confronted with an increasing number of layers and the intricate nature of qualitative covariates. The results from the graphical method showed that the AG mill covariates were not dependent on time for each reliability and maintainability indicator. The shift work covariate was demonstrated based on the three shifts work (morning, noon, and night). As seen in Figure 4, the parallelism of the curves indicates the layers' independency on time.

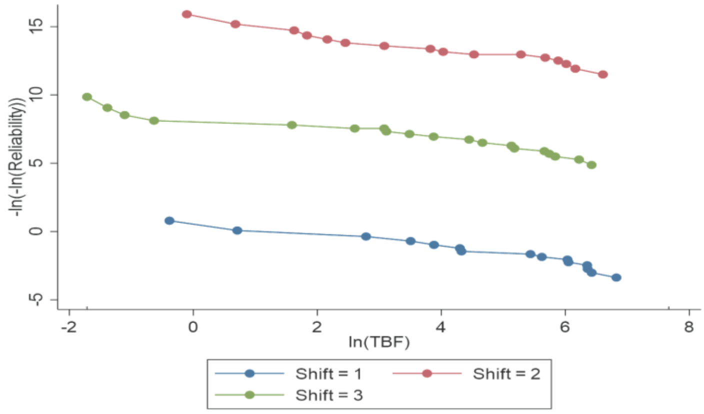

Figure 4. Log -Log chart for Shift work covariate [***Author's own creation***]

Results from the analytical method (Schonfield's residuals) in Table 8 demonstrate that AG mill's covariates are time-independent. Thus, PHM and PRM models will be used for reliability and maintainability, respectively (Cox, 1972).

Table 8. PH test of RMS indicators

AG	Covariates	ρ	Chi2	df	P-Value	PH assumption
Reliability	Shift	-0.04	0.07	1	0.79	accepted
	Team	0.00	0.00	1	0.99	accepted
	Environment Temp	-0.15	1.15	1	0.28	accepted
	Gearbox Vibration	-0.06	0.26	1	0.61	accepted
	System Temp	0.07	0.21	1	0.64	accepted
Maintainability	Shift	0.02	0.05	1	0.8	accepted
	Environment Temp	-0.12	1.04	1	0.30	accepted

The results of identifying the significant covariates for the AG mill system are shown in **Feil! Fant ikke referansekilden.**. Based on the result obtained, the vibration of the gearbox subsystem has a significant influence on the reliability function of the AG mill system. and also after two steps, there is no influence covariate on the maintainability function of the system. According to Table 9, the fourth column is the regression coefficient of the covariates used in reliability or maintainability models. The fifth column indicates the Wald statistics of the factors; the sixth column shows the significance level of the factors and the most critical column in this Table. Also, the seventh column represents the hazard rate of each risk factor, and the increase or decrease of this rate significantly affects the increase or decrease of behavior indicators.

Table 9. Risk factors and their significance in equation with reliability and maintainability

Index	Step	Covariates	α	Wald	p-value	Hazard Ratio
Reliability	Five	Gearbox Vibration	1.11	4.73	0.03	3.04
Maintainability	two	Environmental temp	0.00	0.06	0.79	1.00

Table 10 shows the AIC and BIC values of the Weibull and exponential distribution for the reliability model and the exponential, Weibull, and lognormal distribution for the maintainability model. The results showed that the Weibull function was chosen for the basic reliability and maintainability of the AG2 system. The Weibull function was selected for reliability and maintainability when selecting distribution functions for the AG2 system.

Table 10. AIC and BIC goodness of fit tests statistics

Baseline	System	Function	AIC	BIC
Reliability	AG	Weibull	236.44	250.23
		Exponential	265.66	277.48
Maintainability	AG	Weibull	442.64	454.94
		Exponential	507.40	519.70
		Lognormal	648.12	660.42

The scale and shape parameters of the Weibull function are presented in Table 11.

