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Proposing a New Dynamic Maintenance Model for Reliability Improvement By Antifragility Approach: A Case Study in Iranian Gas Transmission Company-Zone10

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ABSTRACT

Reliability is one of the most important performance evaluation indicators in maintenance and repair filed. The present study is a mixed design attempting to identify the antifragility components and their effect on the system reliability using the system dynamics. In the qualitative section, using by the thematic analysis method, with the participation of 10 organizational and academic experts, antifragility factors were identified in the form of 254 open codes, 18 organizing codes and two global codes with the review of literature and using Maxqda 2020 software. In the quantitative part of the research, the relationship between the antifragility factors with the system reliability was investigated using multiple regression method. The three criteria of learning, redundancy and exploratory discussions were identified and selected as the factors that have the highest impact on system reliability. The effect of these indicators on system reliability in a dynamic environment was simulated using the Vensim software, DDS version. The results show the positive effect of all three criteria of learning, redundancy and exploratory discussions on improving the reliability of the system in the area in gas transmission Company-zone 10. Also, the redundancy index had the highest effect and learning components and explorative discussions were in the next classes of impact on improving the system reliability.

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1. Literature review

Today's community heavily depends on reliable performance and high reliability of complex systems to enhance performance and deal with the increasing uncertainties due to the growing complexities of environment [Kobbacy and Murthy, 2008; Derbyshire and Wright, 2014]. Reliability is defined as the probability of a system operating at a given time under certain environmental conditions [Ben-Daya et al., 2016; Elsayed, 2012]. If t is a random time variable of disruption and f (t) is a function of the disruption probability density, the reliability function will be as follows:

$$R(t) = \int_{t}^{-\infty} f(t)\ d(t) \tag{1}$$

F(t) represents the failure probability until moment t. Given the area under the curve in Figure 1, the probability density function is equal to one, thus we have:

$$R(t) = P(T \geq t) = 1 - P(T < t) = 1 - \int_{o}^{t} f(t)\, dt = 1 - F(t) \tag{2}$$

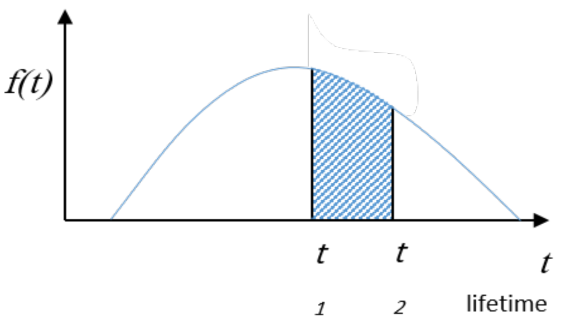

Figure 1. Component lifetime curve [109]

$$h(t).\Delta t = \frac{F(t+\Delta t) - F(t)}{1 - F(t)} \rightarrow h(t) = \frac{\frac{F(t+\Delta t) - F(t)}{\Delta t}}{1 - F(t)}$$

Accordingly, the probability that the lifetime of a system is in the time interval t_1 to t_2 is obtained from the following equation.

$$P(t_1 \leq t \leq t_2) = \int_{t_1}^{t_2} f(t)\, dt = F(t_2) - F(t_1) \tag{3}$$

Failure rate and degradation function are two very important issues in evaluating system reliability. This function indicates the probability of failure at the time interval t and $t + \Delta t$, provided that no failure has occurred until time t. In the calculation of this probability, we are encountered with the conditional probability ($x \mid y$), where x is the failure event of the system during $t, t + \Delta t$ and y is the system surviving until time t.

$$P(x|y) = \frac{P(x \cap y)}{P(y)} = \frac{P(t \leq T \leq t + \Delta t)}{P(T \geq t)} = \frac{\int_{t}^{t+\Delta t} f(t)\, dt}{\int_{t}^{\infty} f(t)\, dt} = \frac{F(t+\Delta t) - F(t)}{1 - F(t)} \tag{4}$$

