UiT The Arctic University of Norway

Faculty of Science and Technology
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Resilience, Reliability, and Recoverability (3Rs) in Engineering Systems A review

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Review of Resilience, Reliability and Recoverability (3Rs) in Engineering Domain

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Abstract

Recent natural and human-made disasters, mortgage derivatives crises, and the need for stable systems in different areas have renewed interest in the concept of *resilience*, especially as it relates to complex industrial systems with mechanical failures. This concept in the engineering systems (infrastructure) domain could be interpreted as the probability that system conditions exceed an irrevocable tipping point. But the probability in this subject covers the different areas that different approaches and indicators can evaluate. In this context, reliability engineering is used the reliability (uptime) and recoverability (downtime) indicators (or performance indicators) as the most useful probabilistic tools for performance measurement. Therefore, our research penalty area is the resilience concept in combination with reliability and recoverability. It must be said that the resilience evaluators must be considering a diversity of knowledge sources. In this thesis, the literature review points to several important implications for understanding and applying resilience in the engineering area and The Arctic condition. Indeed, we try to understand the application and interaction of different performance-based resilience concepts. In this way, a collection of the most popular performance-based resilience analysis methods with an engineering perspective is added as a state-of-the-art review. The performance indicators studies reveal that operational conditions significantly affect the components, industry activities, and infrastructures performance in various ways. These influential factors (or heterogeneity) can broadly be studied into two groups: observable and unobservable risk factors in probability analysis of system performance. The covariate-based models (regression), such as proportional hazard models (PHM), and their extent are the most popular methods for quantifying observable and unobservable risk factors.

The report is organized as follows: After a brief introduction of resilience, chapters 2,3 priorly provide a comprehensive statistical overview of the reliability and recoverability domain research by using large scientific databases such as Scopus and Web of Science. As the first subsection, a detailed review of publications in the reliability and recoverability assessment of the engineering systems in recent years (since 2015) is provided. The second subsection of these chapters focuses on research done in the Arctic region. The last subsection presents covariate-based reliability and recoverability models. Finally, in chapter 4, the first part presents the concept and definitions of resilience. The literature reviews four main perspectives: resilience in engineering systems, resilience in the Arctic area, the integration of "Resilience, Reliability, and Recoverability (3Rs)", and performance-based resilience models.

Keywords: Resilience, Operation and maintenance, Performance indicators, Covariates-based models.

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1- INTRODUCTION

1.1. Background and problem statement

Extensive analysis of engineering systems reveals that in many cases, “failure” is at best a statistical certainty or, at worst, a part of a “normal” operation. The dominant approach to preventing failure in engineering systems is performance analysis, which consists of key performance indicators assessment such as reliability, recoverability, availability, etc. However, in complex systems, performance analysis alone is inadequate to fully protect system functions and components. In this regard, resilience has been introduced as a new idea in the engineering domain. This concept can be considered a process that makes it possible to effectively respond to unanticipated changes and unexpected events, vulnerabilities, and opportunities lying outside the scope of formal procedures (Hosseini *et al.*, 2016). A prerequisite to viable resilience metrics is an understanding of the resilience performance of the system. As Hollnagel (Hollnagel, 2011) said, resilient performance requires four system abilities: respond, monitor, learn, and anticipate. On the other hand, when engineers want to use any idea, they need to quantify them. In this view, a resilience assessment method requires these principles to be translated into some measurable items. Here reliability engineering addressed the key performance indicators (KPI) for measuring the system behavior in different conditions of a whole lifetime (Barabadi *et al.*, 2016; Lindberg *et al.*, 2015; Parmenter, 2015). In making a connection between KPI and resilience concepts, the resilience attributes of the system can be characterized as (Yarveisy *et al.*, 2020):

- Absorptive capacity: The extent of the system's ability to reduce the adverse effects of disturbances and maintain higher residual performance
- Adaptive capacity: the reaction to the stressor's effect, the system's ability to continue operations in the stable disturbed state, and the readiness to initiate the recovery after the failure.
- Restorative: The system's capability to be rapidly repaired requires minimal support and higher performance levels than the disrupted state.

These attributes evoke the most useful probabilistic and analytic indices such as reliability, recoverability in the mind that finding the connection between them and resilience is the main purpose of the present research. The idea of reliability, recoverability, and resilience integration is named “3R”. A prerequisite to 3R is to understand these performance-based resilience assessment approaches that a broad literature review can reach. When performance indices are measured in the Arctic region, the operating condition makes it more challenging for researchers. Therefore, the divergences of these indicators will also contain the same challenges. Accordingly, resilience assessment in the Arctic can be faced with new barriers.

1.2. Aims and Objectives

The main aims of this master thesis are to evaluate and determine suitable methods and tools for performance measurement of engineering facilities and activities. More specifically, the objectives of this master thesis are:

• To define and review the recent research and developments for 3Rs and their statistical approaches in the engineering field.

• To determine suitable methods to quantify resilience using the performance indicators (reliability and recoverability).

• To assess and evaluate how Arctic operational and environmental risk factors can affect 3Rs.

1.3. Research Questions

The following research questions are posed to achieve the research objectives of the thesis:

RQ1. What are the available research and developments literature for 3Rs and their statistical approaches in the engineering field?

RQ2. How can the performance indicators (reliability and recoverability) quantify the resilience?

RQ3. How operational and environmental risk factors in the Arctic can affect 3Rs?

1.4. Outline of the master thesis

I. At the first step in *sections 1 and 2 of chapters 2 and 3, each chapter's literature distribution by domains, years of publication, and journals are* evaluated. The Web of Science (WOS, 2020) and Scopus (Elsevier, 2020) database is the most comprehensive multidisciplinary content search platform for academic researchers to search and analyze related papers. In this stage, using keywords to search, we selected those papers only relevant to modeling and measuring each index in engineering systems and research done in the Arctic area. Recent research and developments for 3R and its approaches, mainly from 2015 to 2020, are reviewed in more detail. This literature review approach was applied to the papers published in WOS from 1978 to 2020 and Scopus from 1851 to 2020. Moreover, *section 3 of chapter 4* is allocated for performance-based-resilience papers review.

II. Secondly, in *section 3 of chapters 2 and 3; and section 4 of chapter 4, we try to find how resilience can be quantified* using the performance indices (reliability and recoverability). These indices could be shown the necessary and sufficient characterization of the infrastructure or system over its lifetime (Reliability covers the uptime and recoverability cover the downtime). The mentioned indices improvement has been the subject of many research and articles. The primary objective in this part is to study probabilistic methods that characterize infrastructure systems' resilience using performance indices such as reliability and recoverability metrics. These metrics can easily be influenced by operating environment conditions named “risk factors” or “covariates” in the reliability engineering. The covariate could be classified as observable and unobservable risk factors. *Observable risk factors* describe the recovery process characteristics. Environmental conditions such as wind speed, wind direction, temperature, and polar low must be described and quantified based on how they can affect the performance, update the safety procedure, and organizational management rules. *Unobservable risk factors* are independent variables that may significantly impact recovery and operating time. However, these are not reported or directly unquantifiable (and thus not available in databases) but cause heterogony. For example, external managerial advice might help the repair crew maintain the failures and recover the system (Gutierrez, 2002; Hougaard, 1995; Wienke, 2010). Thus, a comprehensive study of covariate-based models needs to consider the risk factor effect of performance indices and, finally, resilience.

III. In this regard, the outline of *section 3 of chapter 2* starts with the primary statistical definition of reliability. It will then provide a review of covariate-based methods used to describe environmental effects on reliability. Since basic theory and recoverability models are like reliability. Also, *section 3 of chapter 3* presents a brief introduction and description of recoverability. The focus is on the mixture frailty model (MFM). *Section 4 of chapter 4* illustrates several models and frameworks to predict system resilience over time under various concepts. This chapter's main objective is to understand the subject with quantification vision and mathematics or statistics.

This chapter provides a comprehensive statistical overview of the research in the reliability domain. Then, a detailed review of publications in the reliability assessment of the engineering systems field is provided in recent years. Then, the focus is on research done in the Arctic systems. Ultimately, the statical theory of reliability will be presented as classical and covariate-based models.

2- RELIABILITY

Reliability is a general concept that can be applied freely to diverse subjects with needed adjustments: function, performance, and lifetime are concepts that will be discipline-specific. Reliability analysis is an important and often the most time-consuming step in design and performance assessment under uncertainty. However, the estimation ability of reliability and the probability of failure is critical to reducing maintenance costs, operation downtime, safety hazards and is an indispensable requirement tool in most engineering and management fields. Numerous methods have been proposed to analyze engineering product reliability while considering various uncertainty sources (e.g., loads, material properties, and geometric tolerances). Design parameters are usually considered random variables to formulate reliability analysis in a mathematical framework. The “International Electrotechnical Commission” (IEC) defined reliability as the ability of an item to perform a required function under given conditions for a given time interval (IEC, 2019). Traditionally, reliability analysis of an asset is done just based on failure event data that couldn't be applicable in real-life situations due to poor data management (Barabady, 2005, 2007; Barabady and Kumar, 2008; Gao *et al.*, 2010a; Kumar, 1990; Kumar and Huang, 1993; Kumar and Klefsjö, 1992; Rahimdel *et al.*, 2013). In real situations, many parameters could be affected the system performance, which is defined as "Covariate" or "Risk factor" in performance analysis. Covariates are different indicators that influence and/or indicate the lifetime of a piece of equipment (Gorjian Jolfaei, 2012). Condition indicators and operating environment indicators are two types of risk factors that are normally obtained in addition to failure events and suspended data (or censored data). Risk factors contain important information about an asset's state and operating condition. They reflect the level of assets' degradation while operating environment indicators accelerate or decelerate the lifetime of assets and change the performance. For example, in the Arctic region, known to have a harsh climate and a sensitive environment in a remote location, the severe and complex operational conditions can significantly affect a system's lifetime, the repair processes, and the support activities. Hence, considering the operational conditions' effect on the production facility/systems/equipment and machines' performance, the related reliability and maintainability characteristics are essential. In this situation, if data are available and observable, an alternative approach to the traditional reliability analysis is modeling risk factors using a "Covariate-based hazard model". This approach considers risk factors an "Observable risk factor," and their development began in the 1970s to overcome the traditional one's deficiency. From the 1970s to 1990s, reliability models with covariates have been originated and then have been applied in the field of engineering assets (Ahmadi *et al.*, 2010; Barabadi, 2011; Barabadi *et al.*, 2011a; Barabadi, 2014; Ghodrati, 2005; Ghodrati and Kumar, 2005a;

Giorgio *et al.*, 2014; Gorjian, Ma, *et al.*, 2010a, 2010b; Gorjian, Mittinty, *et al.*, 2010). Some of the most used covariate-based hazard models, which have been applied to estimate the hazard of an asset using its age and covariates, is included as the semi-parametric Explicit Hazard Model(EHM) such as Weibull Proportional Hazard Model (WPHM) (Lakshmi and Sundari, 2012), Accelerated Failure Time Model (AFTM) (Barabadi *et al.*, 2010), Proportional Odds Model (POM) (Gorjian Jolfaei, 2012), Additive Hazard Model (AHM) (Pijnenburg, 1991), Aalen Linear Regression Model (ALRM) (Kumar and Westberg, 1996), Proportional Covariate Model (Ghodrati, 2005), Proportional Intensity Model (PIM) (Prasad and Rao, 2002), Extended Cox Regression Model (ECRM) (Barabadi *et al.*, 2010), …. Sometimes, the evaluator couldn't foresee the risk factor or predict but couldn't be quantified it. These factors are defined as " Un-observable risk factors" in reliability engineering, and the covariate-based hazard models need an improvement to consider them in performance analysis (Aalen, 1992; Gutierrez, 2002; Hougaard, 1995; Rod *et al.*, 2020; Wienke, 2010; Zaki *et al.*, 2019).

The scientometrics[1] of reliability subject could help understand citations' processes, map scientific fields, and use research policy and management indicators. It can be considered the study of the quantitative aspects of science and technology seen as communication. Its initial purpose was not research evaluation but rather to help researchers search the literature more effectively. Successful quantitative analysis needs a comprehensive and accurate source of data. Thomson Reuters ISI Web of Science (WoS) and Scopus as major data sources are studied in the present report. WoS is a specialized database covering journal papers, conference proceedings and is beginning to cover books. Since 2004, as a similar rival database, Scopus has been available from Elsevier. It also covers journals, conferences, and books. Scopus retrieves back until 1996, while WoS has been available for all years since 1900 (Elsevier, 2020; Falagas *et al.*, 2008; WOS, 2020). In Figure 2-1, we can see the histograms of reliability application in different area that reaches from Scopus data source.

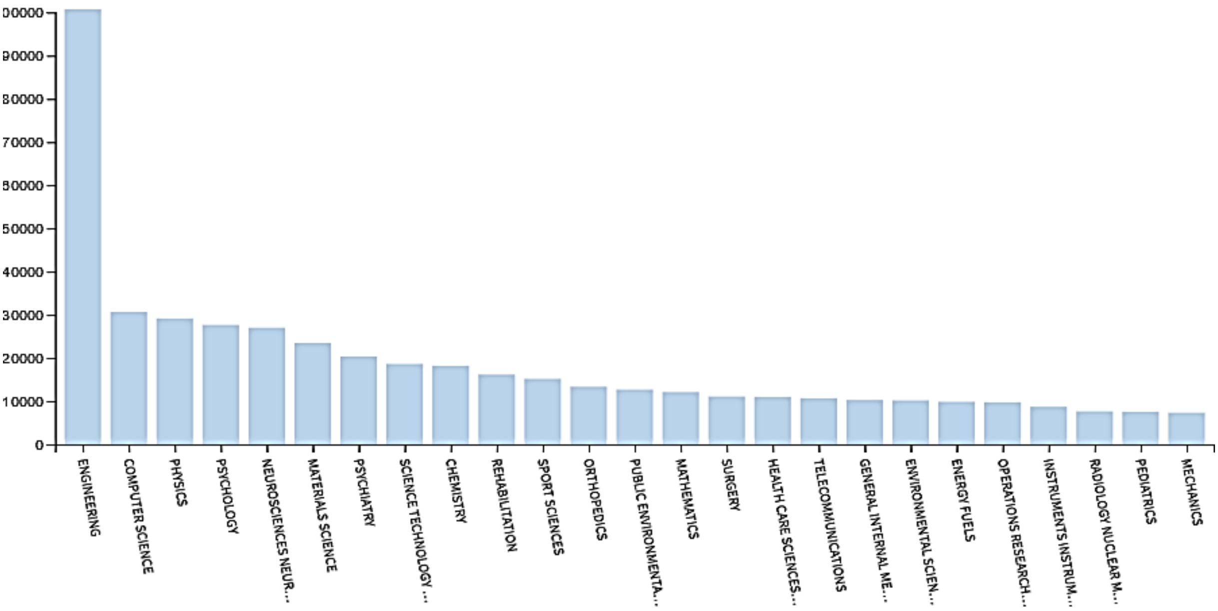

Figure 2-1- Research areas histograms of reliability publications from *Scopus* database in 1997-2020

[1] - Scientometrics is the study of the quantitative aspects of the process of science as a communication system.

This figure shows the engineering field is the most highly applied area of reliability from 1997 to 2020. Computer Science and Physics are the next priorities. The main categories of publications are shown in Figure 2-2 using a WoS data source. This chart shows that the large area belongs to engineering, especially the electrical field.

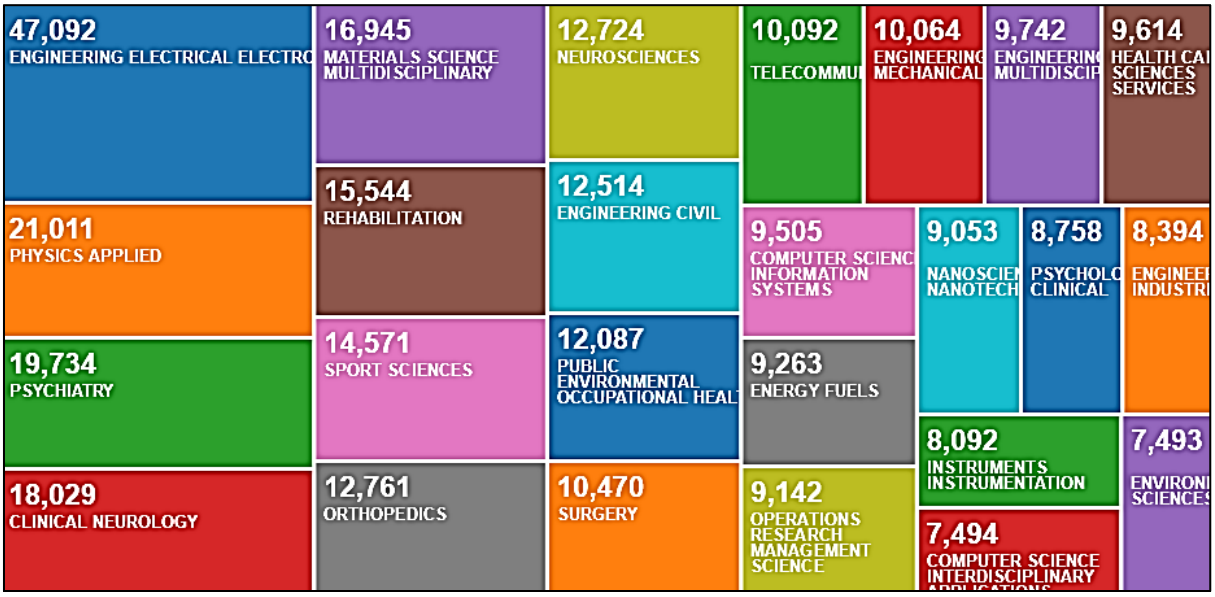

Figure 2-2- Area chart of science categories for reliability publications from *WoS* database

In Figure 2-3, the publication data source is clustering by year. The histogram's sharp increasing trend from 1997 to 2020 using the Scopus database shows the enormous attention to reliability subjects. Keep in mind that the frequencies for 2020 are most likely incomplete.

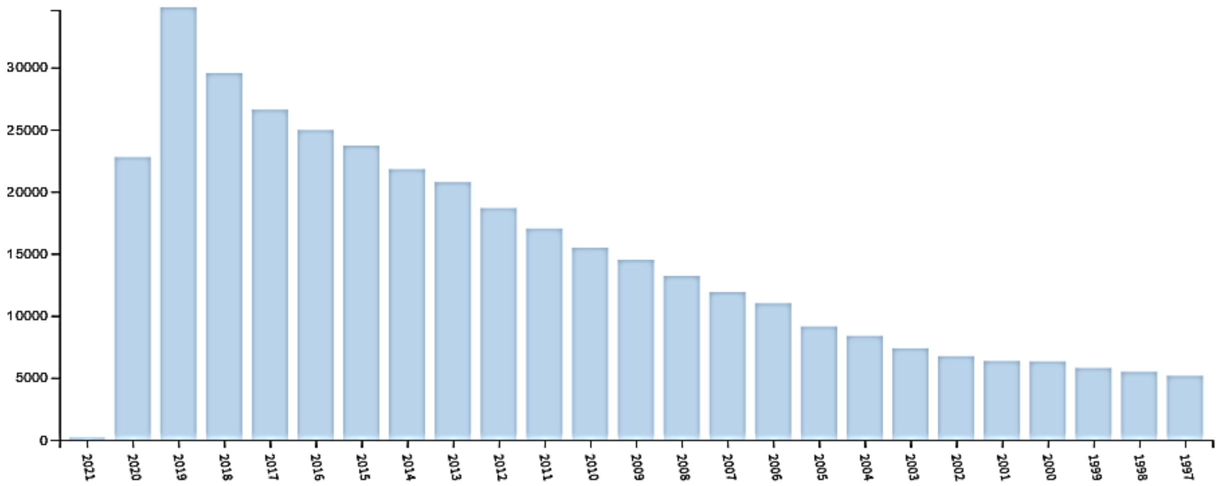

Figure 2-3- Published year histograms of reliability publications from *Scopus* database in 1997-2020

As a result, it can be concluded that one of the key problems facing scholarship today is the growth in the size of its literature. Researchers interested in scholarly communication quickly recognized that the Web is for scholars as a “nutrient-rich resource space. The scientometric perspective adds a quantitative focus on texts and communication to science and technology studies' interdisciplinarity. Our data source studies show that the reliability subject, especially in the engineering area, is still one of the most interesting domains and new opportunities for the new application. The main reasons for keeping researchers interested in the reliability domain are the increasing complexity of new systems and infrastructures and the quality of customers' demands in a different part of a supply chain in different industries and communities. Moreover, it can be concluded that integrating reliability with new concepts is another reason for the present condition. Of course, the statistical and mathematical aspects of reliability assessment also contribute to this concept's further engineering field growth.

2-1- The state of reliability concept in engineering systems

With the widespread manufacture and use of increasingly worldly engineering assets and systems, reliability engineering plays an important role in analyzing these systems' reliability performance. It is defined as an engineering discipline closely related to statistics and probability theory. This discipline applies scientific know-how to a component, product, plant, or process to guarantee intended function performance, without failure, for the required time duration under specified operating environment conditions (Kiran, 2016). The change in the number of scientific research results reflects, to a certain extent, the changes in the attention paid by international experts and scholars to a specific subject area. The increasing number of publications in Figure 2-4 based on scientific database information such as Scopus shows that engineering reliability still is one of the topics of interest. As seen in Figure 2 that the greatest number of articles was published last decade. We can see in this figure that the scientific production in the field of reliability in engineering has a slow increase from 1997 to 2007; however, in some year's fluctuations can be observed in the trend. There is a significant increase in 2019. Keep in mind that the frequencies for 2020 are most likely incomplete.