Table 11. Parameter values of reliability and maintainability functions

AG	Function	Parameter values	
		Shape (θ)	Scale (β)
Reliability	2-parameter Weibull	0.57	44110
Maintainability	2-parameter Weibull	0.57	24.8

After determining the coefficients of the effective risk factor and the basic function, the reliability and maintainability of the system were determined using Eq.(12) and Eq. (13), respectively

• AG reliability

$$R(t,z) = (exp(-(\frac{t}{44110})^{0.57})^{exp(1.115 \times z_4)} \quad (12)$$

• AG maintainability

$$M(t,w) = 1 - (1 - (1 - (exp(-(\frac{t}{24.809})^{0.58})))) \quad (13)$$

Figure 5 and Figure 6 present the reliability and maintainability functions of the AG system, respectively. In the Figure 5. If a risk factor is present, the classical model is represented by

“*AG-B*” which shows the reliability function without covariates, and “*AG-PHM*” shows the reliability function based on covariates.

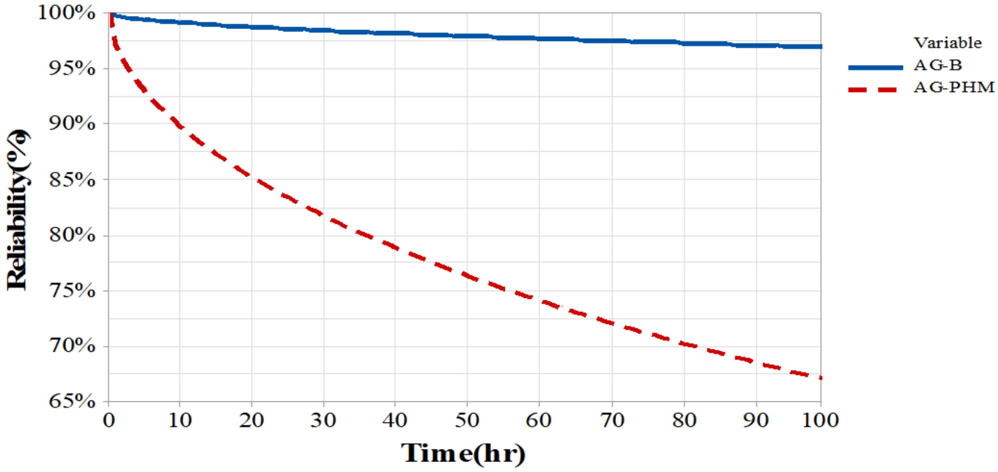

Figure 5. Reliability of AG mill system [*Author's own creation*]

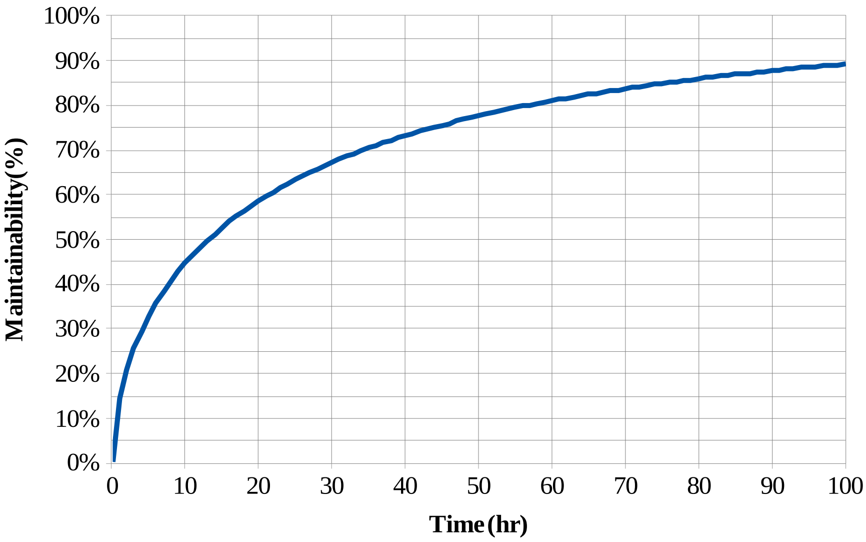

Figure 6. Maintainability of AG mill system [*Author's own creation*]