Now if we denote the failure rate with the instantaneous failure rate by r (t) or h (t), the product of $h(t).\Delta t$ is equal to the failure probability during Δt after time t on the condition the system functions until time t, so we have:

$$h(t).\Delta t = \frac{F(t+\Delta t) - F(t)}{1 - F(t)} \rightarrow h(t) = \frac{\frac{F(t+\Delta t) - F(t)}{\Delta t}}{1 - F(t)} \tag{5}$$

In the above limit, Δt approaches to zero, the nominator is the same derivative of F (t), ie f (t) and we have:

$$h(t) = \frac{F'(t)}{1 - F(t)} = \frac{f(t)}{R(t)} \tag{6}$$

The failure rate function is different for various systems and equipment. When the failure of a device is due to the failure of a large number of system components, its distribution of failure is usually normal [205]. Since one of the methods to find the failure rate in gas transmission is using historical data statistics and system failures in the present study, the normal distribution in the system failure rate has been used. Despite the development of knowledge in reliability field, degradation is a critical factor in this regard. In a division, four general models - remaining useful life, random processes, physics-based and multi-state processes - have been proposed for it [Zio, 2016].

Remaining useful life statistical models are based on degradation data [Lu and Meeker, 1993]. Zhang and Shi used this model using data geometry in cases where there is no or very little information on system interruptions [Zhang and Shi, 2020]. Wujun Si et al. have used microstructure imagery to model material degradation and predict interruption. The results of their study showed considerable progress in predicting the interruptions caused by material degradation compared to optimal mining models [Si et al., 2018]. Interruptions are rarely found in high reliability systems. There are various methods to overcome this problem. Life cycle acceleration using internal or external covariates is one of these cases. Vilijandas Bagdonaviius and Mikhail Nikulin used time-lapse regression models, most commonly, to examine the data on degradation and remaining useful life. They defined interruptions as traumatic and non-traumatic. If degradation reaches the specified limit Z_0, it is called non-traumatic, otherwise it is traumatic [Bagdonavičius and Nikulin, 2009]. In many industrial applications, it is possible to build a database of time-consuming and non-economical interruptions. Accordingly, Nagi et al. used the interruption data - preparing which is easier compared to sensor installation approaches, considering maintenance history - in Bernstein distribution, and used its parameters to estimate the initial distribution of the degradation model [Gebraeel et al., 2009]. Given the problems mentioned, stochastic process modeling methods were developed and various investigations [Kjell et al., 1992; Chen et al., 2015; Lawless and Crowder, 2004] were conducted in this regard. In most of the studies conducted in this area, the error rate in degradation process is considered a function of Wiener-process or Gamma-process [Tseng and Peng, 2007].

Physical models are used in cases where statistical model information is not enough due to the high reliability of the system such as nuclear power plants and are based on knowledge of degradation physics and factors such as mechanical loads frequency and environmental critical conditions in modeling fatigue, corrosion, destruction mechanism or cavity corrosion [Chookah et al., 2011; Ma et al., 2016; Keedy and Feng, 2012; Zhu et al., 2016; Hao et al., 2010; Wang and Pham, 2012]. Multi-stage models describe and examine the underlying processes of degradation in the finite states such as Semi-Markov simulations. In this model, the state of the system is divided into several stages from full performance to full stop. It is crucial to obtain time-dependent probabilities in this method to evaluate the system reliability dynamically [Yu et al.,].

Besides the mentioned divisions, other approaches are also seen in the literature to predict the role of degradation in system reliability, which are generally categorized into four groups: experience-based, knowledge-based, model-based, and data-based. The latter two approaches are more common in reliability evaluation. The knowledge-based approach is mostly used in combination with other approaches such as data mining. Experience-based approaches need less data and are the simplest approach since they do not consider the degradation index in predicting the lifetime of the equipment. Such approaches are widely used when historical information on maintenance and interruptions is based on the distribution of logs from a population of identical and similar items. Many conventional reliability approaches, such as exponential distributions, log-normal and Weibull have been used to model equipment reliability. Weibull distribution approach is more popular than other materials because of the capability to cover various types of behaviors in bathtub curve [Gorjian et al., 2010]. Model-based approaches are commonly used with the mathematical dynamics models and are sometimes incorporated into physics-based or statistics-based models. Knowledge-based approaches are suitable for solving problems solved by expert individuals and do not require a specific model. Expert and rational fuzzy systems are among these approaches [Shin et al., 2018; Zhou and Thai, 2016; Zhang et al., 2015].