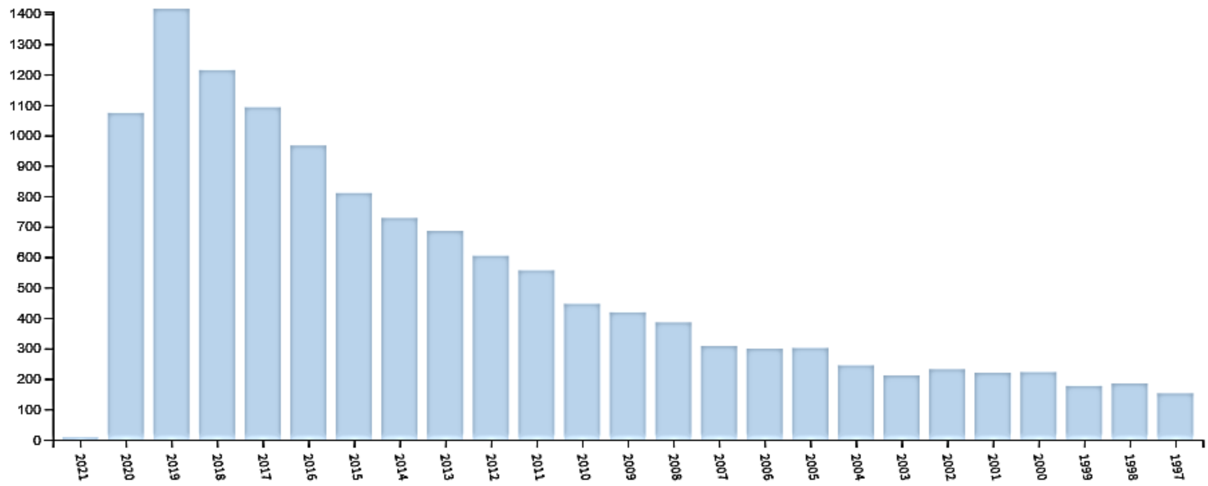

Figure 2-4- Published year histograms of reliability publications in an engineering field from *Scopus* database in 1997-2020

Moreover, to determine the literature's growth rate, scientometrics aims to determine subject areas of the literature. In this regard, Figure 2-5 indicates that a major contribution of the total output came from five engineering fields: Civil, Electronic, Multidiscipline, Mechanical, and Industrial. According to the figure, most of the research was published in Civil and Electronic science. The authors' next most popular research areas were Multidiscipline, Mechanical, and Industrial.

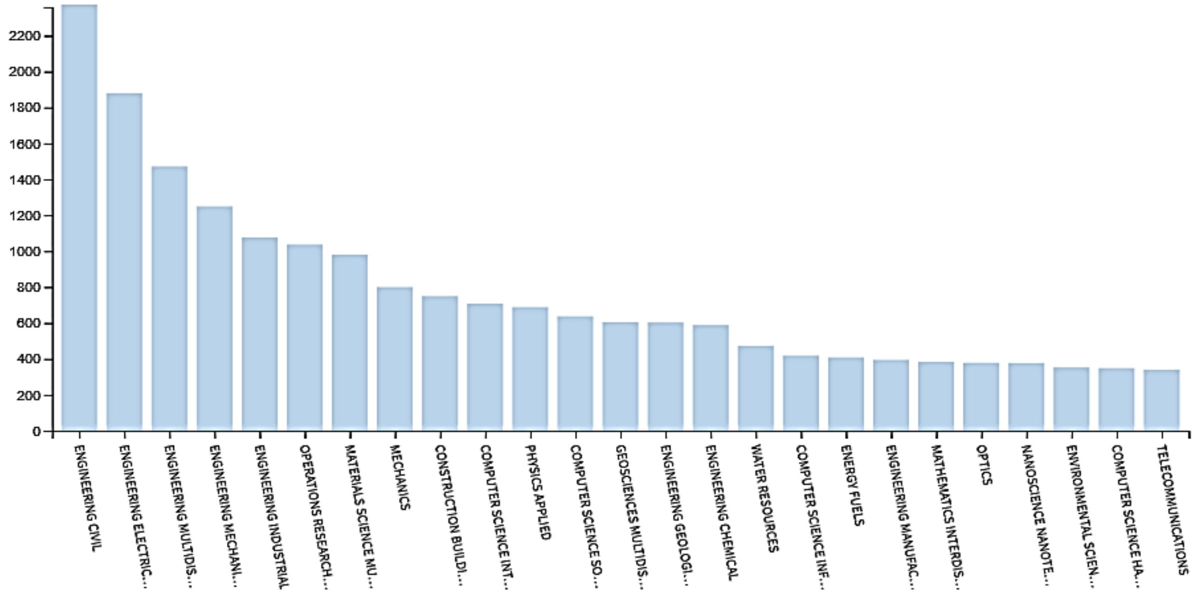

Figure 2-5- Field of study in engineering categories for reliability publications from *WoS* database

Thus, this section highlights the assessment approaches and works of reliability and reliability engineering in the engineering field. As mentioned, reliability analysis as a specific field of statistics studies the system failure times and their probability of occurrences. Identifying reliability as a specific field to engineering disciplines can be dated back to the 1930s (Dhillon, 1999; Lawless, 1983; Zio, 2009). Probability assessments became more popular in the 1940s (Birolini, 2013; Dhillon, 1999). After that, the probability-based approaches were developed by U. Kumar, A. Ghodrati, A. Ahmadi, J. Barabady, and A. Barabdi's thesis and papers in different domains of engineering such as mining equipment, aviation industry, oil and gas production equipment, electrical instruments, etc. (Barabadi *et al.*, 2010, 2011b; Barabadi, 2014; Barabadi and Markeset, 2011; Barabady, 2005, 2007; Barabady *et al.*, 2010; Barabady and Kumar, 2008; Ghodrati, 2005; Ghodrati *et al.*, 2015; Ghodrati and Kumar, 2005a; Kumar, 1995; Kumar and Klefsjö, 1994a, 1994b; Kumar, 1989, 1990; Kumar and Klefsjö, 1992; Qarahasanlou *et al.*, 2017; Zaki *et al.*, 2019). Even though reliability analysis is based on probability theory, which has been widely studied and used, it sometimes meets one main problem: the system may have only a few or even no samples; thus, we cannot estimate their probability distributions via statistics. The methods and concepts such as uncertainty and Bayesian theories have been proposed (Ait Mokhtar *et al.*, 2017; Li and Liu, 2016; Wen and Kang, 2016). Nannapaneni and Mahadevan used a Bayesian probabilistic approach to model epistemic uncertainty about the random input variables (Nannapaneni and Mahadevan, 2016). In this context, Artificial Neural Network (ANN) algorithms are introduced as universal function approximators used for reliability assessment. It is based on the brain's neural structure to establish a functional relationship between two data spaces during a learning process and reproduce that connection during a recall process. Chojaczyk et al. presented the review of ANN models' development and used it in structural reliability analysis with the different ANNs methods (from 1989 to 2014). In the second part of this paper, the application of ANNs in the reliability analysis of a ship stiffened panel was shown (Chojaczyk *et al.*, 2015).

The reliable performance of *production processes* is the other subject of engineering systems reliability analysis. The reliability of a production system depends on its configuration and how it is managed in operation. Chlebus and Werbińska-Wojciechowska presented a literature review in reliability engineering to compare well-known reliability models for production systems performance (Chlebus and Werbińska-Wojciechowska, 2016). Many different approaches and aspects of production process reliability can be found that are under investigation in the analyzed literature. An in-depth review of the relevant research literature in the context of mathematical methods of water distribution system reliability was presented by Gheisi et al. This research classified reliability measurement techniques into three major categories (Gheisi *et al.*, 2016):

1) *Analytic or Reachability- or Connectivity-Based Approach* breaks down a system into its rudimentary components and studies the interactions or connections among them.
2) *Systemic-Holistic or System-Performance or Simulation-Based Approaches* are an event-based technique that studies a system as a unit containing several subunits or components (does not break down a system). Any disturbance in the system's operation due to component failure is studied using discrete simulation.
3) *Heuristic or Surrogate-Measure-Based Approaches* are an experienced-oriented technique using intuitive judgment.

In modern engineering systems with complex characteristics such as multi-state properties, epistemic uncertainties, common cause failures (CCFs), reliability analysis is done by new approaches such as the multi-state system (MSS) with epistemic uncertainty and CCFs, and accelerated performance degradation information: Mi et al. used the Bayesian network (BN) method and the Dempster-Shafer (DS) evidence theory to express the epistemic uncertainty. The case study of the feeding control system for computer numerical control (CNC) heavy-duty horizontal lathes (HDHLs) confirmed the feasibility of this comprehensive method and realized a quantitative analysis of the system failure state (Mi *et al.*, 2018). The reliability analysis method of accelerated performance degradation based on Bayesian strategy is proposed by Yuan et al. This introduced method combines historical degradation data and practical information illustrated by an engineering example of a CNC-machine tool function milling head (Yuan *et al.*, 2019).

All mentioned authors have taken possession of a common evolutionary path in reliability development. The reliability analysis approach in the works began using the classic models and continued with covariate-based models. This approach can be found because the engineers need a deep and easily understandable analysis process to use the reliability approach. On the other hand, making correct decisions in a dynamic environment is a major challenge for engineers and managers worldwide. The covariate-based models could be quantified these uncertainties with the various covariates (risk factor). Recently, in this regard, Thijssensa and Verhagen extended the Cox regression model by incorporating the operating environment and aging of components and fleet of components. Examination of the model is illustrated by aviation components (Thijssens and Verhagen, 2020). Like other engineering fields, in mining engineering with huge equipment, reliability analysis effectively monitors efficiency and performance and ensures that performance goals and quality criteria are met. Mismanagement of equipment causes production target shortages and unfulfilled sales agreements. Recently, Ugurlu and Kumral proposed an approach for drilling equipment (Is a primary operation in open pit mining) reliability analysis and discrete event simulation under uncertainty (Ugurlu and Kumral, 2020).

2-2- The state of reliability concept in the Arctic area

This section describes several types of research investigating reliability in the Arctic area that focuses on this review. The Arctic is a region on the planet (Figure 2-6) north of the Arctic Circle and includes the Arctic Ocean, Greenland, Baffin Island, Russia, Alaska, and Canada. The Arctic circle is an imaginary line located at 66º, 30'N latitude. The Circle climate is very cold, and much of the area is always covered with ice. In the mid-winter months, the sun never rises, and in the summer months (further south), 24 hours of sunlight a day melts the seas and topsoil. It is the main cause of icebergs breaking off from the frozen north and floating south, destroying the North Atlantic's shipping lanes (Barabadi *et al.*, 2016).

Figure 2-6- The Arctic region ("SOFREP | Military Grade Content", 2020)

For engineering systems and infrastructures in the Arctic, engineers, and designers must deal with several unique environmental conditions not normally present in other world regions. These include cold, harsh climate; darkness; the remoteness of the location; the sensitivity of the environment; lack of suitable and insufficient infrastructure, long-distance from customer and suppliers' markets, ice scour, permafrost thaw, and/or frost heave. In the Arctic region, the interaction between the operational environment, humans, and equipment is more severe than in other places. In the Arctic, as far as the climate and location are concerned, the Arctic condition is a big challenge to manufacturing and industries. It will not only affect human performance but the overall organizational performance. For example, machinery and equipment are amongst the factors of making cost-effective organizational operation or decision making as to cost and time effectiveness of both is a crucial challenge to the managers that are characterized for the cold environment (Barabadi *et al.*, 2010; Fu *et al.*, 2018; Rahimi *et al.*, 2011). The existence of high-quality petroleum resources and the oil and gas industry in this area caused the pipeline to be raised as one of the top infrastructures in the Arctic. The assessment and analysis of pipeline performance require a good understanding of pipeline material behavior, soil loading conditions, ice loading mechanisms, and the consequences associated with product release. DeGeer and Nessim described some reliability-based and strain-based design methods that address the challenges and lead to optimal design decisions for onshore and offshore Arctic pipelines. They also provide a brief history of pipeline developments in the North American Arctic, including some design issues and mitigating the environmental effects most significantly influencing pipeline structural integrity. (DeGeer and Nessim, 2008). On the other oil and gas industry work, Gao et al. presented a covariate-based reliability approach for considering the influence of mentioned Arctic conditions factors in system production performance analysis. The proportional repair model (PRM) was developed to predict repair rate in Arctic conditions (Gao *et al.*, 2010b). Barabadi et al. was used "Offshore Reliability Data" (OREDA) from the oil and gas industry to develop a methodology to predict the reliability of equipment in the Arctic region using an accelerated failure time (AFT) model that is established by the oil and gas industry. The AFT can be considered a suitable alternative, where the proportional hazards family models display a significant lack of fit. Their work consists of three main parts: a brief review at the first stage and a proposed methodology. Finally, its application has been demonstrated by a simple numerical example of an electronic component used in the North Sea (Barabadi *et al.*, 2010). A. Barabadi in Ph.D. Thesis and papers, a survey of technological and operational challenges in the Arctic region from a maintainability and reliability performance perspective. Besides, the literature consists of covariate-based reliability and maintainability performance statistical approaches (Barabadi, 2011; Barabadi and Markeset, 2011). The OREDA as a valuable database was used again by Kayrbekova et al. for discussing operation and maintenance challenges under the Arctic conditions and propose a methodology to assess systems' reliability, maintainability, and maintenance costs under the influence of the Arctic operational environment. The maintenance cost is important because, in the Arctic region, preventive maintenance can be increased the wear and failures of moving parts. Furthermore, maintenance tasks may become difficult with a longer time than normal (Kayrbekova *et al.*, 2011). Rahimi et al. tried to outline and discuss important Arctic conditions that influence topside offshore oil and gas equipment's reliability by using the OREDA data source to integrate technical data, environmental data, regulations and standards, expert judgment, and test data. Also, they presented approaches to reliability prediction based on levels of data availability (Rahimi *et al.*, 2011). Based on experience in the Arctic offshore oil and gas industry, the inspection reliability is rather pushy, especially for tubular joints in jackets. Dong et al. studied the fatigue reliability designed for a northern North Sea site in this field for wind turbines. The reliability analysis was based on fracture mechanics (FM) analysis of crack growth of a jacket's welded tubular joints. (Dong *et al.*, 2012). More details about the reliability analysis of wind turbines can be found in Jiang et al.'s state-of-the-art review paper that had been done on the domain of structural reliability analysis of wind turbines between the 1990s and 2017 (Jiang *et al.*, 2017). As said before, FTA is a systematic approach to estimate the safety and reliability of complex systems both qualitatively and quantitatively. In another oil and gas industry (a three-phase horizontal separator by OREDA database) in the Arctic, Naseri, and Barabadi presented a methodology for system-reliability assessment fuzzy FTA that can be used in the design phase for optimizing maintenance and spare parts provision plans. In trying to cover the lack of adequate reliability data in this region, they used the expert-judgement process to modify available life data gathered in normal climate regions to include the effects of Arctic operating conditions on the components' reliability performance systems. For this purpose, the expert's judgments as Gaussian fuzzy numbers are combined with the exact values of mean time to failures (Naseri and Barabady, 2015). These researchers also assessed the reliability of an oil processing train in the Western Barents Sea by an expert-based model. In this study, the available life data model (which is derived in analogy with PHMs) of normal-climate locations was modified by expert opinions to account for the effects of operating conditions (Naseri and Barabady, 2016a). Recently, Bolvashenkov et al. present an approach to estimate the operational availability and performance of icebreaker gas tankers with a hybrid-electric (Diesel-Electric) propulsion system. For this propose, the availability of each operating modes (Loading and unloading, navigation in the ice-free water, autonomous movement, navigation in heavy ice supported, and maneuvering of a ship) is estimated, followed by calculating their total impact on the value of the ship's operating speed and, accordingly, the amount of cargo transported per unit of time. The research results showed that the hybrid motor has a significant potential to improve operational availability, technical performance, and, consequently, economic efficiency (Bolvashenkov *et al.*, 2019).

2-3- The reliability analysis approaches

Massive costs arising from Process system failure or unreliability features are hitting the productivity standards of companies. Thus, a reliable system configuration has a vital role in the system design (or redesign) while considering its reliability. Reliability analysis approaches linked to overall system performance include a clear understanding of equipment status, life-cycle costs reduction, process performance optimization, and safety operation assurance. Correspondingly, it is considered a quality concept extension essential for technological systems and infrastructures. As well, high-reliability organizing is a vital concept to crisis inhibition and mitigation. Good reliability management will collect critical information about the system's performance throughout the operation phase used in improvement processes.

This concept initiates in the mid-1980s with the discussion about culture, decision making, complexity, and technology. This metric is more suited for the existing operations and related to maintenance issues and equipment lives (Jardine *et al.*, 1987; Kumar, 1990). Reliability is recently used as a useful tool in new concepts such as resilience (Asadzadeh *et al.*, 2020; Gu *et al.*, 2020). Several approaches can be used to evaluate the reliability, such as the reliability block diagram (Barabady and Kumar, 2008), fault tree analysis (Choi and Chang, 2016), Monte Carlo simulation (Naseri *et al.*, 2016), and Markov chain (Cai *et al.*, 2012). Mostly, the base of these models is the stochastic independence assumption (i.e., each component of the model is stochastically independent of the others), which sometimes is not satisfied. For example, a system's dynamic behavior caused by a time-dependent covariate cannot be modeled. Thus the models such as dynamic reliability block diagram (DRBD), reliability phase diagram (RPD), dynamic fault tree (Distefano and Puliafito, 2007), and reliability graph with general gates (Kim and Seong, 2002) have been developed to solve drawbacks. Dynamic fault trees (DFTs) have been had the main disadvantage as assumptions of precise failure data and statistical independence among events, which are unrealistic assumptions. Recently, Kabir et al. proposed an improved approach to reliability analysis of dynamic systems that analyze uncertain failure data and statistical and stochastic dependencies among them (Kabir *et al.*, 2018). Some researchers broadly categorize the traditional reliability performance analysis methods into two main groups as parametric and non-parametric methods. In parametric methods, the central assumption is that the data come from a type of probability distribution and that interferences are made about the distribution parameters, but in the non-parametric method no specified distribution is assumed for the lifetime of the system (Furuly *et al.*, 2013, 2014).

As a general conclusion, the most commonly used models for times between events datasets are renewable process (RP), non-homogeneous Poisson process (NHPP), and homogeneous Poisson process (HPP). The times between events are assumed to be independent and identically distributed in a renewal process. An HPP is a renewal process where it is assumed that the times between events are exponentially distributed. This means that the dataset indicates any trend due to its deterioration or improvement; these models are not appropriate. A model with time-dependent failure intensity, such as a non-homogeneous Poisson process (NHPP) such as the power low process (PLP), may be a better choice. The models mentioned above consider the time between failures as the sole variable of interest, and this analysis requires the following process (Ahmadi *et al.*, 2019; Gao *et al.*, 2010b):

- The life data gathering for the product
- Lifetime distribution selection that will fit the data and model the life of the product
- The parameters estimation that will fit the distribution to the data
- Generation of plots and results that estimate the life characteristics of the product, such as the reliability or mean life

Consequently, these models cannot be used to analyze the effect of operational conditions (covariates) on reliability evaluation. Thus, in this current work, the regression model (or covariates-based models) is proposed to calculate engineering systems' reliability and subsequent resilience by considering different environmental factors. Applicable models for analyzing the covariate effect on reliability performance (covariate-based approaches) can broadly be classified as the class of proportional hazards models and accelerated failure time models based on proportional hazards assumption (Furuly *et al.*, 2013, 2014). Ph.D. thesis of N. Gorjian is a broad collective review of the existing literature on reliability approaches (i.e., traditional reliability approach, model-based approach, and data-driven approach). It also highlighted various models and algorithms and discussed their merits and limitations (Gorjian Jolfaei, 2012). The method used is a probabilistic model based on random variables, including their functional and operational condition. It is considered one of the most useful models in the field of probabilistic knowledge representation and reasoning. In the following, firstly a brief description of basic reliability concept by time variable is presented and then covariate-based approaches and models is discussed.

Reliability measures the probability of failure-free operation over a specific period. It depends on conditions of use and risk factors such as quality of components, materials, and dimensions. Simply put, reliability analysis uses the calculation of failure probability, which provides a convenient approach for many engineering and technology fields. The mathematical function of reliability includes the relationship between the time to failures (TBFs) of the system or components (T > 0) and the time interval of proper function (t). Then, reliability can be defined as Eq. (2-1) (Ascher and Feingold, 1984):

$$R(t) = P[T \geq t] = 1 - F(t) = \int_0^t f(x)dx \quad \textbf{(2-1)}$$

where R(t) is the probability that the time to failure is greater or equal to t and has the boundary conditions of $R(t) \geq 0$, $R(0) = 1$ and $\lim_{t\to\infty} R(t) = 0$. $f(x)$: probability density function (PDF) of random variables. “x”: is the vector of random variables. $F(t)$: cumulative distribution function $\left(f(x) = \acute{F}(t)\right)$. The failure characteristic of this item can be modeled by the hazard function, *h(t)*, given the following relationship (Birolini, 2013; Stamatis, 2017):

$$h(t) = \frac{f(x)}{1 - F(t)} = -\frac{d}{dt} ln\left(R(t)\right) \quad \textbf{(2-2)}$$

Using the cumulative hazard function $\left(H(t)\right)$ the connection between hazard and reliability can be made. The cumulative hazard function looks like this:

$$H(t) = \int_0^t h(x)dx \quad \textbf{(2-3)}$$

This results in the associated survival function (Birolini, 2013; Stamatis, 2017):

$$R(t) = exp\left(-H(t)\right) \quad \textbf{(2-4)}$$

The reliability metric in Eq. (2-1) depends on the time and type of configuration in a system it needs to develop for operating conditions. Because in general, the degradation process of an asset is influenced by various environmental and operational mechanisms that affect it along the chronological time since it is starting to work.