3-3 Analysis of the efficiency of the system (PHM)

The efficiency of the PHM system depends on the ability to detect events and accurately diagnose defects in the AG mill system of the Chadormalu mine. The article mentions using the FFTA method to estimate these values, and a questionnaire was designed to gather expert opinions, which are presented in Table 12.

Table 12. PHM questionnaire to obtain experts' opinions

No	Symbol	Question	Linguistic variables symbol				
			VL	L	M	H	VH
1	Λ_D	What is the probability of correctly diagnosing failures in the mill system?					
2	Λ_P	What is the probability of correct prognostics in the mill system?					

After quantifying the experts' opinions, these opinions should be integrated using Eq. (8) to calculate the fuzzy values of each event. Next, the fuzzy numbers from integrating opinions were determined using Eq.(9), and each of the basic events' failure probability (FP) was estimated. The efficiency possibility of the PHM system or the efficiency index of the PHM system was calculated using Eq. (11). The results of the above steps are presented in Table 13.

Table 13. The results of the questionnaire survey

Event	Merged comments				Possibility of failing events	Possibility of PHM failure	Possibility of PHM performance
Λ_D	0.27	0.44	0.44	0.61	0.441	0.221	0.799
Λ_P	0.32	0.50	0.50	0.68	0.500		

3-4 Estimation of The AG Mill System Resilience

Eq. (3) was used to determine the resilience of the AG mill system in the Chadormalu mine processing plant. Figure 7 shows the influence of covariates, system efficiency of PHM, and organizational resilience in the resilience of AG mill over 200 hours of operation. In this figure:

- AG1 denotes resilience using organizational resilience and system efficiency PHM by expert judgment and RMS based on covariate(gearbox vibration).
- AG2 indicates resilience using organizational resilience and system efficiency PHM by expert judgment and RMS estimation without considering covariate.
- AG3 demonstrates resilience using a constant value of 85% for organizational resilience and system efficiency PHM and RMS estimation while considering covariate(gearbox vibration).
- AG4 shows resilience using constant value of 85% for organizational resilience and system efficiency PHM, and RMS estimation without considering covariate(gearbox vibration).
- As can be seen, there are differences in the amount of resilience with considering covariates and expert judgment in the estimation of RMS, system efficiency PHM, and organizational resilience.