Data-based approaches have been shaped based on statistical and learning techniques derived from pattern recognition theory. Various methods from multivariate statistical methods, partial least squares, and so on to the black box, Bayesian network, Hidden Markov Model (HMM), and neural networks are among them, of which neural networks and HMM are the most widely used ones in recent studies [Song et al., 2017; Li et al., 2007; Saidi et al., 2017; Eleuteri et al., 2003].

Nassim Nicholas Taleb introduces unknown events around the world in his book "Black Swans" to further explore risk. Black swan has three characteristics: it is unpredictable, it has a huge consequence, and seems predictable after incidence if it cannot be predicted before occurrence. According to the antifragility theory, systems are divided into three categories: fragile, stable, and antifragile. Figure 2 shows the response of these three types of systems to stress exposure [Taleb, 2012, 2010]. Table 1 depicts some recent researches on antifragility applications in various businesses.

The knowledge development, methods, techniques, multiple models and finally the increase of information sharing about reliability assessment have provided the opportunity for analysts to present new methods [Zio, 2016]. Some of the mentioned methods have been used in assessing the reliability of gas transmission companies [Ren et al., 2020; Chen and Wu, 2020; Gaur et al., 2019; Yu et al., 2018].

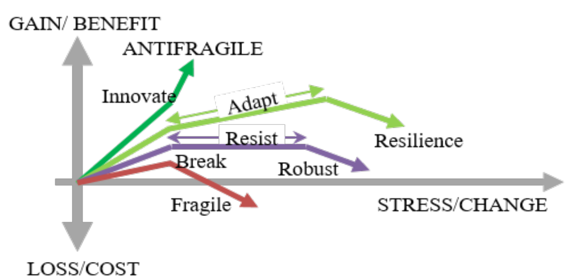

Figure 2. The evolution of systems from failure to antifragility [31]

The present study was conducted to present a new antifragility approach in evaluating system reliability. On the other hand, identifying the antifragility components are the additional results but important and practical results of the present study that have not been addressed in any research so far and can be used as a suitable basis in other researches. Their impact on the reliability index by systems dynamics are among the major stages of this research.

The identification of antifragility components, their relationship with reliability and examining Innovations of this research include simultaneous attention to structural and behavioral factors in assessing reliability, considering the small risks with serious consequences called black swan, reducing the complexity of the problem and the possibility of adding or reducing other variables using a dynamic approach and finally defining different strategies and observation of the long-term and short-term effects of decisions on the reliability index

Table 1. Some recent researches on antifragility

Year	Title	Author/ authors.
2020	Relativistic antifragility [36]	Succi and Sauro
2020	Approach to resilience and antifragility in business ecosystems	Ramezani et al.,
2020	Dynamic model of optimization in development of water supply with uncertain flow	Moudi et al.,
2019	Multilayer structures in production of antifragile systems in Boolean Network	Kim et al.,
2019	Anatomy of an incident: A hydrogen gas leak showcases the need for antifragile safety systems	Smith
2018	Resilience and anti-fragility engineering: accident occurring on a mobile elevating work platform	Martiny et al.,
2018	Antifragile communications	Lichman et al.,

2. Methodology and model structure

As shown in Figure 3, the present study is a mixed design and designed in four stages. In the qualitative section, antifragility components have been identified using the content analysis method and Maxqda 2020 software. The qualitative method of thematic analysis is used to analyze the textual data and diverse data in five stages: data familiarization, creation of raw codes, search of themes through selective codes, review of themes and creation of organizing themes and definition and naming of main themes to detailed data [Braun and Clarke, 2019]. In researches such as the present study where the number of texts and their data is high, the themes format is used Guest et al., 2012]. Then, the most important antifragility factors affecting reliability have been identified using stepwise multiple regression method. Multiple stepwise regression identifies significant input variables and eliminates multicollinearity between variables; multicollinearity would incur when the selected input variables are correlated. Several recent studies have applied stepwise regression as the variable selection technique [Mohsenijam et al., 2017].