The mean time to failure (MTTF) or mean time between failure (MTBF) are the expected value of T (Ma, 2008; Thijssens and Verhagen, 2020):

$$MTBF\ (MTTF) = E(T) = \int_0^\infty xf(x)dx = \int_0^\infty R(x)dx \quad \textbf{(2-5)}$$

The systems are often designed, built, and tested in an environment with moderate conditions such as a comfortable temperature and good lighting (Kumar *et al.*, 2009). Thus, as mentioned before, various regression models have been suggested to obtain more realistic estimates of the reliability parameters, and the operating environment factors are included in the models as explanatory variables. The basic theory of covariate-based hazard models in Figure 2-7 is to build the baseline hazard (underlying hazard) function using historical failure time data and the covariate function using covariate data. The selection and formulation of risk factors in these models are crucial as the statistical inference is based on their formulation. The failure mechanisms of equipment must be precisely studied for this purpose because they are influenced by various risk factors and/or indicated by different indicators.

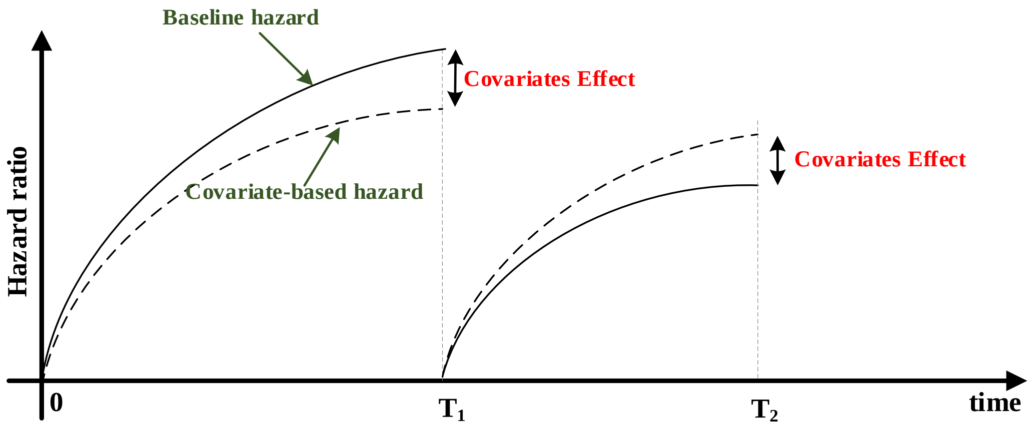

Figure 2-7- Basic theory of covariate-based hazard models (Ghodrati, 2005; Ghodrati and Kumar, 2005a)

The valuable information of covariates could be well covered with the difficulty and costly data gathering process of risk factors. But sometimes, this factor couldn't be easily identified. Some of them couldn't be viewed, and someone unquantifiable. Thus, they classify into two main classes:

- *Observable risk factors* describe the recovery or operating process characteristics, and environmental conditions such as wind speed, wind direction, temperature, polar low must be explained. They must also be quantified based on how they can affect the maintenance works, system operation, the update of the safety procedure, and organizational management rules. These covariates can be combined in data processing and make new covariates (Barabadi and Aalipour, 2015). Observable risk factors generally classify as (Ghodrati, 2005; Ghodrati and Kumar, 2005a):
  - ✓ External covariates or operating environment indicators are not directly involved with the failure mechanism and are generated by a process independent of a system (Kalbfleisch and Prentice, 2011). Such as loads, ambient temperature, humidity, dust, contaminations, etc.
  - ✓ Internal covariates or condition indicators are the output of stochastic processes generated by the system, such as vibration, the thickness of the shell, level of metal particles, etc. They are observed and measured as long as the system is operational and used as degradation level measurement (Finkelstein, 2004).
- *Unobserved risk factors* are independent variables that may significantly impact the recovery time. However, these are not reported or directly unquantifiable and thus not available in recovery databases but cause heterogony. For example, external managerial advice might help the repair crew repair the failures and recover the system in some situations. However, it helps to reduce recovery time, but it is not recorded in the corresponding databases. In this regard, their effect on recovery time should be modeled using unobservable risk factors (Gutierrez, 2002; Rod *et al.*, 2020; Wienke, 2010; Zaki *et al.*, 2019).

The proportional hazard model (PHM) is a base covariate-based hazard model introduced by Cox in 1972 in the medical field (Cox, 1972). It is general and flexible and a simple approach in the interpretation of the results. Thus, it was quickly and widely adopted in reliability fields from the 1970s to the early 1990s (Bendell, 1985). However, the popularity of PHM in the reliability field suffers from several drawbacks like (Caroni, 2004; Ciampi and Etezadi-Amoli, 1985; Huber-Carol and Nikulin, 2008; Kleiner and Rajani, 2001):

- Any deletion or change in covariates could be had a vulnerable effect on PHM results, and a new model must be fitted.
- Precise estimation of PHM needs adequate data.
- In PHM, the covariate influences assume as time-independent. It is named as proportionality assumption (PH assumption). PH assumption imposes a severe limitation in which the reliability (or log-log hazard) curves for assets with different covariates must never cross. Due to this drawback, PHM's baseline hazard is always altered proportionally to the absolute condition indicators or operating environment indicators observed and measured.
- PHM considers condition indicators and operating environment indicators as homogeneous data.

Due to the drawbacks mentioned above, several covariate-based hazard models such as stratified regression mode (SCRM), accelerated failure time model (AFTM), extended hazard regression model (EHRM), etc., were developed (Ciampi and Etezadi-Amoli, 1985; Kumar and Klefsjö, 1994b). None of the existing hazard models have not explicitly and effectively integrated three available asset information, including failure event data (i.e., observed and/or suspended), observable, and unobservable risk factors. The methodology surrounding the development of different forms of the covariate-based hazard model and their related parameter estimation methods that fully utilize all three types of system data in modeling hazard and reliability has been recently addressed in the literature. (Aalen, 1992; Gutierrez, 2002; Hougaard, 1995; Rod *et al.*, 2020; Wienke, 2010; Zaki *et al.*, 2019). Thus, a novel covariate-based hazard model, the Mix Proportional Hazard Model (MFM) in semi-parametric forms proposed by R.Zaki and et al., has been used and tested in this research (Zaki *et al.*, 2019). Usually, the semi-parametric model has fewer parameters than the nonparametric one to be estimated. Additional uncertainties introduce the prediction results by increasing the number of unknown parameters in the model. MFM jointly utilizes three types of the mentioned information. This model assumes that the baseline hazard is a function of time, and risk factors help update the model's baseline hazard according to the system's state under different operating conditions. Risk factors can increase or decrease the value of the hazard from the baseline hazard. Some of the most used covariate-based methods are briefly described below:

2-3-1- Proportional hazard model (PHM)

As mentioned earlier, PHM assumes that failures occur independently, and the value of the covariate function for one system does not influence any other assets' survival time. Cox (1972). In general, PHM is influenced by time and the covariates under which it operates. This model is a distribution-free approach to the tools used in reliability analysis. In PHM, the failure rate of a system is the product of a baseline failure rate, $\left(h_0(t)\right)$, that depends on time only, and a positive functional term, $\left(\varphi(z\beta)\right)$ which describes the effect of covariates as a positive function. This function has a linear form $(1+\alpha z)$, the log-linear $(\exp{(z\alpha)})$ and the Logistic form $\left(\log{(1+\exp{(\alpha z)})}\right)$ forms (Kumar and Klefsjö, 1994b). The PHM can be written as follows (Ghodrati and Kumar, 2005b):

$$h(t,z) = h_0(t)\varphi(z\beta) \tag{2-6}$$

The common form of PHM is log-linear that can be expressed as (Ghodrati, 2005):

$$h(t,z) = h_0(t)exp(z\beta) = h_0(t)exp\left(\sum_{i=1}^{n} z_i\beta_i\right) \tag{2-7}$$

The component reliability influenced by covariates is expressed by Eq.(2-8) (Ghodrati *et al.*, 2003):

$$R(t,z) = \left(R_0(t)\right)^{exp\left(\sum_{i=1}^{n} z_i\beta_i\right)} \tag{2-8}$$

Where z is a row vector consisting of the covariates and is associated with the system. β is a column vector consisting of the regression parameters and is the unknown parameter (regression coefficient) of the model, defining the effects (weight) of the covariates. The baseline hazard rate and baseline reliability $\left(R_0(t)\right)$ represents the hazard rate with zero effectiveness of covariates $(\varphi(z\beta) = 1)$:

$$R_0(t) = exp\left(-\int_0^t h_0(x)dx\right) \tag{2-9}$$

The baseline can be modeled as a parametric form by a suitable parametric distribution or nonparametric form by an unspecified distribution used frequently when there is no exact theoretical reason for positing a particular distribution (Barabadi, 2014). An estimate of the β parameters can be obtained by maximization of the partial likelihood function. In the PHM, the proportionality assumption (PH assumption) of the existing covariate-based hazard models imposes a severe restraint that the reliability curves for assets with different covariates must never cross. The PH assumption is that the covariates are time-independent variables; this means the ratio of any two hazard rates is constant over time (Barabadi *et al.*, 2011a). Various approaches have been used to determine whether the PH assumption fits a given data set: a graphical procedure, a goodness-of-fit testing procedure, and a procedure involving the use of time-dependent variables (Kleinbaum, 2011).

2-3-2- Stratified Cox regression model (SCRM)

In some cases, the PH assumption may be violated, and a stratified Cox regression model (SCRM) can be used. The “stratified Cox model” extends the PHM that allows for control by “stratification” of a predictor that does not satisfy the PH assumption. The system is stratified in s different strata based on one or more covariates. The system is presumed to have different hazard rates in different strata and baseline hazard rates. The system is assumed to have proportional hazard rates; this is not necessarily the case for a system with different strata. The hazard of an asset in the s^{th} stratum can be expressed as (Barabadi *et al.*, 2011a; Ghodrati and Kumar, 2005b):

$$h_s(t,z) = h_{0s}(t)exp\left(\sum_{i=1}^{n} z_i\beta_i\right) \quad s = 1,2,\dots,r \qquad \textbf{(2-10)}$$

As with the original SCRM, there are two unknown components in the model: the regression parameter β and the baseline failure function $h_{0s}(t)$ for each stratum. The baseline failure functions for r remain utterly unrelated in the different strata.

2-3-3- Extended Cox regression model (ECRM)

The ECRM is an extension of the PHM for simultaneously analyzing time-dependent and time-independent covariates. The hazard rate of ECRM for time-dependent covariates can be written as follows (Gorjian Jolfaei, 2012):

$$h(t,z) = h_0(t)exp\big(\beta z(t)\big) = h_0(t)exp\left(\sum_{i=1}^{n} z_i(t)\beta_i\right) \qquad \textbf{(2-11)}$$

The expansion of Eq.(2-11) for time-dependent and time-independent covariates can be written as (Gorjian Jolfaei, 2012):

$$h(t,z) = h_0(t)exp\left(\sum_{i=1}^{n} \beta_i z_i(t) + \sum_{j=1}^{m} \delta_j z_j\right) \qquad \textbf{(2-12)}$$

where δ_j and β_i are column vectors consisting of the regression coefficient for time-dependent and time-independent covariates, respectively, z_j is a time-independent covariate, and $z_i(t)$ is a time-dependent covariate. “m” is the number of time-independent covariates, n is the number of time-dependent covariates.

2-3-4- Mixture frailty model (MFM)

In the Mixture frailty model (MFM), the hazard rate of an item is the product of a baseline hazard rate multiplied by two positive functions: *i)* observed covariate function and *ii)* an unobserved covariate function (frailty function). Suppose we have a fleet of *j* items, the hazard function for an item at time *t* > *0* is:

$$h_j(t;z;\alpha) = \alpha_j h_0(t)\psi(z;\eta) \qquad \textbf{(2-13)}$$

where $\lambda_0(t)$ is an arbitrary baseline hazard rate, dependent on time alone, z is a row vector consisting of the observed covariates associated with the item, η is a column vector consisting of the regression parameters for identified observed covariates, and α_j is a time-independent frailty function for item *j* and represents the cumulative effect of one or more unobserved covariates. In general, the baseline hazard rate ($h_0(t)$) may either be left unspecified or modeled using a specific parametric form such as Weibull distribution or Non-Homogeneous Poisson Process (NHPP).

According to the MFM, the fleet of items (the population) is represented as a mixture, in which the $\lambda_0(t)$ and $\psi(z;\eta)$ are common to all items, although each item has its frailty. The observed and unobserved covariates can affect the hazard rate so that the actual hazard rate ($\lambda_j(t;z;\alpha)$) is

either greater (e.g., in the case of higher vibration level or poor maintenance) or smaller (e.g., better training for operators, installation of a new ventilation system) than the baseline hazard rate. Moreover, the items with $\alpha_j > 1$ are said to be frailer, for reasons left unexplained by the observed covariates, and will have an increased risk of failure. The items for whom $\alpha_j < 1$ are less frail; hence, they tend to be more reliable given a particular observed covariate pattern.
For MFM, given the relationship between the hazard rate and the reliability functions, it can be shown that the conditional (item) reliability function, $R(t;z;z(t)|\alpha)$, conditional on the frailty, α, is (Gutierrez, 2002):

$$R(t;z;z(t)|\alpha) = \{R(t;z;z(t))\}^{\alpha} \quad \textbf{(2-14)}$$

The unconditional (population) reliability function can then be estimated by integrating the unobserved α. If α has probability density function $g(\alpha)$, then the population or unconditional reliability function is given by:

$$R_{\theta}(t;z;z(t)) = \int_0^{\infty} \{R(t;z;z(t))\}^{\alpha} g(\alpha) d\alpha \quad \textbf{(2-15)}$$

We use the subscript θ to emphasize the dependence on the frailty variance θ. The relationship between the reliability function and the hazard function still holds unconditional on α, and, thus, we can obtain the population hazard function using (Gutierrez, 2002):

$$h_{\theta}(t;z;z(t)) = -\frac{d}{dt} R_{\theta}(t;z;z(t))[R_{\theta}(t;z;z(t))]^{-1} \quad \textbf{(2-16)}$$

Having the gamma distribution with unobserved covariates (Gutierrez, 2002):

$$R_{\theta}(t;z;z(t)) = [1 - \theta ln\{R(t;z;z(t))\}]^{-1/\theta} \quad \textbf{(2-17)}$$

Having the event times (t_{0i}, t_i, d_i), for $i = 1, \dots, n$ with the ith observation corresponding to the period $(t_{0i}, t_i]$, with either failure occurring at a time t_i $(d_i = 1)$ or the failure time being right-censored at time t_i $(d_i = 0)$, the likelihood function for survival data is given by:

$$LnL = ln \prod_{i=1}^{n} \frac{\{R_{\theta i}(t_i, z_i, z_i(t)\}^{1-d_i} \{f_{\theta i}(t_i, z_i, z_i(t)\}^{d_i}}{R_{\theta i}(t_i, z_i, z_i(t)} \quad \textbf{(2-18)}$$

Where $f_{\theta i}$ is the probability density function.

2-3-5- Accelerated Failure Time Model (AFTM)

Unlike PHM with proportionality assumption as the main limitation, AFTM could be evaluated on time-dependent and time-independent covariates. It can be written as (Barabadi *et al.*, 2010):

$$h(t, z(t)) = h_0\left(t \times exp(\beta z(t))\right) exp(\beta z(t)) \quad \textbf{(2-19)}$$

According to whether $(exp(\beta z(t)) > 1)$ or $(exp(\beta z(t)) < 1)$, covariates could accelerate or decelerate the failure time relative to the baseline hazard, respectively. A. Barabadi and T. Markset research about performance indicators under Arctic conditions shows that some developments of AFT, that in addition to analyzing and exploring the available data, could be used for 1) redesigned or modified equipment performance estimation and 2) modeling some climate phenomena effects on reliability performance (Barabadi and Markeset, 2011).

This chapter provides a comprehensive statistical overview of the research in the recoverability (which is defined as maintainability in reliability engineering) domain. Then, a detailed review of publications in the recoverability assessment of the engineering systems field is provided in recent years. Also, the focus is on research done in the Arctic systems. Ultimately, it gives a short description of the recoverability index; it includes the definition, statical approaches for recoverability analysis, and regression models for considering operating environment effects.

3- RECOVERABILITY

As a report of “Oilfield Publication Limited” (OPL), maintenance expenses can be as high as 60% of the operating cost for the offshore oil and gas business (Levy, 1991). This factor can greatly reduce maintenance costs and increase resilience as an identifier of the ease and time of recovery action. Since the failure is ingrained like engineering systems, the recovery concept's main purpose is to minimize downtime and back time, thus reducing related costs. Moreover, it tries to increase efficiency and safety when maintenance is performed under given conditions and using stated procedures and resources. Maintenance and related indexes such as maintainability in the resilience field can be considered a branch of the vast concept named “Recoverability”. Recoverability measures the infrastructure system's ability to restore its capacity and performance by recovering from the adverse effects of adverse events during a period under given conditions, using the available resources. The four components include 1) supportability of disrupted components, 2) maintainability of disrupted elements, 3) the resilience of the owner’s organization in the case of disruption, and 4) the prognostics and health management (PHMa) efficiency of the system can be influenced the recoverability (Rod *et al.*, 2020; Youn *et al.*, 2011).
Moreover, recoverability influences and is also influenced by how the different processes and infrastructures are designed and manufactured. These factors are called recoverability attributes that are directly or indirectly affected by the operational environment that is considered as “risk factors” or “covariates” (Rod *et al.*, 2020). In this context, Kayrbekova et al. was discussed operation and recovery challenges under Arctic conditions. They showed that the operating environment has a considerable influence on failure occurrence, recovery activities, repair times, and, consequently, costs (Kayrbekova *et al.*, 2011). Bijarte et al. recently evaluated the risk factors (observed and unobserved risk factors) effect of the recovery process of Norwegian electric power distribution grid infrastructure disruptions. To this aim, the accelerated failure time (AFT) model is used to analyze the recovery time of disrupted critical infrastructures. This is achieved by considering the operating conditions and other covariates, where the recovery time is selected to be the random variable of interest. The analysis indicates that disruption in the regional grid, natural conditions, area affected, and disruptions in the operational control system significantly impact the recovery process. (Rod *et al.*, 2020). Due to the infancy of the recoverability concept and many commonalities of this concept with maintainability, this section mainly focuses on the research that had been done in the field of maintainability. ". A superficial scientometrics study of maintainability in Figure 3-1 shows that publications rose from 1996 to 2006. But after one decade of totalitarianism, maybe because of the integration of this concept

with availability and maintenance, the publication trend is decreased. Then the number of publications slowly was rising by a continuous upward trend up to 2019. Keep in mind that the frequencies for 2020 are most likely incomplete. It shows that international experts and scholars had paid continuous attention to the field of maintainability after 2006.

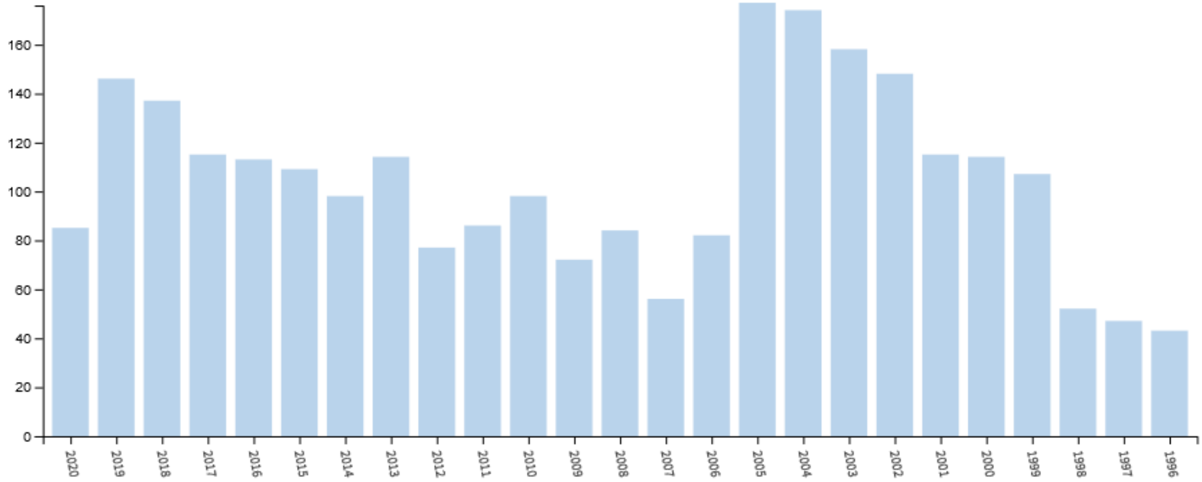

Figure 3-1- Published year histograms of maintainability publications from *Scopus* database in 1996-2020

The citations of scientific literature in Figure 3-2 reflect the objective laws of scientific development in the maintainability field.