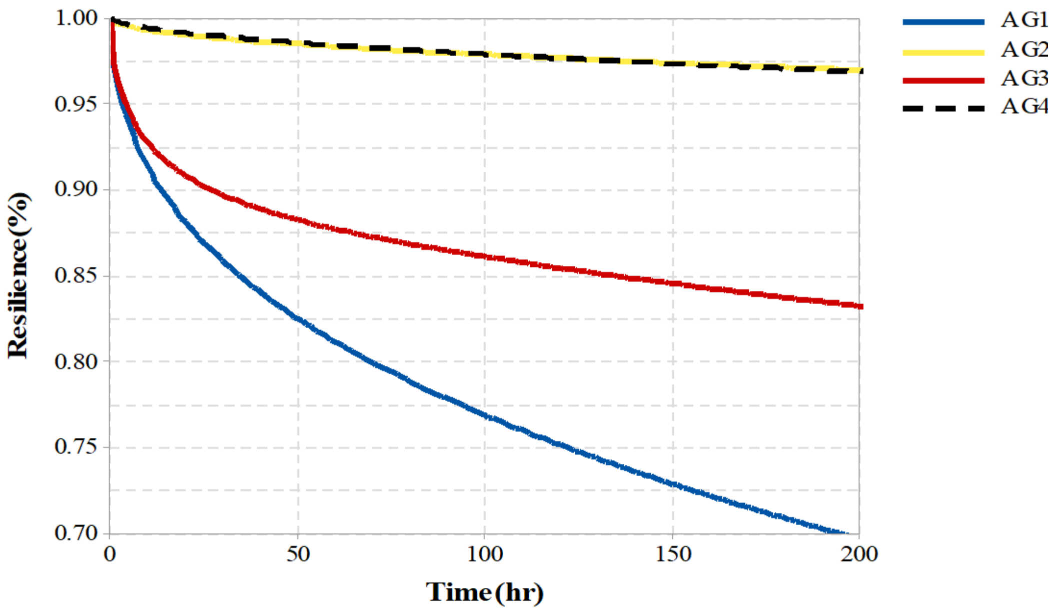

Figure 7.The resilience of the AG mill system [*Author's own creation*]

4. Conclusion

Resilience is the ability of a system to withstand and recover after a disruptive event. One of the key components of systems resilience management is the estimation of the amount of system resilience. In this article, the estimation of resilience based on the concept of resilience has two main parts. The robustness of the resilient system before disruption and recovery of the resilient system after disruptions. Reliability was introduced for the first part, and recovery(maintainability, supportability, system efficiency PHM, and organizational resilience) was introduced for the second part. Expert opinions have been utilized to estimate the organizational resilience and system efficiency PHM and environmental and operational factors that affect the performance of the system have been used to estimate reliability, maintainability, and supportability. The mill system of the production line at the Chadormalu mine was chosen as a case study. The mill system of the processing plant is crucial because it acts as a bottleneck in the production line. Results in Figure 7 showed there are significant differences in the amount of resilience if covariates or risk factors and experts' opinions are considered during 200 hours of operation. If we consider the risk factors in RMS estimation and the opinions of experts in organizational resilience and system efficiency PHM, after 200 hours of operation, the system has a value of 70%. Despite without considering the risk factors and experts' opinions in the estimation of the mentioned indicators, the amount of resilience reaches 97%. Therefore, they are very important to consider risk factors such as gearbox vibration in estimating RMS indicators and attributes like situation awareness in organizational resilience. The PHM index plays a crucial role in the resilience and reliability of systems. In the previous articles on measuring resilience, the index value of PHM was assumed to be constant. In this article, it was tried to use experts' opinions and fuzzy logic in the estimation of the mentioned index. It is recommended to use data analysis(sensors, monitoring equipment, historical records), modeling, and predictive algorithms(statistical analysis, machine learning, deep learning, and time-series analysis) to estimate PHM.

5. Resources

Ahmed, S., Dey, K., & Fries, R. (2019). "*Evaluation of transportation system resilience in the presence of connected and automated vehicles*". Transportation Research Record, *Vol. 2673, Issue 9, pp. 562–574*(9).

Aleksić, A., Stefanović, M., Arsovski, S., & Tadić, D. (2013). "*An assessment of organizational resilience potential in SMEs of the process industry, a fuzzy approach*". Journal of Loss Prevention in the Process Industries, *Vol. 26, Issue 6, pp. 1238–1245*(6).

Barabadi, A., & Aalipour, M. (2015). "*Maintainability management of production facilities in complex and challenging operating conditions*". 2015 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM).

Barabadi, A., & Ayele, Y. Z. (2018). "*Post-disaster infrastructure recovery: Prediction of recovery rate using historical data*". Reliability Engineering & System Safety, *Vol. 169, pp. 209–223*.

Barabadi, A., Barabady, J., & Markeset, T. (2011a). "*A methodology for throughput capacity analysis of a production facility considering environment condition*". Reliability Engineering & System Safety, *Vol. 96, Issue 12, pp. 1637–1646*(12).