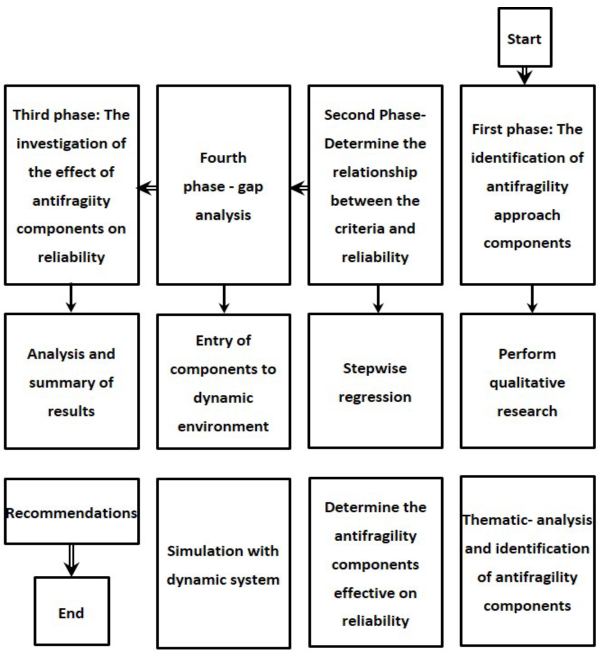

Figure 3. Flowchart of research implementation method

Then, the effective indicators on reliability were entered into the dynamic model of maintenance and repair using the systems dynamics approach and their separate and simultaneous impact on the reliability of the system has been simulated and evaluated.

System dynamics is a methodology for framing, understanding and discussing complex issues and problems [Sterman, 2018]. It allows a system to be represented as a feedback system. Compared to other simulation approaches, a system dynamics model is more beneficial to explain the developing trends of dynamics behaviors in the long-term (simulation duration) due to its feedback structure and capability to function under different parameter setting and initial inputs [Sterman, 2000]

Unlike other approaches that have a linear view to the problem and its effect, the system dynamics focuses on the information returned from the problem variables and cause-and-effect loops [Sterman, 2018]. According to system dynamics' standpoint, system dynamics model judges object system's changing trend by simulating object system dynamically in order to study and plan future action and corresponding decision-making of the object system. This approach, which focuses on cause-and-effect processes based on information retrieval processes, is designed to overcome complex problems. In this method, a combination of quantitative and qualitative methods using mathematical equations is used to simulate system behavior [Sterman, 2000].

As antifragility has many components, the inclusion of each variable in the model is well investigated and analyzed in system dynamic approach. Figure 4 shows the Causal loop diagram representing the main loops of the antifragile model structure [De Bruijn et al., 2020].