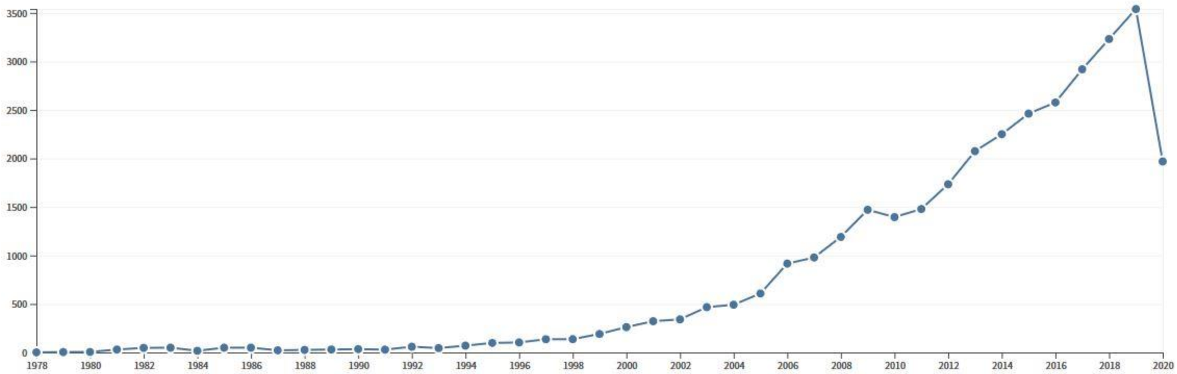

Figure 3-2- The citations of maintainability publications from the *WoS* database in 1978-2020

In analyzing the scientific output, we find that the literature on maintainability research shows increasing nominally year by year. The histogram of the research area in Figure 3-3 presents that the engineering area is the most prolific field. The authors' next most popular research areas were Computer Science and Operation Research Science. In the next section, the application of this concept in engineering is discussed.

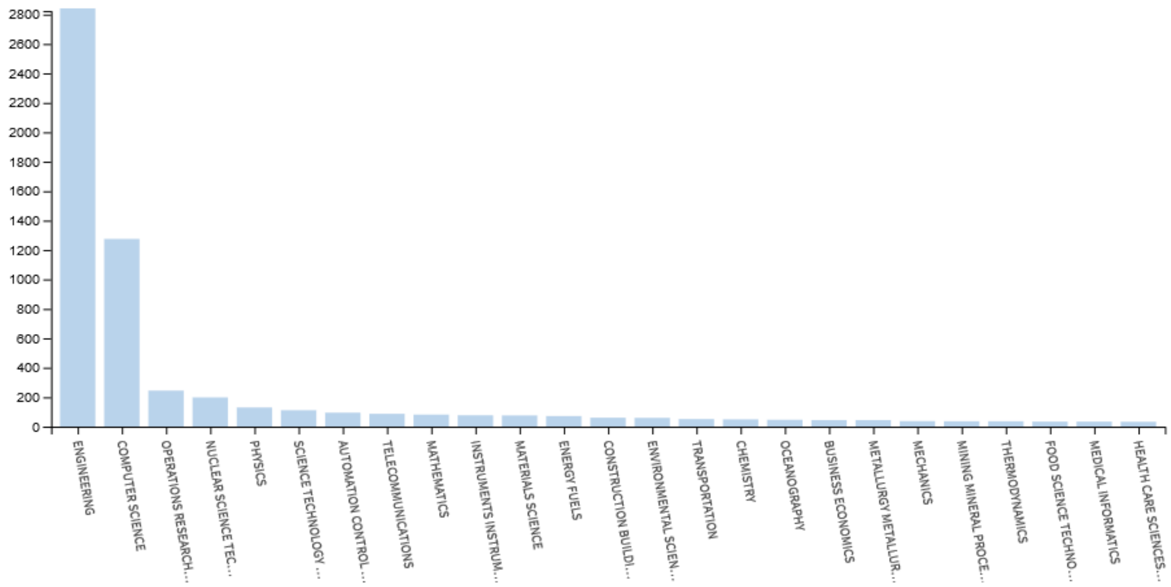

Figure 3-3- Research areas histograms of maintainability publications from *Scopus* database in 1997-2020

3-1- The state of recoverability concept in engineering systems

In the engineering field, recoverability is rarely studied as a whole concept. But the maintainability as one of the most important and influential components of recoverability has been extensively reviewed in the literature. Maintainability is used to improve the system's performance based on adequate maintenance or recovery activities. The scientometrics literature output of maintainability in Figure 3-4 shows a similar trend variation, with Figure 3-1 presenting engineers' recent attention to maintainability and its topics.

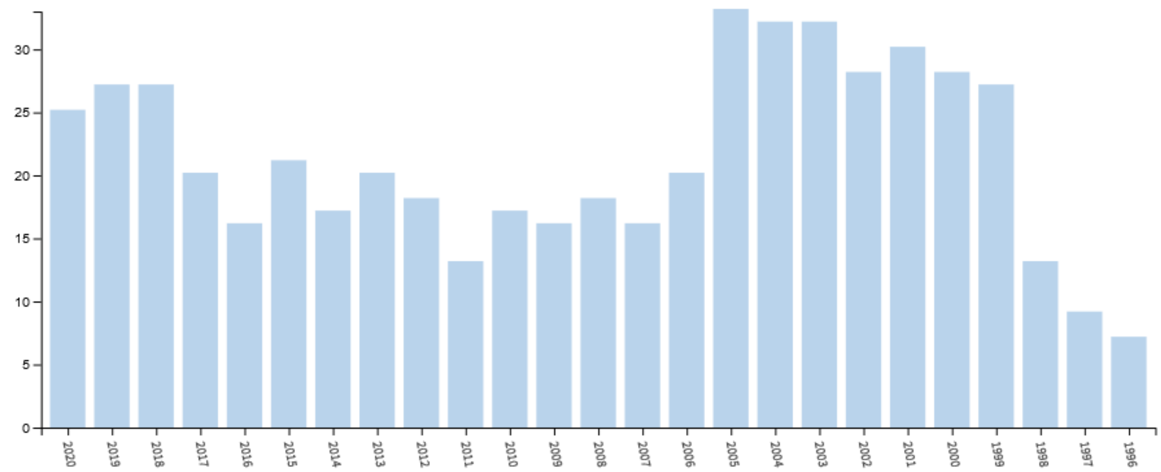

Figure 3-4- Published year histograms of maintainability publications in an engineering field from *Scopus* database in 1997-2020

The maintainability in mathematics is defined as the probability that a failed system will be restored to operational effectiveness within a given period (t) when the repair action is performed according to the prescribed procedures (Barabadi and Markeset, 2011). Tsarouhas used the maintainability analysis to find the best possibilities for cost reduction on a yogurt production line. The classic probability method (like reliability analysis (Barabady and Kumar, 2008; Kumar and Klefsjö, 1992)) used were carried out, and the best fitness index parameters were determined (Tsarouhas, 2015). Facility layout, which studies and determines how to locate the given facilities in the narrow space, is another essential item for system design and maintenance (recovery) support activities. To improve the maintainability design's efficiency and quality, Luo et al. presented maintainability optimization of a ship cabin with a layout design perspective. The maintenance operating space, amount of hoisting, the balance of cabin, distance requirement, personnel movement distance, mechanical functional constraints, and some important layout experience had been considered and formulated in the proposed design. Then, these multiple constraints and multiple objectives function is solved by the particle swarm optimization algorithm (Luo *et al.*, 2015). Li et al. studied testability besides maintainability as a design characteristic that represents the ability to determine its states timely and accurately and effectively diagnose its faults. They believed that fault detection rate, fault isolation rate, fault detection time, and fault isolation time are the most important testability analysis factors. This paper optimizes testability combined with reliability and maintainability based on the generalized stochastic Petri nets model (Li *et al.*, 2015). The Logistics and Supply Chain (LSC) is the other field of maintainability application. All specialties, logistics, reliability, and supply chain management (SCM) use the same or similar data but differently. All of these in working together can be optimized supply chain, availability, and maintenance requirements. Gillespie, in 2015 presented a short paper on reliability and maintainability applications in the logistics and supply chain area (Gillespie, 2015). Mohammadi et al. used the classic approach of reliability and maintainability to critically analyze mining equipment's inherent availability (dragline) availability. In this light, the dragline understudy was broken into seven major subsystems connected in series and represented by a reliability block diagram. Then required data as the time between failure and time to repair was extracted, and the best models were fitted. Finally, Therefore, inherent availability of the subsystem was computed (Mohammadi *et al.*, 2016). This approach is abundantly used by researchers in different areas (Barabady and Kumar, 2008; Hall and Daneshmend, 2003; Hoseinie *et al.*, 2012a; Kumar, 1989). With the high complexity of technological systems in the Oil & Gas and Electrical industries, the availability and productivity improvement to meet demanding criteria is very important. The study of assessing the operational performance of a reciprocating compressor system package and Insulated Gate Bipolar Transistor was presented by Corvara et al. (Corvaro *et al.*, 2017) and Memon and Alam. (Memon and Alam, 2016). The main aims of these research works were; availability assessment, the equipment, subsystem identification and ranking, and proposing the potential cost-effective optimization options to ensure the target availability. The study demonstrated the methods' usefulness and could also be used by the engineers to apply RAM principles in process design (Corvaro *et al.*, 2017; Memon and Alam, 2016). In the other oil & gas industry work, Aly et al. presented an integrated RAM model for the K-out-of-N system performance evaluation and bottleneck identification. Their proposed approach was applied in the Egyptian Petrol Company system and discussed the effect of failure and repair rates at different mission times (Aly *et al.*, 2018). As mentioned in this section and reliability section, RAM studies are common in oil and gas but applying it to a wine plant maybe is unique. Tsarouhas, through the case study of a wine packaging production line, demonstrated how RAM analysis is very useful for maintenance strategy planning and organizing. The line consists of nine automated, repairable machines in series. RAM analysis to f Velásquez and Lara performed a RAM calculation of a series capacitor banks located at Cotaruse 220 kV substation in Peru. The work's main objective was to create a simple and highly reliable design, which will give high availability and low maintenance costs (Velásquez and Lara, 2018). Soltani et al. were evaluated the performance of the conveying process of an automotive company by using the RAM principle. They proposed a framework for RAM evaluation and maintenance optimization that could improve operational performance and sustainability of the production process (Soltanali *et al.*, 2019). In late Agrawal reports the study on RAM of an earth pressure balance tunnel boring machine (EPB-TBM) deployed for excavating an irrigation tunnel located in Central India and the impacts of these parameters on the penetration rate of the machine. The RAM analysis of the four major subsystems includes: cutter head, hydraulics, screw conveyor, and structure were modeled by Markov chain (Agrawal *et al.*, 2019). Ahmadi et al. are using the same process for RAM analysis of from main conveyor system of Tabriz Metro Line 2 EPB-TBM. To carry out the analysis, the main conveyor system was divided into three sub-systems including conveyors 1, 2, and 3, which are located on the TBM machine, inside the tunnel and station (Ahmadi *et al.*, 2019). In the other work of India, Choudhary et al. aim to improve the availability of a cement plant by avoiding failures and reducing maintenance time through RAM analysis of its subsystems. The result analysis serves as a reference for reliability and maintenance managers in deciding maintenance strategies of cement plants as well as in improving their capacity utilization (Choudhary *et al.*, 2019).

Maintainability is also considered in ergonomics for considering the human factors in maintenance activities. The International Ergonomics Association (IEA) defines ergonomics as “the scientific discipline concerned with understanding human interactions and other system elements. The profession applies theory, principles, data, and methods to design to optimize human well-being and overall system performance”. Bernard et al. performed a detailed maintainability study of the aeronautic field for comprehending which ergonomic skills and tools should be used and how design engineers utilize them to evaluate the human factor. Their observations showed that ergonomics was integrated with the design process mainly by a physical approach using engineering tools and not ergonomic tools. Also, maintainability must be integrated with other organizational, cognitive, and human factors. (Bernard *et al.*, 2017). The green maintainability of buildings concepts as a new branch of maintainability application originated from the “green building” concept for facilities management. The construction industry began to design and construct more sustainable buildings in the green building attempt to incorporate sustainable development principles. Chew et al. found a knowledge gap about the green maintainability concept. Thus, they did a literature review on green practices and methods that can valuably contribute to the existing theories, practices, and methods concerning building maintainability and facilities management. Also, they proposed a conceptual framework for the green maintainability of buildings evaluation (Chew *et al.*, 2017). Che et al., in their short paper, tried to answer the questions "Why is it Important to Measure Maintainability, and What Are the Best Ways to Do it?" in the field of software engineering. After discussing maintainability importance, they earned a deep understanding in assessing software maintainability by performing a comparison study between automated maintainability metrics and human-assessed maintainability metrics (Chen *et al.*, 2017).

3-2- The state of recoverability concept in the Arctic area

The system with a low level of resilience of being deployed in a cold climate such as the Arctic often needs special and additional focus on recoverability characteristics to achieve a higher performance level. For example, in the petroleum industry, which is one of the most crucial industries for Norway and the Arctic region (It is estimated that 14% of the world's remaining oil and natural gas reserves are found in Arctic areas, most of these offshore (Coomber, 2008)). The performance issues, especially the recoverability, generate critical challenges for this industry's successful and effective operation in the Arctic environment as the working conditions are made very difficult by low temperature, ice, a short period of daylight, and lack of support facilities. Various researchers have studied the operating condition and system condition issues in the Arctic. For example, Kumar et al. explored the potential risk factors with a human factors/ergonomic principle view to reduce their effect and increase maintainability. They summarized the influencing human performance factors in recovery activities in the cold environment as below (Kumar *et al.*, 2009):

- The manual skills, agility, coordination, and accuracy reduction can impact productivity and safety.
- The injuries and accidents such as musculoskeletal injuries and peripheral circulation reduction will be increased.
- Discomfort from cold, stiff hands and feet, runny nose, and shivering
- Impaired ability to perceive cold, cuts, pain, and heat.
- Reduction of decision-making ability.

Also, they identified features that affect maintainability as standardization, interchangeability, accessibility, special tools, removal/installation, mounting-proof, safety precautions, ease of handling, troubleshooting, and skill level. Moreover, recovery activities from an ergonomic issues perspective can be influenced by anthropometric factors (that is, deal with the measurement of the human body), human sensory factors (that is related to sight, hearing, smell, feel or touch, and so on), physiological factors (that is referred to environmental stresses on human performance efficiency) and psychological factors (that is related to the characteristics of the human mind) (Kumar *et al.*, 2009). Barabadi and Markeset reviewed the Arctic environmental challenge's effect on maintainability and discussed the appropriate statistical approaches for quantifying the moon maintainability performance. This paper studied maintainability under the broad dependability concept defined as a collective term that describes availability performance and its influencing factors, namely reliability performance, maintainability performance, and maintenance support performance. Their research showed that three main items influence maintainability: personnel (maintenance crew) attributes, design attributes, and logistic support (Barabadi and Markeset, 2011). Since historical data and covariates play an important role in RAM analysis, the data must reflect the conditions that the equipment has experienced during its operating time. Barabadi et al., in continuing their research, studied the data collection process and challenges under Arctic conditions and proposed a methodology for it. The proposed methodology's application is considered for a centrifugal pump of Norway's oil and gas industry-offshore industry (Barabadi, Gudmestad, *et al.*, 2015). Recoverability principles also must be applied in the design phase to affect the time, accuracy, ease, and safety requirements of the repair process. Barabadi and Aalipour proposed a systematic management approach to effectively design for maintainability during the design phase.

To highlight the application of the proposed step-by-step methodology, Svea Coal Mine's conveyor belt (the northernmost coal mine in the world) as a case was discussed (Barabadi and Aalipour, 2015). Naseria et al. are the other researchers who studied the RAM attributes of Oil and Gas processing plants operating under dynamic Arctic weather conditions for scheduling preventive maintenance tasks. This work developed a virtual age model, which described the impacts of RAM's time-varying and stressing operating conditions. The case study sensitivity analysis results showed that the plant availability was more sensitive to weather conditions on equipment hazard rates than maintenance duration (Naseri *et al.*, 2016). This researcher also broadly reviewed and discussed different elements of offshore operating conditions specific to the Barents Sea and further investigated various effects of such conditions on Arctic offshore O&G facilities and operations' RAM (Naseri and Barabady, 2016b). Naseri additionally discussed maintainability considering the effect of winterization of oil and gas equipment. In this regard, a mathematical framework for maintainability analysis was proposed. He used a Monte Carlo system simulation technique for system downtime analysis (Naseri, 2017).

3-3- The recoverability analysis approaches

One of the main sides of the resilience triangle is the recoverability that, like reliability, can be affected by different influencing risk factors such as the number of crew members, available resources, environmental conditions, region, and technical condition of the system. These parameters lead to a great deal of uncertainty and, thus, unreliable analysis results. Therefore, recoverability deals with the criteria that consist of time and the effects of environmental conditions. It could be said that the recoverability goal is that the system should be recovered without a considerable investment of time, at the lowest cost, with a minimum impact on the environment, and with a minimum expenditure of resources. Recoverability is also considered a pivotal index to enhance system performance and measure system recovery ability. The significance of these indicators (recoverability, reliability, resilience, etc.) has increased due to rising energy costs, the competitive market environment, and new concepts such as resilience in different areas. The formal definition of recoverability is an organization's ability to restore an infrastructure unit or system to a level that can deliver required functions as before the disruptive event. In an analogy with the maintainability definition that as “the ability of an item under given conditions of use, to be retained in, or restored to, a state in which it can perform a required function when maintenance is performed under given conditions and using stated procedures and resource,” recoverability defined for infrastructures, organizations and different systems in general shape. This can be paraphrased as “the probability of recovery at a given time” (Barabadi and Markeset, 2011; Rod *et al.*, 2020; Smith, 2011). According to this point, most of the statistical methods in the reliability domain discussed in detail can be used in recoverability analysis. Therefore, a general review of these methods is done in this chapter. Similar to the reliability, the basic statistical approaches were the parametric methods that had been used more frequently the recovery time as the only variable of interest (Barabadi, Garmabaki, *et al.*, 2015; Barabady, 2005; Elevli *et al.*, 2008; Knezevic, 1993; Kumar, 1989). In parametric methods, if "t" is a random variable representing recovery time, the mathematical definition of recoverability is given by Eq.(3-1) (Rod *et al.*, 2020):

$$Rec(t) = F(T < t) = \int_0^t f(x)dt = 1 - exp\left(-\int_0^t \mu(u)du\right) \quad \textbf{(3-1)}$$

where $Rec(t)$ is the recoverability at time t. Also, let $f(x)$ be the corresponding probability density function (PDF). $F(t)$ is the cumulative recovery distribution function and expresses the probability of completing the recovery process at T < t. $f(x)$ is the recovery density function (Hoseinie *et al.*, 2012b). $\mu(u)$ is recovery rate and defined as the probability the recovery is completed in the time interval $(t, t + \Delta t)$ when it is known the recovery has not been completed until time t. Recovery rate can be defined by Eq.(3-2) (Rod *et al.*, 2020):

$$\mu(u) = \frac{f(t)}{1 - Rec(t)} \quad \textbf{(3-2)}$$

It should also be mentioned that recovery activities, in general, are carried out in complex and uncertain environments. In such operational environments, many factors can directly or indirectly affect system performance attributes. Therefore, as the other system performance attribute, the recoverability evaluation can be easily affected by the operational condition and, as a result, affected the resilience. Thus, it is challenging to analyze the effect of the operating environment condition, and the magnitude of their effect must be estimated. This evaluation can be provided as a management decision tool in which operational environments are more important from a recoverability point of view. Influencing factors on the recovery path trajectory like reliability analysis can be categorized into observable risk factors and unobservable risk factors.