Barabadi, A., Barabady, J., & Markeset, T. (2011b). "*Maintainability analysis considering time-dependent and time-independent covariates*". Reliability Engineering & System Safety, *Vol. 96, Issue 1, pp. 210–217*(1).

Benito Del Pozo, P., & López-González, A. (2020). "*Urban resilience and the alternative economy: A methodological approach applied to Northern Spain*". Geographical Review, *Vol. 110, Issue 3, pp. 322–340*(3).

Bristow, G. (2018). "*Reflections on the Welsh economy: Remanence, resilience and resourcefulness*". Welsh Economic Review, *Vol. 26, pp. 13–20*.

Burnard, K., & Bhamra, R. (2011). "*Organisational resilience: development of a conceptual framework for organisational responses*". International Journal of Production Research, *Vol. 49, Issue 18, pp. 5581–5599*(18).

Carlsson, C., & Fullér, R. (2001). "*On possibilistic mean value and variance of fuzzy numbers*". Fuzzy Sets and Systems, *Vol. 122, Issue 2, pp. 315–326*(2).

Chen, C.-T. (2000). "*Extensions of the TOPSIS for group decision-making under fuzzy environment*". Fuzzy Sets and Systems, *Vol. 114, Issue 1, pp. 1–9*(1).

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010). "*Seismic resilience of a hospital system*". Structure and Infrastructure Engineering, *Vol. 6, Issues 1–2, pp. 127–144*(1–2).

Cox, D. R. (1972). "*Regression Models and Life-Tables*". Journal of the Royal Statistical Society: Series B (Methodological), *Vol. 34, Issue 2, pp. 187–202*(2).

Denyer, D. (2017). "*Organizational Resilience: A summary of academic evidence, business insights and new thinking*". BSI and Cranfield School of Management.

Dhillon, B. S. (2006a). (Vol. 128). CRC Press Taylor & Francis Group. c:%5CUsers%5CAli%5CAppData%5CRoaming%5CMozilla%5CFirefox%5CProfiles%5Cwohuknv0.default%5Czotero%5Cstorage%5CETTTA45F%5Cmaintainability-maintenance-and-reliability-for-engineers.html

Dhillon, B. S. (2006b). CRC press.

Dhillon, B. S. (2008). Springer.

Ghodrati, B., Akersten, P.-A., & Kumar, U. (2007). "*Spare parts estimation and risk assessment conducted at Choghart Iron Ore Mine: A case study*". Journal of Quality in Maintenance Engineering, *Vol. 13, Issue 4, pp. 353–363*(4).

Ghomghaleh, A., Khaloukakaie, R., Ataei, M., Barabadi, A., Nouri Qarahasanlou, A., Rahmani, O., & Beiranvand Pour, A. (2020). "*Prediction of remaining useful life (RUL) of Komatsu excavator under reliability analysis in the Weibull-frailty model*". Plos One, *Vol. 15, Issue 7, p. e0236128*(7).

Henry, D. (2012). "*Emmanuel Ramirez-Marquez J. Generic metrics and quantitative approaches for system resilience as a function of time*". Reliab Eng Syst Saf, *Vol. 99, pp. 114–122*.

Holling, C. S. (1973). "*Resilience and stability of ecological systems*". Annual Review of Ecology and Systematics, *Vol. 4, Issue 1, pp. 1–23*(1).

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). "*A review of definitions and measures of system resilience*". Reliability Engineering & System Safety, *Vol. 145, pp. 47–61*.

Javed, K., Gouriveau, R., Zerhouni, N., & Nectoux, P. (2014). "*Enabling health monitoring approach based on vibration data for accurate prognostics*". IEEE Transactions on Industrial Electronics, *Vol. 62, Issue 1, pp. 647–656*(1).

Komal, S. (2019). "*Fuzzy reliability analysis of the compressor house unit (CHU) system in a coal fired thermal power plant using TBGFLT technique*". Int J Qual Reliab Manage, *Vol. 36, Issue 5, pp. 686–707*(5).