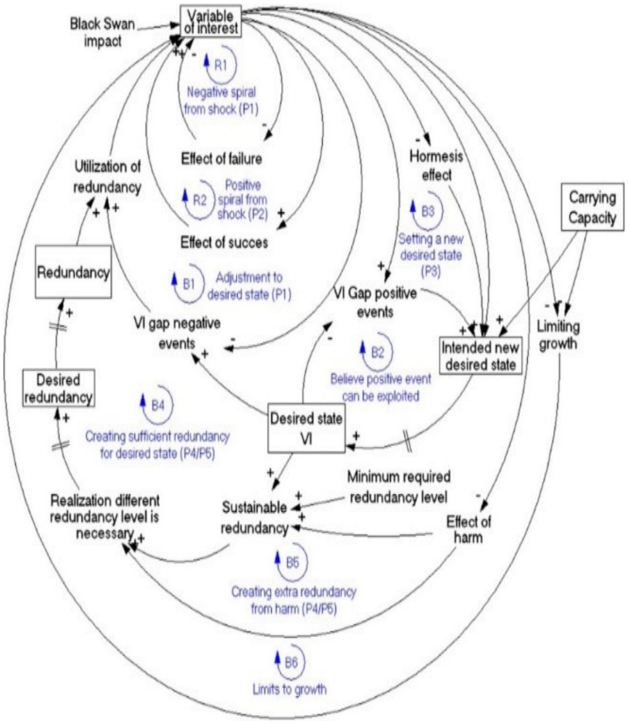

Figure 4. Main loops of the antifragile model Causal loop diagram [De Bruijn et al., 2020]

Recognizing rate and state variables and shaping cause and effect diagrams are so important in dynamic systems. In maintenance systems, the reliability has a key role and is influenced by most of other performance indices of the organization. As shown in Figure 5, total shutdown is one of the factors contributing to the decrease in system reliability. Reliability is calculated by dividing the number of hours of operation by the number of interruptions. Non-stop hours will be the system reliability, which decreases with interruption increasing rates.

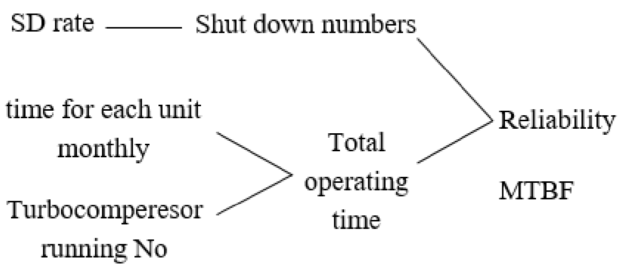

Figure 5. Reliability tree diagram

Figure 6 shows that many interruptions are resolved with emergency repairs and preventive repairs. The role of preventive maintenance is well seen in enhancing reliability in this dynamic model. Increasing preventive maintenance processes reduces the rate of system failures. The role of emergency repairs in reducing existing failures, as shown in the models, is minimized over time and in reducing the amount of existing failures, preventive repairs affect the rate of occurrence of failures and decrease them. Figure 7 shows depots and flows related to the volume of gas transmitted, the volume of gas discharged to the environment, and the internal uses of the facilities. Overall interruptions that reduce system reliability will directly affect production rates as well. Moreover, this increase in facility interruptions will result in increased gas loss due to rebooting and reducing overall system efficiency and greater environmental pollution. Although the purpose of the study is not to discuss the environmental issues and the volume of the transmitted gas, one can deduce the direct relationship of reliability of the system with the volume of gas transmitted and its inverse relationship with the discharge of gas to the environment and its environmental effe

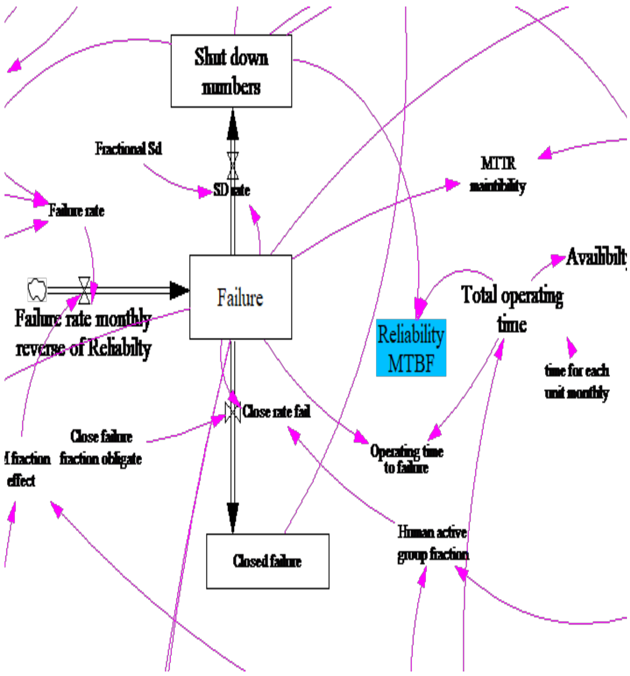

Figure 6. Reliability and failure rate

Preventive maintenance activities to reduce system failures and increase system reliability have a positive effect on environmental performance evaluation indices. This can be very significant in expressing the mission of industrial organizations in responding to the social mission.