A few models are available for predicting the influence of various factors on recoverability. Some researchers used a proportional hazard model as a starting point to model the operational environment effect and developed the **proportional recovery model (PRM)** (Barabadi and Markeset, 2011; Gao *et al.*, 2010b; Kumar *et al.*, 2017; Tsarouhas, 2018). Like PHM in reliability analysis, this model's application is also restricted to the time-independent and observable covariates. AFT, SCRM, and EPHM are the main appropriate statistical approaches that can be used to identify and formulate the time-dependent influence factors discussed in the reliability analysis subsection (Chen and Wang, 2000; Ciampi and Etezadi-Amoli, 1985; Gorjian Jolfaei, 2012). Here, the PRM is discussed as a basic model. The recovery rate $(\mu(t, z))$ can be used to analyze covariates' effect on recoverability performance and can be expressed as Eq.(3-3) (Barabadi *et al.*, 2011a):

$$\mu(t, z) = \mu_0(t)\phi(w\beta) = \mu_0(t)exp\left(\sum_{j=1}^{m} w_j\beta_j\right) \quad \textbf{(3-3)}$$

The component recoverability influenced by covariates is expressed as (Barabadi *et al.*, 2011a):

$$Rec(t, z) = 1 - \left(1 - Rec_0(t)\right)^{exp\left(\sum_{j=1}^{m} w_j\beta_j\right)} \quad \textbf{(3-4)}$$

where $\mu(t, w)$ and $M(t, z)$ are the recovery and recoverability function, respectively, β is a regression coefficient of the corresponding m covariates (w), and $\mu_0(t)$and $M_0(t)$ are the baseline recovery rate and baseline recoverability (cumulative distribution function of TTRs).
A covariate stratifies the model with non-proportional recovery in the stratified Cox regression method for recovery data. The same approach can be useful in time-dependent modeling covariates. Different baseline recovery rates are computed for each stratum, while the regression coefficients for all strata are equal. The recovery rate of an asset in the g^{th} stratum can be expressed as (Barabadi *et al.*, 2011a; Ghodrati and Kumar, 2005b):

$$\mu_g(t, w) = \mu_{0g}(t) exp\left(\sum_{j=1}^{m} w_j \beta_j\right) \quad g = 1,2, \ldots, u \tag{3-5}$$

where β is the regression parameter and μ_{0g} is the baseline recovery function for each stratum. The baseline recovery function for u strata is arbitrary, and all are assumed to be completely unrelated.
The models discussed to this point can only analyze time data and observable risk factors. To remove this restriction, recently, some base covariate-based methods, such as the accelerated failure time (AFT) and proportional hazard (PH) models, have been extended by the frailty model to analyze the observable and unobservable risk factors effects in combination with time data. They named it as **mixture frailty model (MFM),** and its recovery function can be written as (Rod et al., 2020; Zaki et al., 2019):

$$Rec_\theta\big(t, z_i.z_j(t)\big) = 1 - \left[1 - \theta ln\left\{1 - \mathrm{Rec}\big(t, z_i.z_j(t)\big)\right\}\right]^{-\frac{1}{\theta}} \tag{3-6}$$

Where:

- $Rec_\theta\big(t, z_i.z_j(t)\big)$ is the unconditional recoverability function with gamma distribution frailty function, the mean and variance are assumed equal to one and θ (Asfaw and Lindqvist, 2015; Cha and Finkelstein, 2014; Garmabaki *et al.*, 2016; Slimacek and Lindqvist, 2017).
- z_i and $z_j(t)$ are time-independent and time-dependent observed covariates $P; \delta$ are column vectors, consisting of the regression parameters for identified time-independent and time-dependent observed covariates.
- $\mathrm{Rec}\big(t, z_i.z_j(t)\big)$ is the recoverability function of time and observable covariates. If the observed covariate follows the exponential function in the presence of *m* time-independent observed covariates and *n* time-dependent observed covariates, it can be written as:

$$Rec\big(t, z_i, z_j(t)\big) = 1 - [1 - Rec_0(t)]^{\exp\left[\sum_{i=1}^{m} p_k \mathrm{z_i} + \sum_{j=1}^{n} \delta_k \mathrm{z_j(t)}\right]} \tag{3-7}$$

Where covariates p and δ are column vectors, consisting of the regression parameters for identified time-independent and time-dependent observed covariates. $Rec_0(t)$ is the baseline recoverability function dependent only on the time as follows:

$$Rec_0(t) = 1 - exp\left[-\int_0^t \mu_0(t')dt'\right] \tag{3-8}$$

Where $\mu_0(t')$ is the baseline recovery rate $\mu_0(t)$ dependent on time alone, which is modeled using appropriate distributions.

As said before, the main limitation of the PH models such as PRM and SCRM is the proportionality assumption. The AFT can be easily implemented to remove this restriction and does not require any assumptions. Like PH models, AFT can be captured the impact of technical features, organizational aspects, and environmental conditions (also known as influencing variables, covariates, or risk factors) and not require any assumptions. The AFT model is primarily applied in reliability theory, industrial experiments, and alternatives if the proportional hazards assumption does not hold. The recovery rate of the AFT model under the impact of covariates can be rewritten as (Hanagal, 2011; Wienke, 2010):

$$\mu\big(t, z(t)\big) = \mu_0\left(t \times exp\big(\beta z(t)\big)\right) exp\big(\beta z(t)\big) \tag{3-9}$$

Where, $z(t)$ is a vector of covariates, and β is a vector of regression coefficients. Covariates accelerate or decelerate the failure time relative to baseline hazard according to whether $exp\big(\beta z(t)\big) > 1$ or $exp\big(\beta z(t)\big) < 1$. The μ_0 as baseline hazard and a nonnegative function of the covariates may either be left unspecified or is assumed to be parametric. The regression models, such as the exponential and Weibull, can be implemented as AFT models.

Resilience of the engineering system is the central focus of this chapter. The first section presents the concept and definitions of resilience. The literature is then reviewed in its three main perspectives: engineering systems, resilience in the Arctic area, and "Resilience, Reliability, and Recoverability (3Rs)". The third section is followed by a more focused consideration of reliability and recoverability-centered resilience assessment that showed the resilience evaluation procedure generally could be separated into two major categories: qualitative and quantitative. Thus, the last section focuses on quantitative approaches, given our interest in engineering systems.

4- RESILIENCE

The occurrence of significant disruptions or discontinuities that shift the system away from its current equilibrium state is why a deep understanding of system resilience is essential. Such disruptions could include finding new technologies, the appearance of new regulatory and market forces (production improvement), or changes in the availability of resources. The scientometrics review of resilience publication by year in Figure 4-1 illustrates the steady growth in the number of publications focusing on resilience in the engineering research area from 2006 to 2019. Keep in mind that the frequencies for 2020 are most likely incomplete.

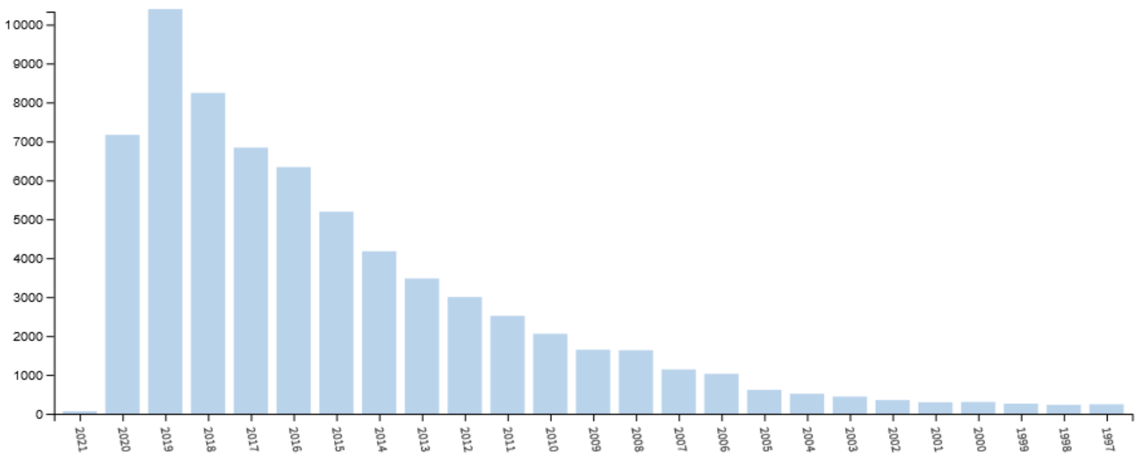

Figure 4-1- Published year histograms of resilience publications from *Scopus* database in 1997-2020

As Figure 4-2 indicates, the total output's major contribution came from four subject areas: Environmental Since, Ecology, Psychiatry, and Environmental Studies. Both indicate that the engineering and technological fields are new and can be more considerate. The pie chart of subjects' areas of the WoS database in Figure 4-3 confirms this. It illustrates that Social science and Environmental science are the most popular research areas among the authors.

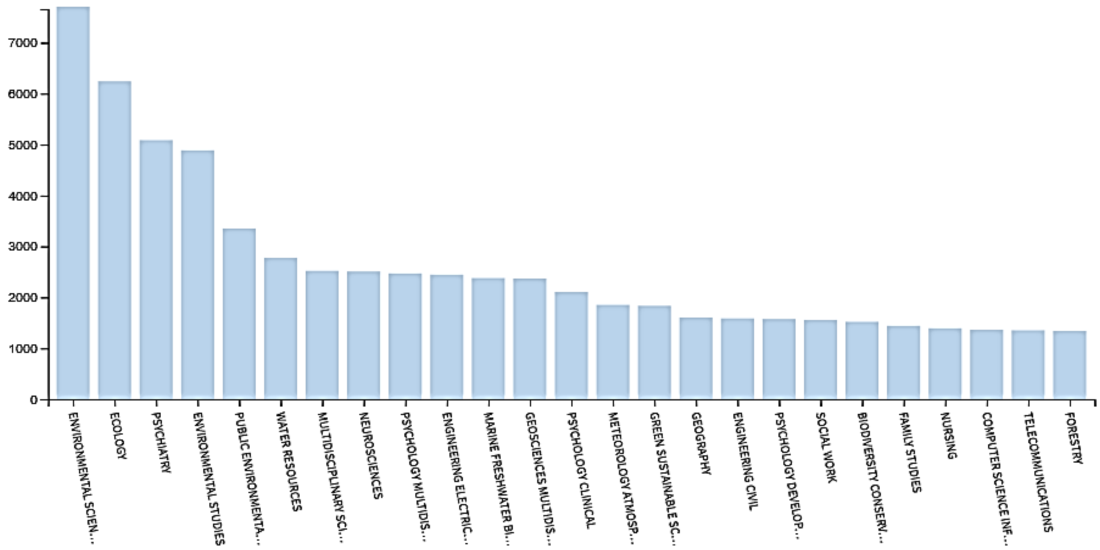

Figure 4-2- Since categories histograms of resilience publications from the *Scopus* database in 1997-2020

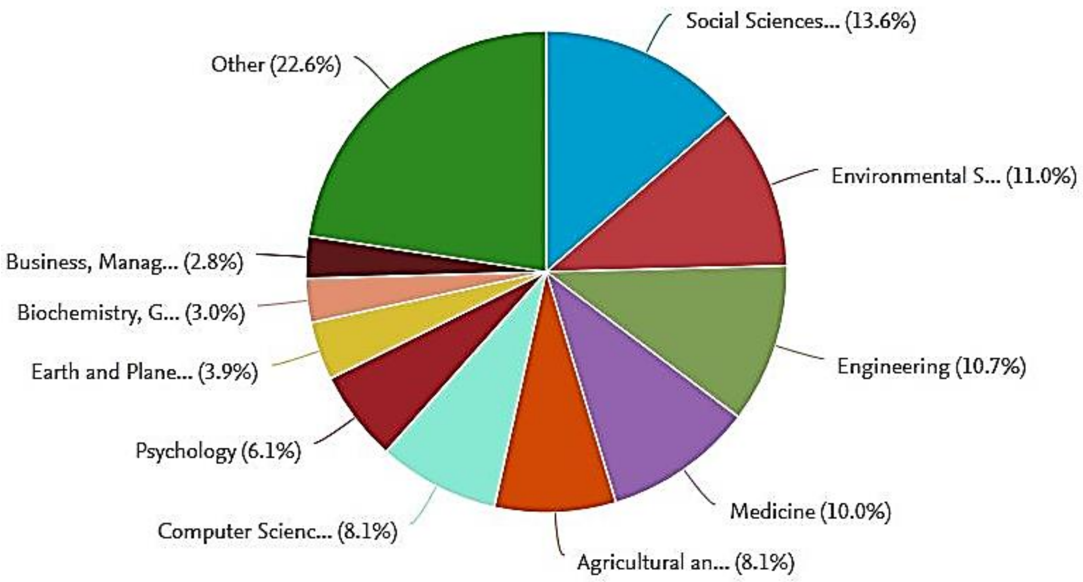

Figure 4-3- Subject areas histograms of resilience publications from *WoS* database in 1978-2020

After a basic familiarity with the resilience concept and before delving into the nuances, it is important to clarify the definition of resilience and its conceptual evolution. In the review paper, pointed out that the word resilience has been originally initiated from the Latin word “resiliere,” which means to “bounce back.” The common use of resilience implies an entity or system's ability to return to normal conditions after an event that disrupts its state (Hosseini et al., 2016). In the following, some of the widely accepted definitions of resilience are presented for finding the root of this concept.

As far back as the early 20th century, resilience was defined as the thermodynamic work required to cause elastic deformation (e.g., stretching) in a solid material. The term resilience was first introduced in materials engineering, where it specified the material's ability to return to the original shape after deformation (Trautwine, 1906). Holling then popularized it in 1973 within the seminal, which has formed the foundation for most studies of the concept of ecological resilience and various other forms of resilience (Holling, 1973). But it must be attention that resilience is related to both the individual and organizational responses to turbulence and discontinuities. In organizational Horne and Orr's context, resilience is the fundamental quality to respond productively to significant change that disrupts an event's expected pattern without introducing an extended period of regressive behavior (Home III and Orr, 1997). Hamel and Valikangas extended the meaning of organizational resilience as continuous reconstruction capacity (Hamel and Valikangas, 2004). Hollnagel et al. defined resilience in the context of engineering as “The ability to sense, recognize, adapt and absorb variations, changes, disturbances, disruptions and surprises” (Hollnagel *et al.*, 2006). Fiksel considered resilience the system's capacity to tolerate disturbances while retaining its structure and function (Fiksel, 2006). For about two decades, brand and Jax reviewed the variety of definitions proposed for “resilience” within sustainability science. They achieved three categories, ten classes, and correspondingly ten definitions of resilience. Then each definition of resilience was explained in more detail concerning its category and class, respectively. These ten definitions represent coverage to the original descriptive concept of resilience as Holling introduces (Brand and Jax, 2007). Haimes believed that resilience is a system's ability to withstand a major disruption within acceptable degradation parameters and recover within an acceptable time and composite costs and risks (Haimes, 2009). Resilience in the context of civil engineering is expressed mechanistically as the ability to "bounce back" after a major disturbance (Reed *et al.*, 2010).

Similarly, the ability to reduce the magnitude and/or duration of disruptive events can be defined as infrastructure resilience (Starr *et al.*, 2003). Several definitions are suggested depending on the assessment objects for engineering systems, such as mechanical engineering, civil engineering, critical infrastructure, etc. In 2014, Francis and Bekeru added the notion of resilience, a conceptual framework composed of multiple dimensions. Absorptive, adaptive, and restorative capacities are at the center of what a system needs to do and how it needs to respond to perceived or real shocks. The objective of defined resilience was to retain predetermined system performance dimensions, and identity is given forecasted scenarios (Francis and Bekera, 2014).

The diverse definition of resilience in the other context such as physical systems, ecological systems, socio-ecological systems, psychology, disaster management has been developed (Bodin and Wiman, 2004; Bruneau *et al.*, 2003; Francis and Bekera, 2014; Holling, 1973; Luthans *et al.*, 2006; Walker *et al.*, 2002). A comprehensive review of recent research articles related to defining and quantifying resilience in various disciplines was done by Hosseini et al. (Hosseini *et al.*, 2016).

Azadeh et al. define resilience engineering that is incorporated both the property to stay away from failures, losses and the ability to react effectually after events. They used flexibility, adaptability, and redundancy as effective resilience engineering factors to optimize supplier selection problems (Azadeh *et al.*, 2017). McDonald had an opinion that Resilience conveys the properties of adapting to the environment's requirements and managing the variability of the environment (McDonald, 2017). Fujita defined the organizational system's resilience as the ability to recognize & adapt to handle random perturbations that call into question the competence model and demand a shift of process, strategies, and coordination (Fujita, 2017).

Cai et al. recently defined resilience as an entity's capability to recover from an external disruptive event (Cai *et al.*, 2018). Another standard definition of engineering resilience is presented by The American Society of Mechanical Engineers (ASME) as the ability of a system to sustain external and internal disruptions without discontinuity of performing the system's function or, if the function is disconnected, to fully recover the function rapidly ("The American Society of Mechanical Engineers - ASME", 2020). Recently Asadzadeh et al. defined resilience as "a process that makes it possible to effectively respond to unanticipated changes and unexpected events, vulnerabilities, and opportunities lying outside the scope of formal procedures" (Asadzadeh *et al.*, 2020).
As a result, it must be said, the resilience of the system depends on the four cornerstones that determine how a resilient system reacts to disturbances:

- The first one is returning to a reliability level after reaching a balance following a disruptive event.
- The second one is the ability of the system to sustain residual reliability after an event.
- The other two are the system's ability to continue operations in an undesirable status (or desirable status) based on the understanding of adaptive capacity hereafter.

However, the current review pointed out that some definitions of resilience compete with "Robustness". Robustness is often used synonymously or in place of resilience to value engineering designs in the engineering field. But it must be mentioned, when the notion of resilience is applied to any field like engineering, communities, and the wider context of organizations, this broad definition is "the capability and ability of an element to return to a pre-disturbance state after a disruption" does not change.

4-1- The state of resilience concept in engineering systems

This section explains how engineering systems' resilience should be understood differently than Holling's resilience. The concept of resilience in the engineering field is moderately new compared to other fields. The engineering area includes technical and industrial systems designed by engineers who interact with humans and technology, such as water distribution systems, nuclear plants, transportation systems, locks, and dams. Also, engineers in the resilience concept try to ensure complex systems that can sustain adverse conditions and recover quickly after disruptions. The examination of the distribution of different countries' output in resilience from 1996 to 2019 indicated that the works were published mainly by authors from 25 different nationalities. The countries contributing most to the field of resilience for 23 years are presented in Figure 4-4. It is illustrated in Figure below; the U.S.A, China, and England were the countries with high contributions.
Interestingly, these three countries accounted for most scientific literature over the studied period on average. Generally speaking, the study indicates that the field has not evolved considerably in different world regions. Although the rosing trend in the distribution of resilience-related journal articles by year and citation in Figure 4-5 and Figure 4-6, using WoS and Scopus databases presents this concept's increasing importance between engineers. According to the increasing appearance of resilience-related research, the current government and policy emphasis on resilience is also seen in academic research.

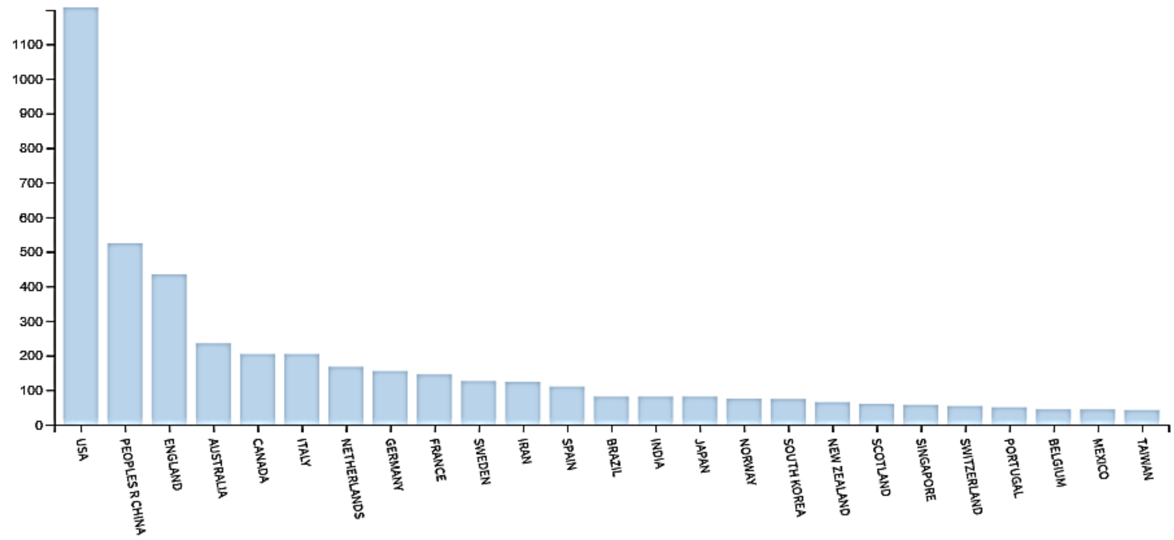

Figure 4-4- Geographical distribution of the resilience publications in the engineering field from *Scopus* database in 1997-2020

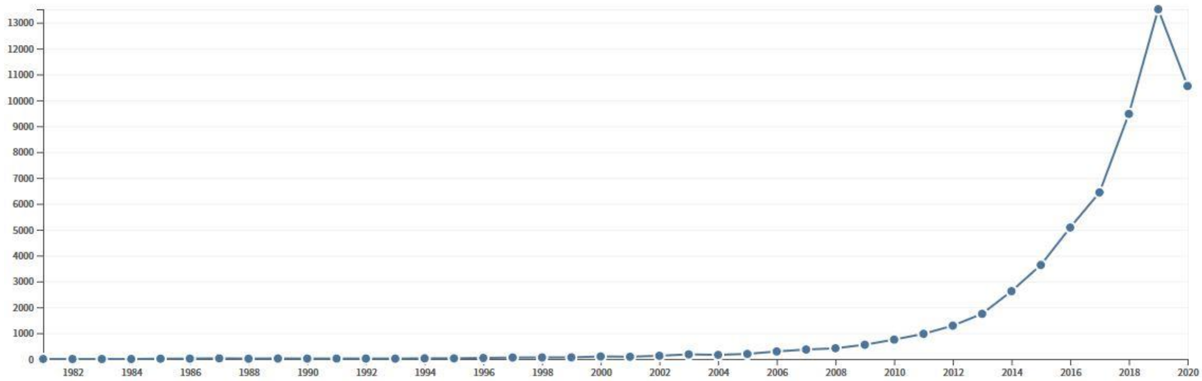

Figure 4-5- Distribution of resilience papers citation in an engineering field from *WoS* database in 1982-2020

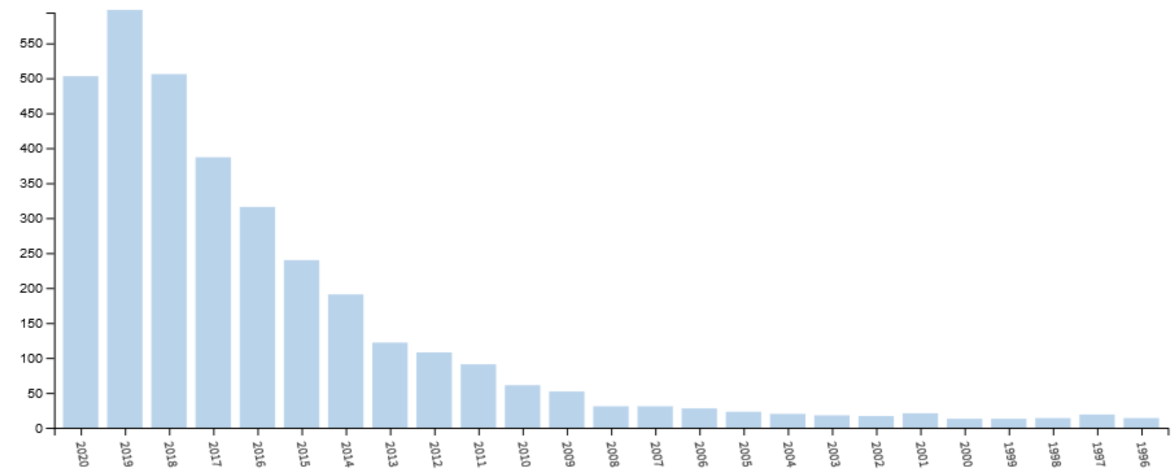

Figure 4-6- Distribution of resilience papers by year of publications in an engineering field from *Scopus* database in 1997-2020

The attention of two industrial giants (USA and China) and the upward trend of publication and related papers to the resilience concept emphasize the importance of further research. The resilience in the engineering domain was introduced in the 17th century in mechanics, describing materials' properties (Righi *et al.*, 2015). In the early 2000s, Fiksel used the resilience concept to industrial enterprise sustainability design by adopting a fresh perspective based on systems thinking. This work had been identified four major system characteristics that contribute to resilience as follows (Fiksel, 2003):

- Diversity: the existence of multiple forms and behaviors;
- Efficiency: performance with modest resource consumption;
- Adaptability: flexibility to change in response to new pressures;
- Cohesion: the existence of unifying forces or linkages.