Kumar, D., & Klefsjö, B. (1994). "*Proportional hazards model: a review*". Reliability Engineering & System Safety, *Vol. 44, Issue 2, pp. 177–188*(2).

Madani, F., & Parast, M. M. (2023). "*An integrated approach to organizational resilience: a quality perspective*". In *International Journal of Quality and Reliability Management* (Vol. 40, Issue 1, pp. 192–225).

McManus, S. (2007). "*Organisational resilience in New Zealand, unpublished doctor of philosophy thesis*". University of Canterbury, Christchurch.

McManus, S., Seville, E., Brunsden, D., & Vargo, J. (2007). *Resilience management: a framework for assessing and improving the resilience of organisations*.

Mottahedi, A., & Ataei, M. (2019). "*Fuzzy fault tree analysis for coal burst occurrence probability in underground coal mining*". Tunnelling and Underground Space Technology, *Vol. 83, pp. 165–174*.

Mottahedi, A., Sereshki, F., Ataei, M., Nouri Qarahasanlou, A., & Barabadi, A. (2021). "*Resilience analysis: A formulation to model risk factors on complex system resilience*". International Journal of System Assurance Engineering and Management, *Vol. 12, Issue 5, pp. 871–883*(5).

Mottahedi, A., Sereshki, F., Ataei, M., Qarahasanlou, A. N., & Barabadi, A. (2021). "*Resilience estimation of critical infrastructure systems: Application of expert judgment*". Reliability Engineering & System Safety, *Vol. 215, p. 107849*.

Omri, N., Al Masry, Z., Mairot, N., Giampiccolo, S., & Zerhouni, N. (2021). "*Towards an adapted PHM approach: Data quality requirements methodology for fault detection applications*". Computers in Industry, *Vol. 127, p. 103414*.

Petersen, L., Lundin, E., Fallou, L., Sjöström, J., Lange, D., Teixeira, R., & Bonavita, A. (2020). "*Resilience for whom? The general public's tolerance levels as CI resilience criteria*". International Journal of Critical Infrastructure Protection, *Vol. 28, p. 100340*.

Rahimdel, M. J., Ataei, M., & Khalokakaei, R. (2016). "*Reliability Analysis and Maintenance Scheduling of the Electrical System of Rotary Drilling Machines*". In *Current Trends in Reliability, Availability, Maintainability and Safety* (pp. 623–632). Springer.

Rød, B., Barabadi, A., & Gudmestad, O. T. (2016a). "*Characteristics of arctic infrastructure resilience: Application of expert judgement*". Proceedings of the International Offshore and Polar Engineering Conference, *Vols. 2016-Janua, pp. 1226–1232*.

Rød, B., Barabadi, A., & Gudmestad, O. T. (2016b). "*Characteristics of arctic infrastructure resilience: application of expert judgement*". The 26th International Ocean and Polar Engineering

Conference.

Seville, E. (2009). *The Goal of Resilient Organisations*.

Sharma, S. K., & George, S. A. (2018). "*Modelling resilience of truckload transportation industry*". Benchmarking: An International Journal, *Vol. 25, Issue 7, pp. 2531–2545*(7).

White, R. K., Edwards, W. C., Farrar, A., & Plodinec, M. J. (2015). "*A practical approach to building resilience in America's communities*". American Behavioral Scientist, *Vol. 59, Issue 2, pp. 200–219*(2).

Youn, B. D., Hu, C., & Wang, P. (2011). "*Resilience-driven system design of complex engineered systems*". Journal of Mechanical Design, Transactions of the ASME, *Vol. 133, Issue 10*(10).

Yu, Y., Peng, L., Chen, L., Long, L., He, W., Li, M., & Wang, T. (2014). "*Resilience and social support promote posttraumatic growth of women with infertility: The mediating role of positive coping*". Psychiatry Research, *Vol. 215, Issue 2, pp. 401–405*(2).