Figure 8 depicts the cost savings, flows, and the effective factors on various costs of maintenance. The level of reliability is defined depending on the type of industry and equipping. This strategy means that maximizing reliability depends on factors like budget and cost savings.

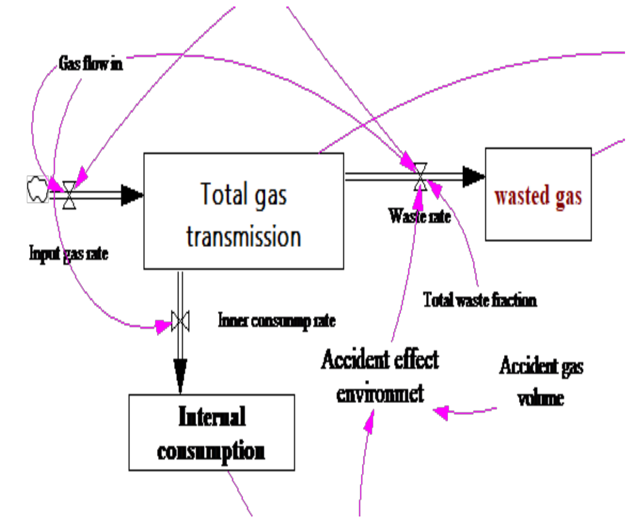

Figure 7. Reliability and environmental effects

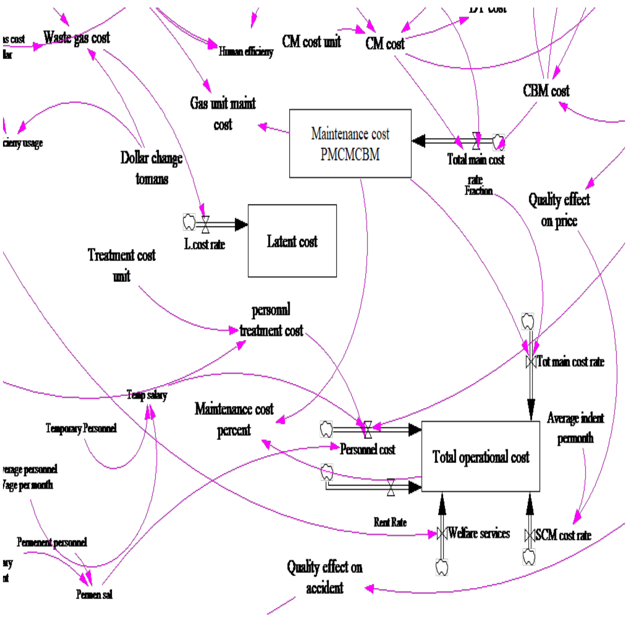

Figure 8: Reliability and total costs

At first glance, it seems that we need to invest in emergency, preventive measurements, salaries and equipment to maximize reliability. Although in some industries it may be true to some degree, the situation in the gas industry is different. Some maintenance processes done to increase system reliability lead to hidden costs such as non-production and export or discharge of gas to the environment, which also results in the cost of wasted gas and environmental pollution. Reaching an acceptable level of risk in maintenance processes and using new and technological approaches coupled with designing a supply chain in the industry can greatly help improve the status of costly and agile processes. Finally, maintenance processes cannot maximize the reliability of a gas transmission network or any industrial organization without neglecting other effective limiting or facilitating components. The dynamic system shows all cases to the researcher in a defined timeframe with a comprehensive view.

Figure 9 shows the event flow diagram. Some events stop operations and, in turn, reduce the reliability of the complex. Accidents that occur in maintenance systems have a variety of factors.