Rydzak et al. examined machine reliability improvement programs using System Dynamics models to illustrate the idea of resilience. The paper focuses on refineries and chemical plants (Rydzak *et al.*, 2006). Moore et al. provided resilience scenarios for the three ice-related species categories in the Arctic. This paper proposed an approach to study the impacts (potential challenges to species' survival associated with recent Arctic ecosystem perturbations such as ice-obligate, ice-associated, and seasonally migrant) and the resilience of Arctic marine mammals to climate change. (Moore and Huntington, 2008). A review of resilience literature in its widest context and later its application at an organizational level in small and medium enterprises (SMEs) provided by Bhamra et al. They identify that the relationship between human and organizational resilience; understanding interfaces between organizational and infrastructural resilience are the main area of resilience researches up to 2011 (Bhamra *et al.*, 2011). Francis and Bekera, in 2014, reviewed the literature to offer guidance to infrastructure system engineers by comparing risk analysis to resilience analysis. Also, They proposed a metric for resilience measurement (Francis and Bekera, 2014). The following year, a comprehensive literature review based on 237 studies from 2006 to 2014 was done by Righi et al. They defined six research areas foe resilience concept as the theory of resilience; identification and classification of resilience; safety management tools; analysis of accidents; risk assessment; and training (Righi *et al.*, 2015). Lundberg and Johansson presented a "systemic resilience model" that is systemic – focusing on constraints emerging from the system context, functional dependencies, and resilience strategies (Lundberg and Johansson, 2015).

Pursiainen et al.'s paper, resilience is linked to the crisis management cycle by seven phases: risk management, prevention, preparedness, warning, response, recovery, and learning. Risk management often includes the first three phases (risk assessment, prevention, and preparedness). Hence, the resilience concept goes beyond traditional risk management and covers more than mere protection and pre-event capabilities (Pursiainen *et al.*, 2016). The concept of resilience has a multi-disciplined background, from economics to social sciences and ecology systems. Recently, the literature on resilience in process system engineering and plants, including technical aspects, has been growing significantly. These publications mostly emphasized safety and/or resilience as an important characteristic (Jain *et al.*, 2017; Jain, Pasman, *et al.*, 2018; Jain, Rogers, Pasman and Mannan, 2018; Jain, Rogers, Pasman, Keim, *et al.*, 2018). Also, the resilience approach with a safety improvement perspective had been used

in critical systems such as healthcare systems, nuclear power plants, process industry, aviation, process industry, and maintenance organizations (Asadzadeh *et al.*, 2019; Azadeh and Salehi, 2014; Carvalho *et al.*, 2008; Dekker *et al.*, 2016; Dinh *et al.*, 2012; Jeffcott *et al.*, 2009; Shirali *et al.*, 2013). Hoseinie et al. attempt to apply the resilience concept to the mining and production systems. The linear recovery function measured resilience (Hoseinie *et al.*, 2020).
Based on available literature from engineering backgrounds, resilience has been characterized and defined in many concepts and different points of view. However, some of those are more general and have been accepted by researchers significantly. As a result, it can be said that engineering resilience is the ability of an engineered system to maintain its functionality by resisting and recovering against adverse events such as failures. The resilience concept as a developing philosophy of production systems could also efficiently support decision-making in advanced engineered systems and infrastructures to reach a high level of product assurance and enterprise asset management.

4-2- The state of resilience concept in the Arctic area

Modern societies rely on complex systems, such as gas turbines, industrial plants, or infrastructure networks. These systems' operation is directly related to the operational, conditional, and environmental attributes highlighted in the Arctic with a harsh environment. Thus, there are new challenges for researchers, designers, and managers, who try to evaluate their performance. This issue becomes more critical concerning a new and multifaceted idea such as resilience. In recent years, resilience research in the Arctic has been widely conducted in Environmental science, as shown in Figure 4-7 and Figure 4-8. Geology is the second discipline

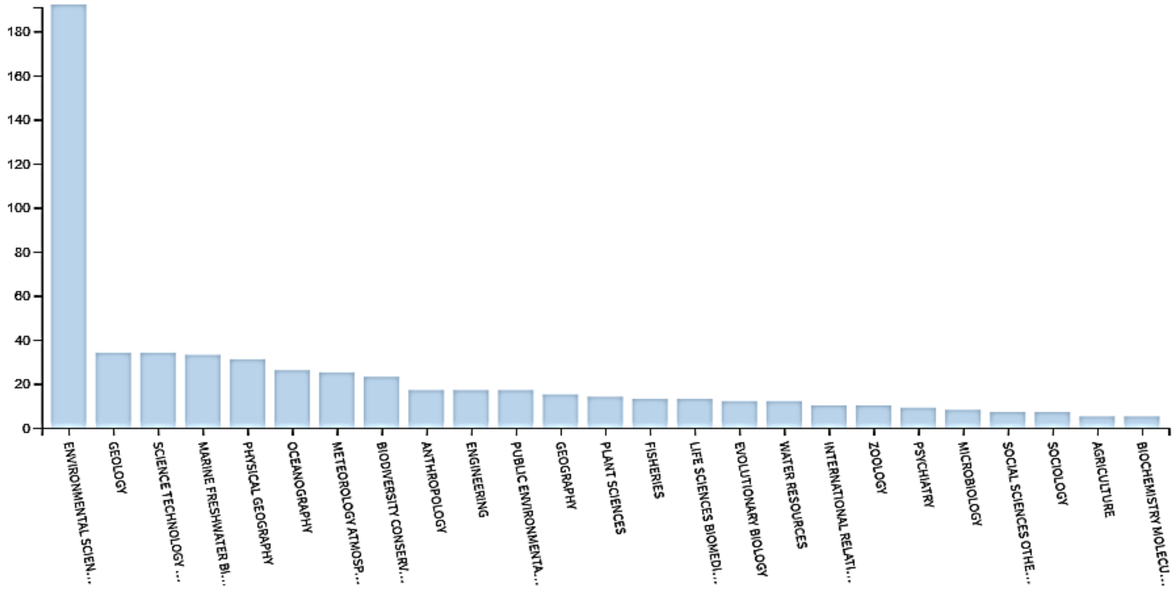

Figure 4-7- Distribution of resilience researches areas in the Arctic from *Scopus* database in 1997-2020

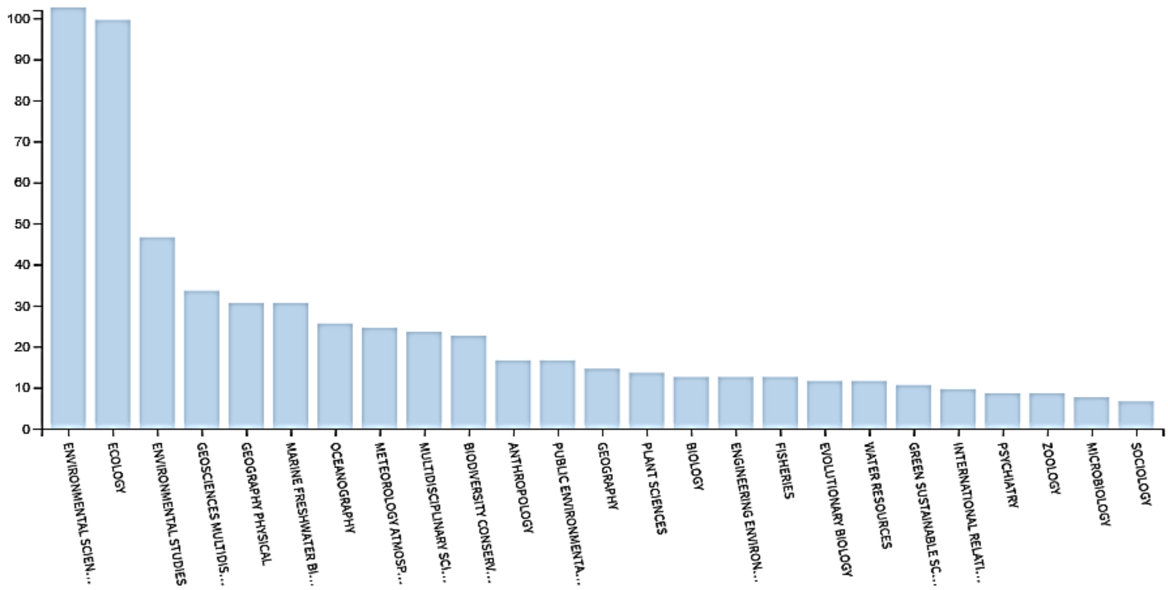

Figure 4-8- Distribution of resilience researches areas in the Arctic from *WoS* database in 1982-2020

In confirmation of the study, the result of Hosseini et al. that "CiteSpace" software clusters had done presented the Environmental, Social, & Ecology were in the highest priority disciplines (Chen, 2006; Hosseini et al., 2016). Moreover, Increasing the resilience of a natural system is a common conservation goal. The geographical distribution of resilience publications in the Arctic field in Figure 4-9 shows the USA is the leader territory and Norway in the second position.

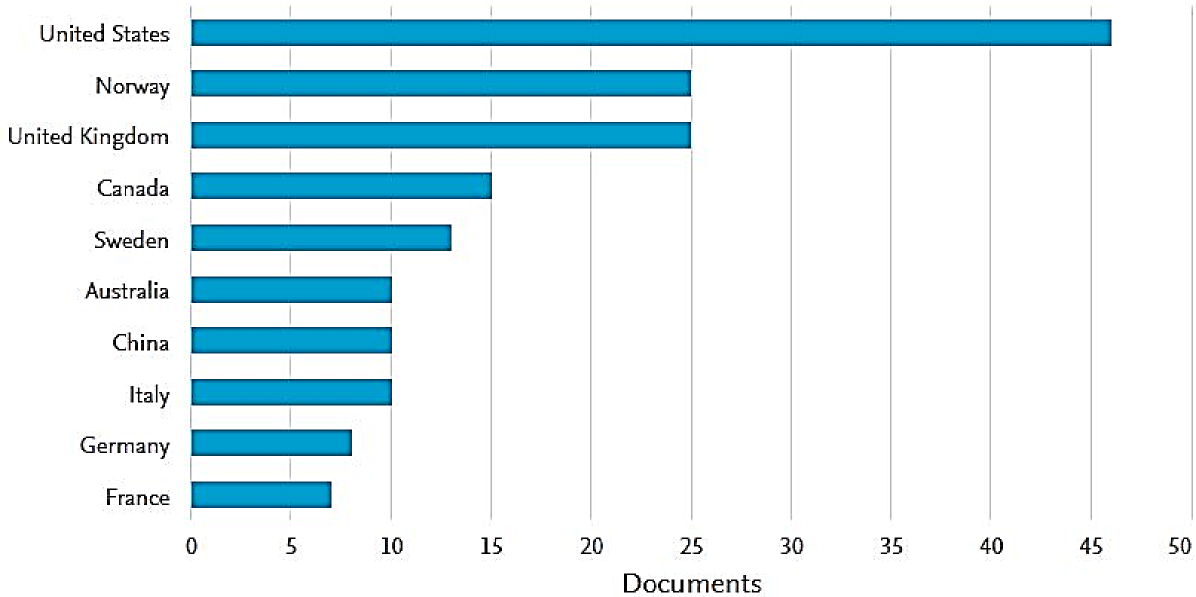

Figure 4-9- Country o territory distribution of resilience researches in the Arctic field from *WoS* database in 1982-2020

When extending the scientometrics study to the affiliation of a published document (Figure 4-10), it can be seen that "The Arctic University of Norway (UiT)" could get the highest rank. Figure 4-11 shows that Bjarte Rød and Barabadi Abbas from UiT, with seven and four publications as first authors, are ranked first and third, respectively. The support of Norwegian universities and researchers of the resilience concept shows that this idea is well established in this country and shows its importance in the Arctic region. It can be seen in recent years' upward trend of publication citation.

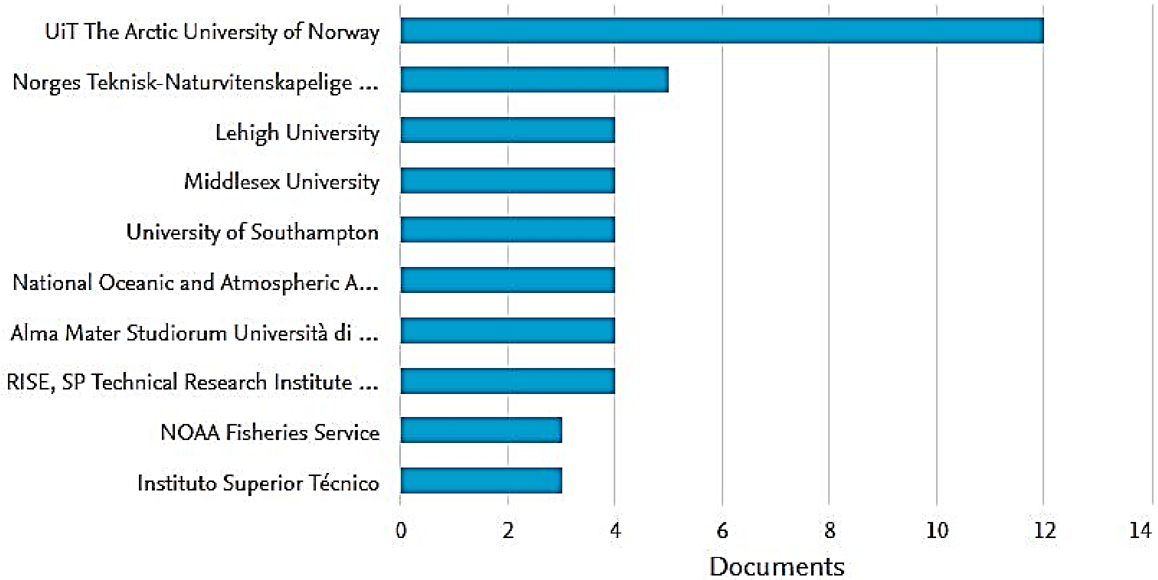

Figure 4-10- Affiliation distribution of resilience researches in the Arctic field from *WoS* database in 1982-2020

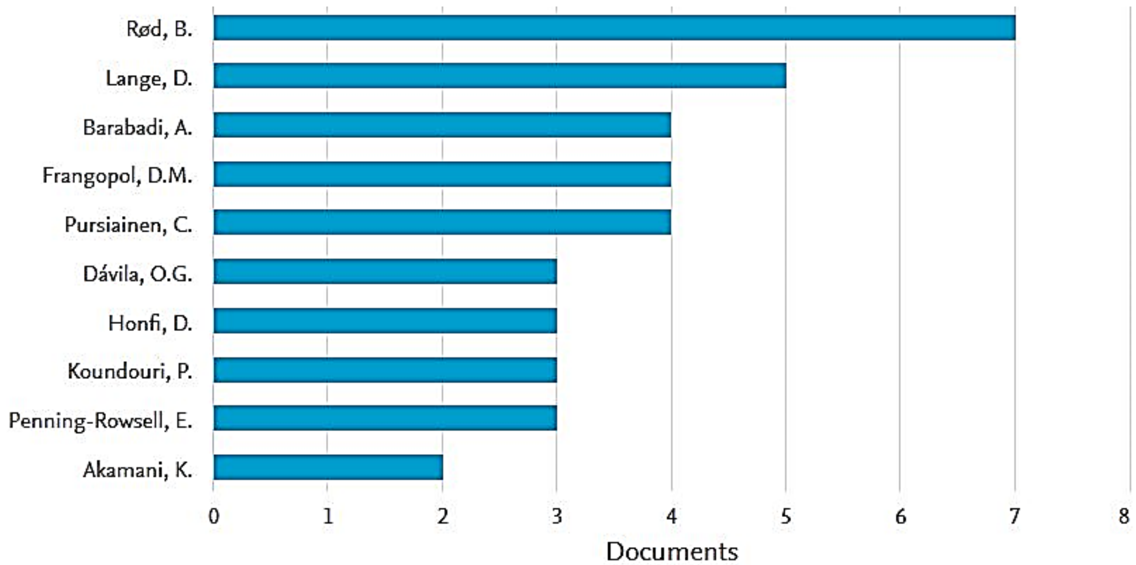

Figure 4-11- Documents distribution of resilience by author in the Arctic field from *WoS* database in 1982-2020

As a result, our literature in the Arctic area also began with environmental, Social, & Ecology area publications. Hansen et al., in the user's manual for building resistance and resilience to climate change in natural systems, tried to assist natural resource and protected area managers as they begin to consider how to respond to this growing threat. It's a proper document for natural resource managers ready to meet the impacts of climate change. This document consists of nine chapters that different authors write with resilience and protection perspectives of the Arctic ecosystem. It defined resilience in an environmental context as the ability of ecosystems, habitat types, and species to maintain a relatively constant state in the face of trouble and stress and to recover quickly after a temporary disturbance (Hansen *et al.*, 2003). In a report of the

Arctic Council project, the resilience of social-ecological systems in the Arctic was analyzed. In the social-ecological system, humans are part of nature, and that these systems function in interdependent ways. The main impression of resilience in this report is human and natural systems' ability to adapt or transform in the face of change. This work aimed to identify the potential for ecosystem services shocks and evaluate adaptation and transformation strategies in the Arctic (Arctic Council, 2013). In the other report of Council, the nature of the Arctic change, including critical tipping points, the factors that support resilience, and the kinds of choices that strengthen adaptive capacity, were evaluated. It is documented slowing Arctic ecosystems change, an overview of tools and strategies for assessing and building resilience, and highlighting the world's stakes. It defined resilience as the capacity to buffer and adapt to stress and shocks, thus navigating and shaping change. It also addressed social-ecological resilience and defined it as "the capacity of people to learn, share and make use of their knowledge of social and ecological interactions and feedback, to deliberately and effectively engage in shaping adaptive or transformative social-ecological change". Ultimately, This report shows that the outcome of resilience in the Arctic will depend on empowering their people to self-organize, challenges definition in their terms, and discover their solutions, knowing that they have the support to implement their plans (Council, 2016). Ikpong and Bagchi assessed highway bridges' resilience or vulnerability against climate change (global warming) impacts in 14 bridges of the Canadian Arctic and proposed the "Bridge Resilience Indicators (BRI)". The objective is to describe a system of rating bridges using a BRI set to catch the resilience in global warming effects. The results illustrated how significant public investments (such as highway bridges) resulting from the failure of public transportation agencies to consider climate-related BRIs could be wasted in infrastructure improvement (Ikpong and Bagchi, 2015).

Bijarte et al., in 2016, published a paper focused on the resilience of Arctic infrastructures. They developed a practical approach for characterizing the expert judgment-based resilience of Arctic infrastructure systems. It also includes the review of resilience quantification methods and highlights the resilience metrics. The focus is on the engineering and technological domain. (Rød *et al.*, 2016). Kenny used the resilience concept about the urbanization of the Arctic. The paper's literature review shows different planning, design, engineering, architectural and technological concepts and solutions to resilience in Arctic settlements adapting to climate changes and social and economic development support. However, comprehensive planning agendas are needed for the Arctic that balances resilient and sustainable growth with climate change challenges. (Kenny, 2017). Taarup-Esbensen posed a risk assessment by utilizing a resilience perspective and evaluating organizations operating in the Arctic. Though, the thinking behind and the structure of the model is not restricted to this specific environment. This approach uses resilience engineering (RE) to improve assessments. RE's focus on the system's ability to respond, monitor, learn and anticipate to improve system resilience to confront events that have the potential to damage or destroy something of value (Taarup-Esbensen, 2020). Bayesian network (BN) is an acyclic graph that connects the multiple interdependent failures and their causes through conditional probability tables. Also, the estimated failure probabilities can be updated when new data and information becomes available by Dynamic Bayesian Network. Zinetullina et al. do the resilience assessment of a separator in the oil production system by Dynamic Bayesian network (DBN). They model the probabilistic relationships between causes and effects of winterized process systems in a dynamic manner (Zinetullina *et al.*, 2020).

The Arctic is known for its undeveloped and harsh environmental conditions, such as icing, snowstorms, strong winds, darkness, and remoteness to emergency support bases. This significantly reduces the equipment lifetime and increases the probability of system failure. Thus, it is challenging to ensure safe and reliable production in this region. Resilience concept as a comprehensive system property consists of four main attributes: absorption, adaptation, restoration, and learning. It tries to cover the different perspectives of performance and quality in various conditions. Therefore, it could easily open itself up among new concepts and be used in different Arctic-related sciences, especially in Environmental science.

4-3- Resilience, Reliability, and Recoverability (3Rs)

In the past few decades, reliability has been widely known as important in engineering product and process design. However, resilience in the engineering field deprives sufficient attention, and several resilience metrics have been proposed for engineering systems. New works and concepts demand a deep understanding of how engineered systems achieve resilience and develop a generic resilience principle that applies to the different engineering fields. A resilience-driven system design (RDSD) framework had been proposed by Youn et al. The proposed framework was used to design complex engineered systems with resilience characteristics. It comprises three hierarchical tasks: resilience allocation problem, system reliability-based design optimization, and system prognostics and health management (Youn *et al.*, 2011). Smart grids as modern infrastructure systems make power distribution more dependable and efficient. Failures in these structures can propagate more quickly and extensively and cause lower reliability. Albasrawi et al. described metrics for assessing the phase before a failure occurs and the recovery phase after a failure in a small smart grid based on the IEEE 9-bus test system. The first phase was characterized by reliability, and the latter was quantified using resilience (Albasrawi *et al.*, 2014). As described, uncertainty quantification is a key requirement and challenge for realistic and reliable numerical modeling such as industrial systems. In this way, software-s are had a bold effect on solving complicated problems and making the non-deterministic analysis a common practice in computational models and numerical simulations. Patelli et al. had an overview of the main capabilities of the recent release of the Matlab open-source toolboxes OPENCOSSAN which includes optimization analysis, life-cycle management, reliability and resilience analysis, sensitivity, optimization, and design under uncertainty (Patelli *et al.*, 2018). Hariri-Ardebili presented a systematic review of uncertainty quantification's fundamental elements: risk, reliability, and resilience. The paper's focus is on an integrated approach for risk analysis and risk management of dam safety (Hariri-Ardebili, 2018). Cai et al. proposed an availability-based engineering resilience metric by using a dynamic Bayesian network. They consider Resilience an inherent ability attribute of an engineering system that affects two main factors: structure and maintenance resources (Cai *et al.*, 2018). Sarwar et al. also used the Bayesian network format to build a resilience metric as a function of reliability, vulnerability, and maintainability for a remote offshore oil and gas facility for a potential hydrocarbon release. The proposed metric developed the resilience capacity to the system's absorptive, adaptive, and restorative capacities (Sarwar *et al.*, 2018). The process design and technology selection are the other areas of the resilience assessment application and other subjects, including technical, safety, environmental, and economic. Moreno-Sader et al. applied the resilience concept to propose an integrated "Return on Investment (ROI) Metric". The proposed methodology was applied to analyze a compressor process system in a hydrocracking process plant (Moreno-Sader *et al.*, 2019). Civil infrastructure is one of the main civilizations and engineering subjects. These systems' reliability is defined as the ability to safely provide essential goods or services that are essentially connected with other systems. Resilience could be raised as a nexus between economic, social, and technological systems and advanced models to narrow the gap between engineering and social science aspects. Since huge systems such as civil infrastructures in the aftermath of a damaging event, lose some of their capacities, and their return to functional condition depends entirely on the coordination of the mentioned systems. In this way, Guidotti et al. introduced the probabilistic to integrating physical infrastructure and social systems in the assessment of the communities' resilience. Their models consist of a four-step probabilistic assessment procedure, which is an integration of physical infrastructure and social systems in community resilience. Also, they studied the reliability and resilience of the potable water network of Seaside, Oregon, as the application of the proposed procedure. (Guidotti *et al.*, 2019). The other new system is the urban transportation network vital to megacities' robust operation. This system is often disturbed by recurrent perturbations such as traffic jams and non-recurrent perturbations such as earthquakes, tsunamis, terrorist attacks, etc., which have their own unpleasant consequences and cost for the population. Thus, like the other systems, here we need the performance measures for pre-perturbations and post-perturbations. Therefore, Recently, a review paper of three concepts including reliability, vulnerability, and resilience in transportation network performance is presented by Gu et al. the main goal of this paper is to clarify, to distinguish, and understand the three mentioned concepts in the context of the transportation network (Gu *et al.*, 2020). In the most recent work, Asadzadeh et al. present an integrated approach of resilience engineering to service reliability improvement in maintenance organizations. The proposed strategy applied for resilience assesses the gas industry. They try to increase service reliability (Probability of undesirable events) by establishing a learning policy that is covering resilience concepts and principles. The paper analysis shows that resilience practice can be improved system reliability (Asadzadeh *et al.*, 2020). Yarveisy et al. study resilience and its measurement definitions with a new attitude. The metric establishes a relationship between system: absorptive, restorative, and adaptive capacities, and satisfies the desired characteristics, the level of dependencies among said capacities. In this paper, firstly, they review the existing definitions of resilience for a revised understanding of the resilience engineering (RE) concept. This work offers new metrics based on reliability and maintainability combined with the system modeling approach. Finally, the proposed metric assay by a case study of the "Self-Sealant Central Tire Inflation System" (SS-CTIS) and "Swiss high-voltage electric power supply system" (EPSS) (Yarveisy *et al.*, 2020)

Reliability analysis approaches as reliability engineering offer relevant contributions to the overall system performance, such as a clear understanding of equipment behavior, optimization of process performance, reduction in system life-cycle costs, and assurance of safety operation and production quality. But it singly can't evaluate all edges of performance, especially in a large and sensitive system such as infrastructures. In this regard, recently, the resilience approach has received great interest. This concept is an inherent attribute of any engineering system, and it can be integrated with different characteristics of the system such as reliability, maintainability (recoverability), availability, supportability, etc. This specification of resilience can be more useful for engineers familiar with the reliability concept for many years. Using this feature, they can quantify the resilience, which provides an implementation guide for engineering planning, design, operation, construction, and management. Besides, when an engineering system is planned and designed, identifying the weak components or missions affecting resilience is important. Quantification of resilience in integration with performance factors can be provided it. Thus, as for the future perspectives, it is planned to find the performance-based resilience assessment approaches to modeling systems and preprogramming their disruptions.

4-4- The resilience analysis approaches

Measuring resilience is crucial to understanding it. The resilience assessment is characterized by (Lange *et al.*, 2017):

- Resilience analysis: The process of comprehending and determining the level of resilience
- Resilience evaluation: The process of comparing the analysis results against some predefined criteria to decide whether the level of resilience is acceptable or not.

This study is mainly put forward in investigating the first part. Although we have devoted most of our discussion to resilience's management principles, a metric reflecting these principles is needed for decision support and design. It has been acknowledged that quantitative metrics are required to support resilience engineering. In this context, the desired approach should be identified organizational resilience indicators such as top management commitment, just culture, learning culture, awareness and opacity, prepared-ness, and flexibility. Despite the consensus regarding the importance of resilience, the existing ones have not yet resulted in a unified practical method for applying the engineering domain approaches. Applications of resilience to engineering problems rely on the availability of quantitative resilience measures. According to the various field and diverse definitions (presented in the literature review report), different resilience metrics and corresponding evaluation methodologies have been developed that depend on accurate knowledge. Therefore, in this chapter, we review some most popular ones in the engineering area with a probabilistic perspective:

First resilience metric: In this approach, the quality of degraded infrastructure is compared to the as-planned infrastructure quality (=100) during the recovery period. However, it can be extended to many systems as quality is a general concept. This metric measures the resilience (Re) loss to an earthquake. Hereafter, for convenience, the measure of performance is assumed to be system reliability. If we suppose the time at which the disruption occurs is t_0 (hazard occurrence time), and the time at which the community returns to its normal pre-disruption state is t_1 (necessary time to restore the functionality of a critical system). The quality of the community infrastructure resilience loss (RL) at time t, is denoted with $Q(t)$ (Bruneau *et al.*, 2003; Hoseinie *et al.*, 2020):

$$RL = \int_{t_0}^{t_1} [100 - Q(t)]\, dt = 1 - \frac{\int_{t_0}^{t_1} [Q(t)]\, dt}{t_1 - t_0} \quad \textbf{(4-1)}$$

This formulation 100% quality means that a system is completely functional; zero percent is entirely non-functional. This entire plot has been used to represent the resilience of a system over time after a disruption. The resilience metric (Re) can be defined as follows (Hariri-Ardebili, 2018):

$$Re = \frac{\int_{t_0}^{t_1} [Q(t)]\, dt}{t_1 - t_0} \quad \textbf{(4-2)}$$

Resilience (Re) and loss of resilience (RL), their complement, are usually shown through a "recovery function" illustrated as the shaded area in Figure 4-12.

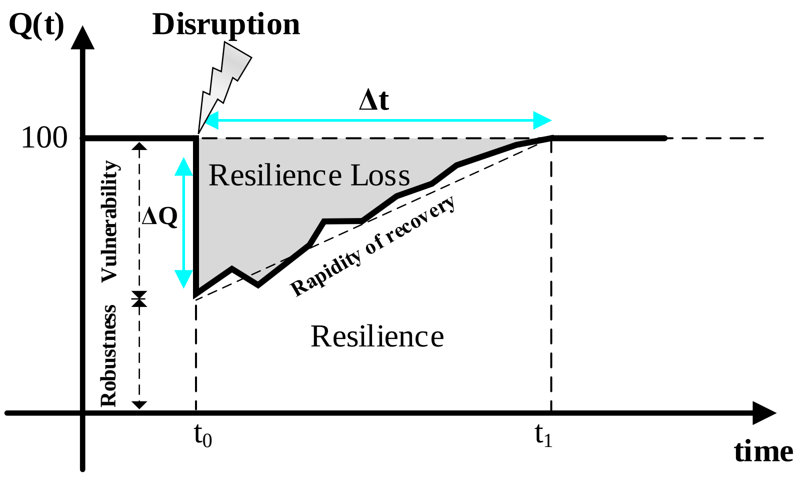

Figure 4-12- The required content of first quantify resilience metric (Hosseini *et al.*, 2016; Kammouh *et al.*, 2017)

If we suppose linear recovery mode for some systems and events and the immediate degradation of performance after a disruptive event, which may be not realistic, then Eq.(4-1) becomes simple to Eq.(4-3) (Bruneau *et al.*, 2003; Hoseinie *et al.*, 2020):

$$Re = \frac{\Delta Q \times \Delta t}{2} \quad \textbf{(4-3)}$$

In Figure 4-12, the resilience triangle (resilience loss) illustrates the performance over time, and the smaller the triangle, the more resilient the infrastructure. In this figure, the resilience triangle's size simultaneously indicates robustness, vulnerability (Susceptibility of the system to failure or perturbations), and rapid recovery. Gu et al. in Figure 4-13 give an attractive illustration of different reliability, vulnerability, and resilience (Gu *et al.*, 2020). Reliability is measured by the probability that system performance satisfies the desired level, and high probability refers to high reliability; vulnerability is measured by the decrease of system performance under non-serious failure or perturbation, where a large reduction refers to high vulnerability; resilience is measured by the size of resilience triangle, where small triangle refers to high resilience (Gu *et al.*, 2020).

As shown in Figure 4-13, the high reliability does not necessarily lead to low vulnerability as different perturbations with their measurements often cause the two concepts. Furthermore, both vulnerability and recovery speed contribute to resilience. Thus, shortening the duration of negative perturbation impact must be considered instead of just focusing on achieving higher resilience by lowering vulnerability.

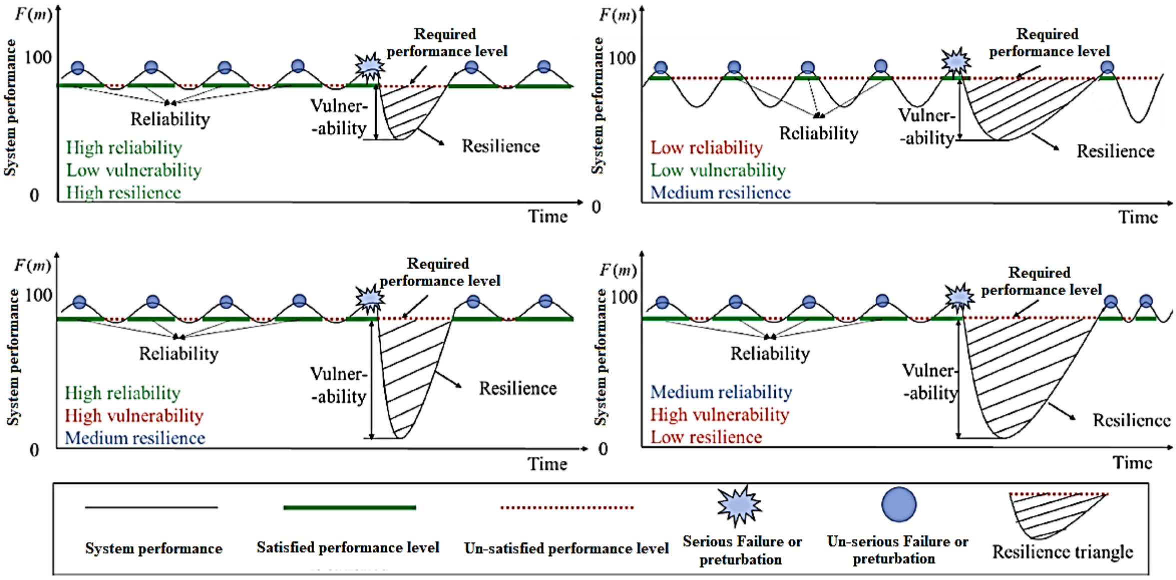

Figure 4-13- The relationship between reliability, vulnerability, and resilience (Gu *et al.*, 2020)

Second resilience metric: This metric is defined as measuring economic resilience. As shown in Figure 4-14 and Eq. (4-4) (Rose, 2007):

$$Re = \frac{\%\Delta DY^{man} - \%\Delta DY}{\%\Delta DY^{max}} \qquad \textbf{(4-4)}$$

It is the avoided drop-in system output ratio and the maximum possible drop-in system output. Parameters include $\%\Delta DY$ as the difference in non-disrupted and expected disrupted system performance and $\%\Delta DY^{max}$ as the difference in non-disrupted and worst-case disrupted system performance are determined.

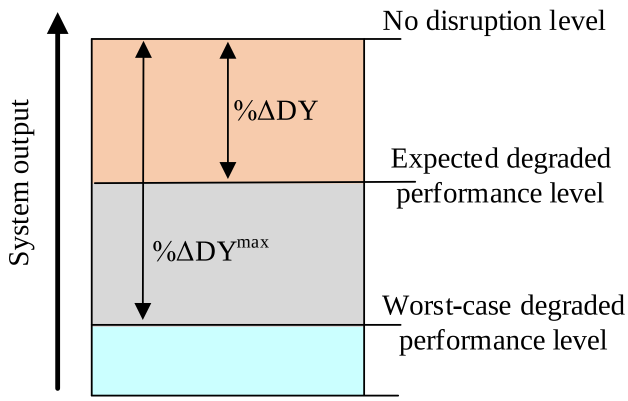

Figure 4-14- The required content of the second quantify resilience metric (Hosseini *et al.*, 2016)

Third resilience metric: It is a time-dependent resilience metric that considers as “Dynamic resilience.” It can be obtained by speeding up the repair and managing capital stock. This metric is defined in Eq. (4-5) (Rose, 2007):

$$Re = \sum_{i=1}^{N} SO_{HR}(t_i) - SO_{WR}(t_i) \qquad \textbf{(4-5)}$$

Where SO_{HR}: is the output of the system under hastened recovery, SO_{WR}: the system’s output without hastened recovery, t_i: is the ith time step during recovery, and N is the number of time steps considered. It is depicted graphically in Figure 4-15 (Rose, 2007).

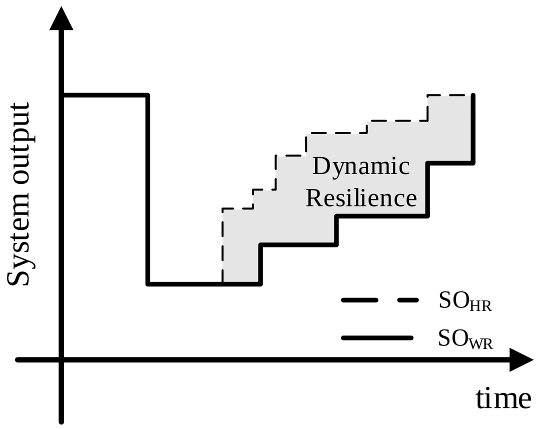

Figure 4-15- The required content of the third quantify resilience metric (Hosseini *et al.*, 2016)

Fourth resilience metric: The other time-dependent resilience metric is developed as the ratio of recovery to loss. This metric is defined based on performance function $\varphi(t)$ for three system states at a point in time that list as follow and depicted in Figure 4-16 (Cutter *et al.*, 2008; Henry and Ramirez-Marquez, 2012; Hu and Mahadevan, 2016):

- *The original stable state* is the Normal functionally of a system before a disruption occurs, starting from the time t_0 to t_e (normal or baseline state). It is usually announced with *reliability* as the probability that the system performs satisfactorily in the presence of disruptive events.
- *The disrupted state* made by a failure or disruptive event $\left(e^j\right)$ at time t_e whose effects set in until the time t_d, defines the system performance from time t_d to t_s (vulnerable state). The system's degraded performance after disruptive events (higher vulnerability means more severe failure).
- *The stable recovered state* is the new steady-state performance level once the recovery action started at the time t_s is ended (recoverable state). It is usually announced with *recoverability* as to how quickly and well a system can recover to its normal state after the disruption.

Thus the time-dependent measure of resilience based on reliability, vulnerability, and recoverability is defined in Eq. (4-6) (Cutter *et al.*, 2008; Henry and Ramirez-Marquez, 2012):

$$Re = \frac{\varphi\left(t \middle| e^j\right) - \varphi\left(t_d \middle| e^j\right)}{\varphi(t_0) - \varphi\left(t_d \middle| e^j\right)} \qquad \textbf{(4-6)}$$

Where resilient behavior is a function of e^j.

Fifth resilience metric: This probabilistic metric had been developed based on mitigation and contingency strategies. It is the degree of a passive survival rate (or reliability) plus a proactive survival rate (or restoration).