Human errors and deficiencies in the equipment and tools used are among the major causes in this regard. Accidents in addition to having negative effects on the reliability of the gas transmission network or any industry in need of high reliability result in a variety of overt and covert human resources costs. These include the cost of training new personnel, the various risks of new employees, and the cost of lost equipment and non-production. In addition, accidents have negative effects on the organization's reputation and the cost of losing market share is predictable in some industries.

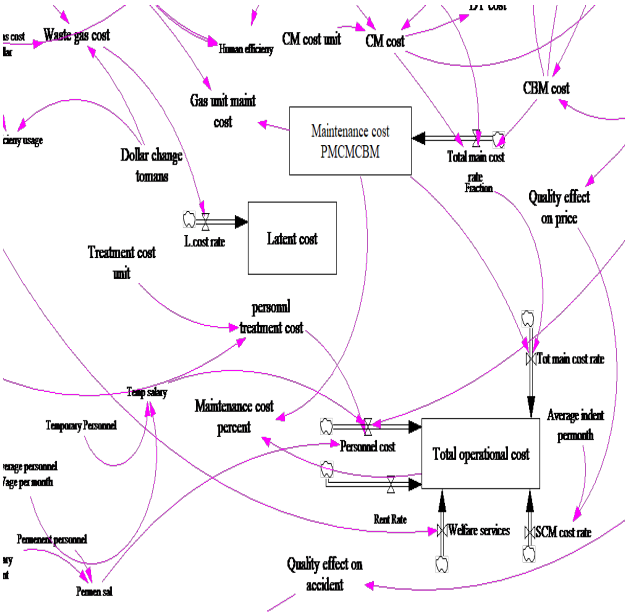

Figure 9. Reliability and human accidents

Establishing a training system in the safety field in repair and improving the supply chain in supplying quality items are some of the solutions that can be used to improve the performance of repair teams. With a dynamic approach and controlling the overall factors affecting the accident rate can ensure the reliability of the system to an optimal level. Doing this necessitates a knowledge-based and comprehensive approach to all issues of the organization to manage the ultimate reliability of other performance indices such as cost and accidents besides the ultimate desirability.

Figures 6 to 9 show the structure of the dynamic maintenance model. Now as is shown in Figures 10 and 11, the learning criterion and exploration discuss are added to the maintenance system model. In the resulting model, the total operation interruptions and failures are resolved in a specific process by analyzing the root cause of the failures in the expert operating sessions and are grouped into different categories. Improper use of equipment, improper installation, improper design and construction, incomplete and ineffective maintenance and installation are the areas that can be examined in each case. After examining each case and recognizing the basic roots, the items related to the manufacturing companies are sent to them and those that need organizational learning are dealt with in problem-based training processes. The manufacturing companies will take steps to improve equipment quality by obtaining reports on defects in design and manufacture. In this case, learning happens outside the organization but its effect can be seen with appropriate delays in the maintenance system.

Figure 10 shows the effect of human resource learning and the results of rooting failures and improving the quality of equipment in design and manufacturing on the monthly failure process. Although failures impose problems and costs on the organization, they can help staff experience equipment and repairs effectively if they are system-based and problem-based. Moreover, in the highly competitive market, suppliers find the best way to compete to create an effective supply chain by obtaining information from the end consumer to survive. These will reduce failure.