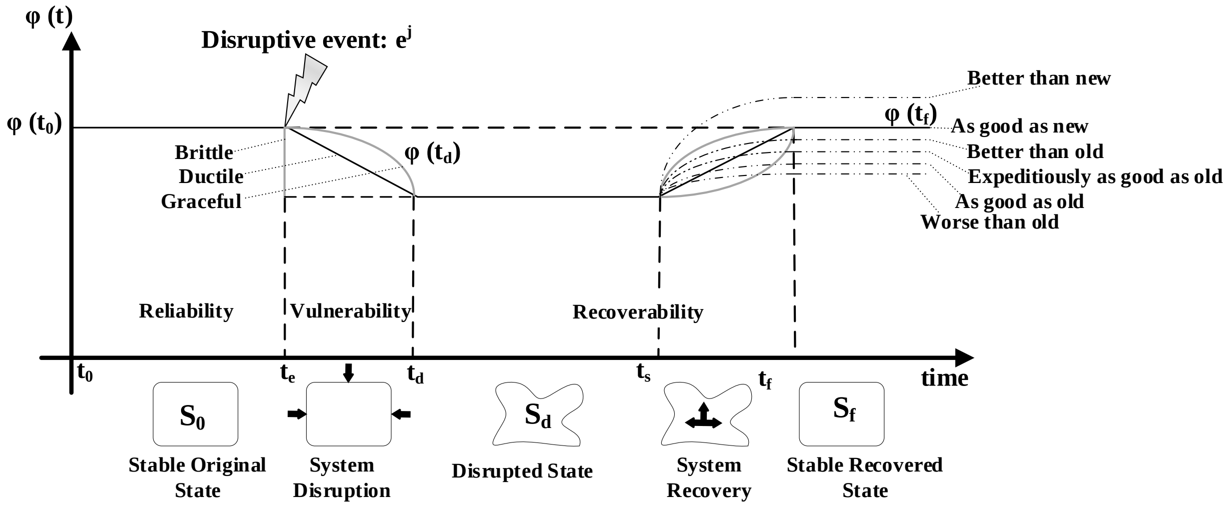

Figure 4-16- The required content of the fourth quantified resilience metric considering different disruption and recovery paths (Hosseini *et al.*, 2016; Hu and Mahadevan, 2016; Sarwar *et al.*, 2018)

Mathematically, the resilience measure can be defined as the sum of reliability and restoration as follow (Youn *et al.*, 2011):

$$Re = R(reliability) + \rho(restoration) = R + \rho\left(R, \Lambda_p, \Lambda_D, K\right) \quad \textbf{(4-7)}$$

where k, Λ_p *and* Λ_D are the conditional probabilities of the mitigation/recovery action success, correct prognosis, and diagnosis. The above definition turns engineering resilience into a quantifiable property, making it possible to analyze an engineered system's resilience potential. Eq. (4-7) metric accounts for the reliability or a preventive means to stave off the occurrence of disruption as a component in quantifying resilience. In contrast, most other resilience assessment metrics are primarily a function of the level of initial impact and duration of recovery. The restoration is further expressed as a joint probability of having an event, correct prognosis, diagnosis, and mitigation/recovery could be rewritten as (Hu and Mahadevan, 2016):

$$Re = R + (1 - R)P_{Diagonosis}P_{Prognosis}P_{Recovery} \quad \textbf{(4-8)}$$

where $P_{Diagonosis}$ is the probability of correct diagnosis, $P_{Prognosis}$ is the probability of correct prognosis, and $P_{Recovery}$ is the probability of correct recovery. This focuses on the restoration of the system using prognostics and health management (PHMa) methods (Youn *et al.*, 2011).

Sixth resilience metric: This metric is probabilistic and represented in Eq. (4-9) (Chang and Shinozuka, 2004):

$$Re = P(A|i) = P(r_0 < r^* \; and \; t_1 < t^*) \quad \textbf{(4-9)}$$

Where "A" represents the set of performance standards for maximum acceptable loss of system performance (r^*): and maximum acceptable recovery time (t^*), for disruption of magnitude (i). So, it measured two central parts: performance losses and (ii) recovery length.

Seventh resilience metric: This stochastic metric had been developed based on system aging. It considers robustness and resourcefulness as two main assessment element and provides as follow (Ayyub, 2014):

$$Re = \frac{T_i + F\Delta T_f + M\Delta T_r}{T_i + \Delta T_f + \Delta T_r} \quad \textbf{(4-10)}$$

where T_i: the time to the incident, T_f: the time to failure, T_r the time to recovery, $\Delta T_f = T_f - T_i$: the duration of failure, and $\Delta T_r = T_r - T_f$: the duration of recovery. Also, "F" is a measure of robustness and redundancy and "M" measures recoverability with Eq.(4-11) and Eq.(4-12) respectively (Ayyub, 2014):

$$F = \frac{\int_{t_i}^{t_f} f\, dt}{\int_{t_i}^{t_f} Q\, dt} \quad \textbf{(4-11)}$$

$$M = \frac{\int_{t_i}^{t_f} r\, dt}{\int_{t_i}^{t_f} Q\, dt} \quad \textbf{(4-12)}$$

Where "f" is any failure event, and "r" is any recovery event.

Eighth resilience metric: This performance base metric is defined resilience as the expectation of the ratio of the integral of the system performance Q(t) over a time interval [0, T] as a stochastic process, and the integral of the target system performance $\mathrm{T}Q(t)$ during the same time interval as a stochastic process (Salomon *et al.*, 2020):

$$Re = E[Y]\ where\ Y = \frac{\int_0^T Q(t)\, dt}{\int_0^T \mathrm{T}Q(t)\, dt} \quad \textbf{(4-13)}$$

The "Re" tolerates between 0 and 1. The value "1" indicates a system performance conforming to the target performance, while "0" presents that the system is not working during the considered period.

Ninth resilience metric: In a recently proposed metric for resilience analysis, Bruneau's concept (Bruneau *et al.*, 2003; Henry and Ramirez-Marquez, 2012) with reliability as the system's measure performance assumption is used. The required content of the metric is illustrated in Figure 4-17. Where R_o and R_f are the initial and the final reliability levels at times T_o and T_f. The disrupted steady-state reliability of the system at times T_{l1} and T_{l2} are R'_{l1} and R'_{l2}, while R_{l1} and R_{l2} are system reliability in the absence of the disturbance (Yarveisy *et al.*, 2020). The resilience metric (Re) is quantified as the Boolean relation among absorptive, restorative, and adaptive capacities of the system (Yarveisy *et al.*, 2020):

$$Re = Ab \cup (Ad \cap Res) = Ab - (Ad \times Res) - (Ab \times Ad \times Res) \quad \textbf{(4-14)}$$

Where:

- Ab is "Absorptive Capacity" and quantified as:

$$Ab = \left(\frac{\acute{R}_{l1}}{R_0}\right) \times \left(1 + \left(\frac{R_0 - R_{l1}}{R_0}\right)\right) \quad \textbf{(4-15)}$$

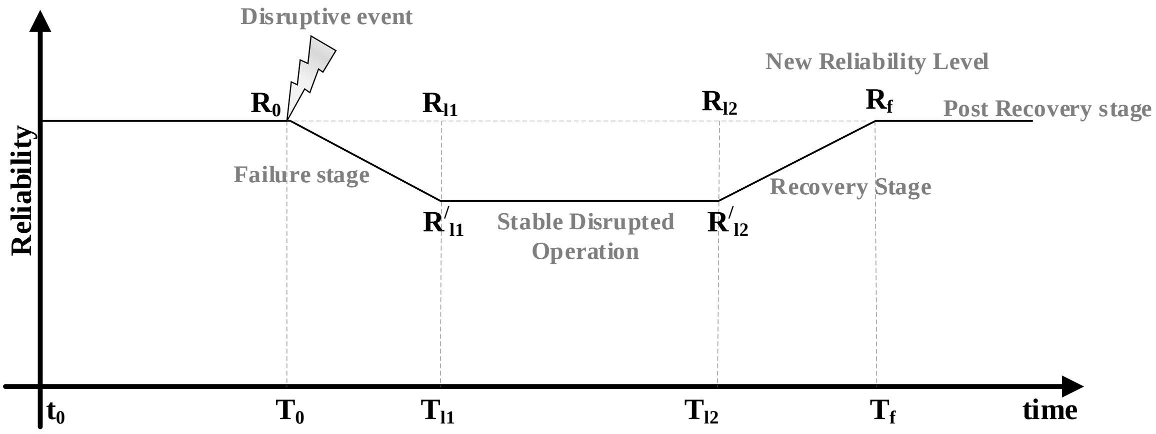

Figure 4-17- The required content of the ninth quantify resilience metric (Yarveisy *et al.*, 2020)

- Res is "Restorative Capacity" and quantified as:

$$Res = \left(\frac{Arctan\left(\frac{\acute{R}_f - \acute{R}_{l2}}{\left(\frac{T_f - T_{l2}}{T_f - T_0} \right)} \right)}{90} \right) \times \left(\frac{\acute{R}_f}{R_f} \right) \times \left(\frac{T_{l2} - T_0}{T_f - T_0} \right) \quad \textbf{(4-16)}$$

Where $\acute{R}_f$: level of reliability between the residual and the "as old" reliability,

- Ad is "Adaptive Capacity" and quantified as:

$$Ad = 1 - \left(\frac{T_f - T_{l2}}{T_f - T_0} \right) \quad \textbf{(4-17)}$$

5- CONCLUSION

In this study, the first part of each section begins with a quantitative analysis performed by using the global publication's scientometrics technique in performance-based resilience in the field of engineering and the Arctic region. The systematic search using the Scopus and Web of Science database was conducted with the search terms include reliability, maintainability, recoverability, resilience, engineering, and the Arctic limiting the search to scientific journal articles written in English. These databases are the large databases of pre-reviewed literature. We found that reliability and resilience publications have increased year by year. Especially in the last decade, their upward trends have a steep slope, showing the birth of new ideas and expanding scholarly and field application of them by researchers. But we can't deduce the same conclusion about recoverability (maintainability). It has an upward and downward slope in the first half of the 2010 decade and slowly increases to 2019. Keep in mind that the frequencies for 2020 are most likely incomplete.

Moreover, the engineering field is the most popular domain for reliability and recoverability concepts. But resilience publications mostly originate from Social science and Environmental science. It is a young seedling in the engineering territory that new work, ideas, applications, and researchers must be strengthened. The Geographical distribution of resilience publications in the engineering field shows that the USA is the leader of this field and China is next. When the search field is limited to the Arctic, the USA keeps its leadership, but Norway and the United Kingdom share second place. Scientometrics study of WoS for Affiliation distribution in the Arctic-related publication indicates "The Arctic University of Norway (UiT)" ranks first.

Furthermore, Rod Bjarte and Abbas Barabadi, the first author from UiT, are ranked first and third. In the second stage, the papers' abstracts and titles were subjected to a first review based on their relevance from 2015 to 2020. Those papers identified as relevant were in a third stage subjected to a full-text review. The full-text review in stage three included 35 engineering reliability articles, 16 the Arctic reliability articles, 25 engineering recoverability articles, nine the Arctic reliability articles, 21 engineering resilience articles, eight the Arctic resilience articles, and 11 the 3Rs articles included in the final review. It should be noted that some articles have been repeated in different fields due to different aspects of research.

The full-text review revealed that the classical time-based reliability approach could be a helpful tool for bulks manufacturers or the primary management level that provided a general perspective. In this approach, the lifetime estimation of equipment in terms of the probability distribution (TBFs) reflects the average behavior of the population's reliability characteristics. The approach can be implemented when many historical repair and failure time data are available. This approach also does not cover the condition and operating environment data. Whereas, as the result of the reviewed study, most researchers believe that the operational conditions may significantly affect the reliability and maintainability performance. In this regard, new models and techniques should be developed, or available approaches should be modified for RAM assessment of systems. One of the early steps in such efforts is understanding the prevailing environmental and operating conditions and their impact on systems. Such an overview and discussion play a key role in building knowledge about operations and their RAM performance and associated risks. That's why, although this approach provides useful information, yet due to limitations, the covariates-based approaches were developed. Covariate (or risk factor) data are commonly obtained in addition to time-based data. While collecting covariate data may be difficult and costly, such data contain more useful information than time data about the system. These models could be addressed the reliability analysis in dynamic operating environment conditions. Our review indicates that several covariate-based hazard models have been developed. These existing covariate-based hazard models were established based on the Proportional Hazard Model principle (PHM). The first advantage of these models, like the classical model, is their ability to incorporate incomplete and suspended data into asset life modeling. These models could be analyzed the system in a dynamic environment considering by covariates effect. Covariate can be classified as observable and unobservable. Observable covariate data are obtained in addition to failure time data. In many cases, collecting covariate data may be difficult and costly, but they contain more valuable information than time data. These models could be parametric or semiparametric such as Cox-PHM. Even though the Cox PHM is less restrictive than a fully parametric model, various underlying assumptions must be valid. First of all, it confides in the assumption of independent censoring for reasonable inference in the presence of right-censored data. Besides, an obvious assumption for most regression models, including the Cox PHM, is that the observations are independent. This is an invalid assumption in the case of multiple observations per subject, i.e., recurrent event analysis. Finally, the most crucial assumption to satisfy is proportional hazards (PH assumption). This limitation of the PH assumption causes extended PHM in a set of covariates at certain strata as the stratified Cox regression model (SCRM) or accelerated failure time model (AFTM).

The quantity and quality of field data in these models are the main limitations required for building the model. Insufficient data availability would introduce further uncertainties into models' parameters. Most of the covariate-based works neglect to fully utilize three types of asset information, including failure event data, observable, and un-observable operating environment data, into a more impressive performance prediction model. Thus, the related and imperative question is how all indicators should be effectively modeled and integrated into the covariate-based hazard model. For instance, in the Arctic, to develop a spare parts prediction model, one should account for the effects of continuous parameters of the weather (e.g., temperature and wind speed), discrete meteorological phenomena (e.g., polar low pressures) and, sea state (e.g., sea ice and iceberg drift) on lead-time and possible supply delivery delays and system RAM. This point has recently received more attention from the authors such as R. Zaki, B. Rod, A.Barabadi, etc... the new works with fresh ideas have been published (Rod *et al.*, 2020; Zaki *et al.*, 2019). Their proposed approaches as the Mixture frailty model (MFM), somewhat resolve the identified limitation of the existing covariate-based hazard models in the field of engineering systems. The risk factors and operating conditions become a more important role for operating systems (or infrastructures) in the Arctic region with a harsh environment.

Recoverability as sconed performance index in this report can be defined as the probability that a failed system item will be restored to its satisfactory operating state. Thus, some of the main objectives of applying recoverability principles to engineering systems are reducing projected recovery costs and time and using recoverability data to estimate system performance. Their maintainability functions depend on the time to recovery (TTR) data and analysis. Since the approaches in this context are similar to reliability analysis; therefore, repetition is avoided. In the context of recoverability in the Arctic, adequate cold-protective clothing is necessary to overcome some of the cold-related problems. The lighting available for visual inspection tasks can influence performance and productivity significantly. Improper illumination can discriminate a defect difficult due to shadows, glare, or too much or too little light. The recoverability (Maintainability) challenges in Arctic conditions can be listed below:

- Increased inspection time or fault detection time
- Increased access time to reach failed component
- Increased removal time for the failed unit
- Higher repair time
- Increased replacement time for the failed unit
- Increased testing time to verify the repair

These may be due to 1) reduced physical mobility, reduced hand dexterity, decreased cognitive performance, reduced motor coordination; bulky clothing; decreased human sensory performance, or 2) improper anthropometric consideration for body dimensions cold environment. Cold protective clothing increases the dimensions of the body. In this regard, some fundamental principles must be considered for designing for recoverability; it is important to implement these in the design and planning phase since it is hard to change after the construction phase; these principles are listed here (Niebel, 1994):

- Minimize the need for maintenance, for example, by materials or design changes
- Optimize the frequency and complexity of the recovery tasks
- Make a recovery easy
- Make good and clear mechanical, electrical, etc. routines
- Establish suitable training and education for personnel
- Have good and easy recovery plans
- Provide accessibility to all departments, equipment, and components requiring recovery
- Provide possibilities of easy fault (failure or event) identification
- Make it easy to use performance measures to predict the needs
- Use visualization approaches to make it easy to identify events and responsibilities.
- Use standard tools wherever it is possible for easy work
- Have a good support philosophy and plans
- Have a plan to use new technology such as long live parts, sensors, robots, etc.

The last section of the presented report shows the priory attempt to develop and investigate the performance-based resilience assessment method that helps evaluators in their work. Considering the subjectivity of expert opinions, lack of information, and the variety of approaches to assessment problems, the author concludes that this research area still demands further investigation and development of a new complex framework for resilience measurement, especially in the field of performance measurement indicators. In reviewing existing approaches, the two core tenets had been considered: first, how resilience is defined, and second, how resilience is statistically evaluated in the engineering field. In highlighting the use of reviewed approaches, it is important to emphasize that there is no one-size-fits-all approach to resilience measurement and assessment. Before choosing which approach to adopt, researchers and engineers should consider several factors, including their core objective of the measurement exercise, theory of knowledge creation, resource and data constraints. Thus, a full review of resilience measurement approaches can make valuable contributions: identifying hotspots, understanding drivers, and inferring impact. The literature review -up to our reading- revealed that although more researchers concentrated on RAM evaluation investigation, little attention is paid to investigating RAM's integration with the resilience concept. Thus, resilience approaches require preparing for the unexpected by performance analysis proceeds from the premise that failures are identifiable. Resilience is a novel way of thinking that cannot be implemented by an incremental evolution of prior design strategies. The term “resilience” appears in several different domains like ecology, economy, psychology, and the context of mechanical and infrastructure systems. It is derived from the Latin word “resilire” which means “to bounce back”. So, a departure from existing practice is not limited to structural or technological changes but can also be achieved through behavioral or cultural innovations. This approach embraces uncertainty and failure via anticipation and adaptation. The resilience evaluation of complex engineering systems such as infrastructures with non-stationarity (wherein path dependencies, changing boundary conditions, or interdependencies generate different responses to identical stimuli that happen at different times) and unexpected shocks (extreme events lead to failure of the engineered systems) attributes become more complicated. There exist highly coupled relationships among transportation, electric power, and telecommunication systems, among other infrastructures. And the resilience of one system can impact the resilience of others. The resilience analysis improves the system response to surprise these two attributes. Recently the resilience approach has received great interest. This concept can be integrated with system characteristics such as reliability, maintainability (recoverability), availability, supportability, etc. This specification of resilience can be more useful for engineers familiar with the reliability concept for many years. Using this feature, they can quantify the resilience, which provides an implementation guide for engineering planning, design, operation, construction, and management. Identifying the weak components or missions that affect resilience is important when an engineering system is planned and designed. Quantification of resilience in integration with performance factors can be provided. Thus, as for the future perspectives, it is planned to find the performance-based resilience assessment approaches to modeling systems and preprogramming their disruptions.

In the last section of this chapter, we look for a suitable quantitative approach for integrating the performance indicators with the resilience concept. The concept of resilience as a new approach in engineering applications has gained growing popularity in recent years. But applications for engineers rely on quantitative measures, which various methodologies have been developed within the last two decades. In summary, a quantitative measure of resilience depends on the specific choice and definition of system performance. We used probabilistic (quantitative) approaches, given our interest in engineering systems. The current report only considers a few performance-based resilience strategies. Simultaneously, other techniques and estimated resilience dimensions can also be explored to find the optimum retrofit strategies.

Other dimensions of resilience, such as social, organizational, and economic, should be addressed to provide a comprehensive resilience analysis using additional parameters like the availability of critical facilities, the number of people served, or the level of economic activities. The illustrated metrics in this report for resilience quantification and valuation are developed considering the reliability, recoverability, and system modeling approach and are thus unitless. Some of the advantages and disadvantages of study approaches are as follows:

- The first metric is based on the resilience triangle, and its general applicability and simplicity are essential advantages. However, it could be a tricky measure to comprehend for evaluators even when given as a percentage. In most applications of this method, the disruptive event has an assumed instantaneous impact, and the recovery efforts begin immediately, which is not in line with the real situation. Also, the linear assumption for recovery may not always be correct. This metric's last issue is that system quality (reliability or other performance measures) after the recovery process does not return to old conditions, or the system does not have complete performance quality.
- The most important limitation of the second metric is the difficulty of parameter estimation. Because, for unknown disruptions, the attributes such as depth, width, and intensity might not be precisely estimable.
- The third metric is relatively simple. However, it is not bounded between 0 to 1, and it can't be provided a convenient understanding of the resilience concept.
- The fourth metric is complete than the first metric. This metric considers three states: stable original, disrupted state, and stable recovered. It measures resilience using reliability, vulnerability, and recoverability indicators. The main restriction of this metric is the impossibility of observing the main functions of the three mentioned indicators in the calculations. It expresses all the parameters based on a performance function.
- The fifth metric could be more suitable for the engineering field due to its reliability. This criterion considers both pre-disaster and post-disaster activities, and how to use statistical performance indicators can be seen in it. It is noteworthy that this metric is bounded on [0,1]. It could be said that the calculation of performance indicators probability is the hard part of this metric.
- The distinguishing feature of the sixth metric is considering the uncertainty in the quantification of resilience. However, when performance loss and recovery length exceed their maximum acceptable values, it does not consider an extra penalty.
- The assumption of system performance in the seventh metric is similar to the fourth metric. It is among the most comprehensive resilience measures, using reliability (as the ratio of robustness to redundancy) and recovery (as the ratio of resourcefulness to rapidity) strategies. It introduces a specific meaning of vulnerability and recoverability and incorporates the aging effects in the analysis.
- The eighth metric also has a probabilistic vision that takes 0 and 1. This metric's performance response process in a disruptive event is divided into three stages: system-resistant, absorptive, and restorative capacities. It is adequate for both single and multiple hazard types, including their simultaneous occurrence, capturing the frequency

variations, and including fluctuations. It may also vary for the n'th event due to the resource allocations or the preventive measures taken for other hazard events.

- The ninth metric's central concept is also based on the widely accepted concept of the resilience triangle first introduced by Bruneau et al. This metric studied the resilience performance in various phases and for convenience. The reliability index measured performance. It considers the effects of degradation due to aging on the system operating at a given level of reliability. In this concept, the recovered reliability can reach any desired level between residual reliability and reliability at the disruptive event. The formulation of resilience in this metric is based on adaptive, absorptive, and restorative capacities.

In a final word, the system behavior itself may depend on a wide variety of attributes that influence its performance, named risk factors or covariates. The main drawback of the existing methods can be found in excluding observable operational factors into resilience analysis: literature lacks resilience studies incorporating risk factors. Moreover, unobservable covariates had been scarcely studied in reliability engineering; therefore, dealing with this idea in the resilience concept is rare.

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