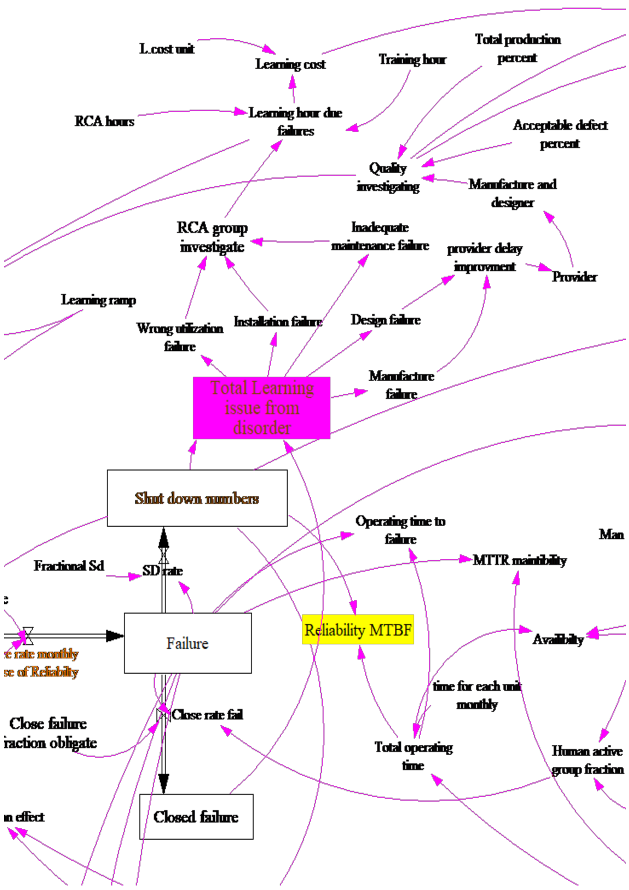

Figure 10. Learning and failure rates

As the reduction in failures has a positive effect on system reliability, the role of the learning mechanism in improving reliability will be undeniable. Figure 11 shows the effect of increased exploration discuss on the maintenance system. The partnership system is the main symbol of heuristic discourses in the organization. Indeed, personnel identifies problems or points of improvement in the organization and reports on the systematic processes according to their experiences and knowledge. Most of the suggestions made in this area are the same black swans that Nassim Taleb has mentioned in his study: significant risks that can pose numerous problems for industry and other stakeholders if they occur, though unlikely. The elimination of black swans, the risks of unforeseen events in the organization will reduce, adversely affecting the possible events and making the maintenance system more reliable.

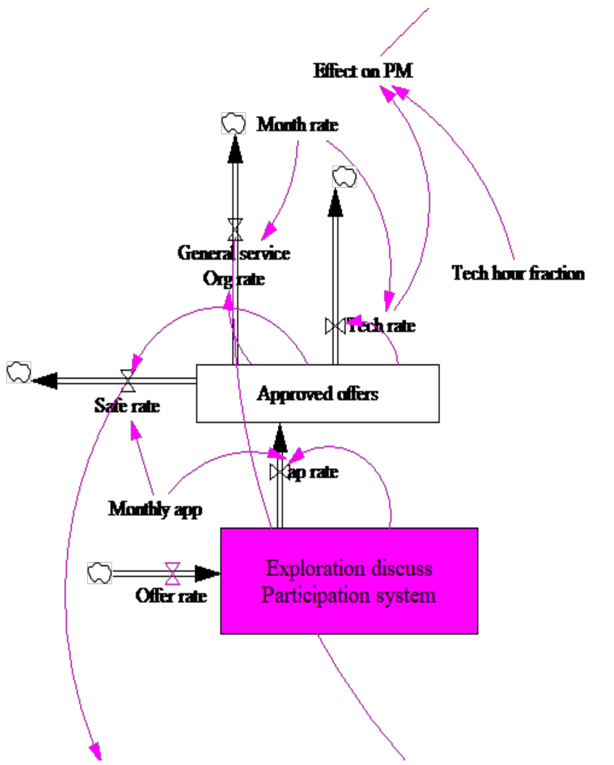

Figure 11. Exploration discussion and the effects on reliability

Figure 12 shows the effect of redundancy, an important criterion of antifragility on the maintenance system. There have been many studies on the effect of redundancy on reliability, but so far, there have been no studies using a dynamic approach examining some simultaneous criteria. It is critical to develop replacement unit designs and layouts according to systems that require high reliability.

As the cost of designing, purchasing, installation and operating spare parts is a decisive factor in any industry, one cannot independently and certainly hope for an increase in spare units or backup systems. Purchasing expensive turbochargers or designing and implementing high-pressure gas transmission lines needs more budgets; this must be addressed in a dynamic process with other organizational criteria in mind.

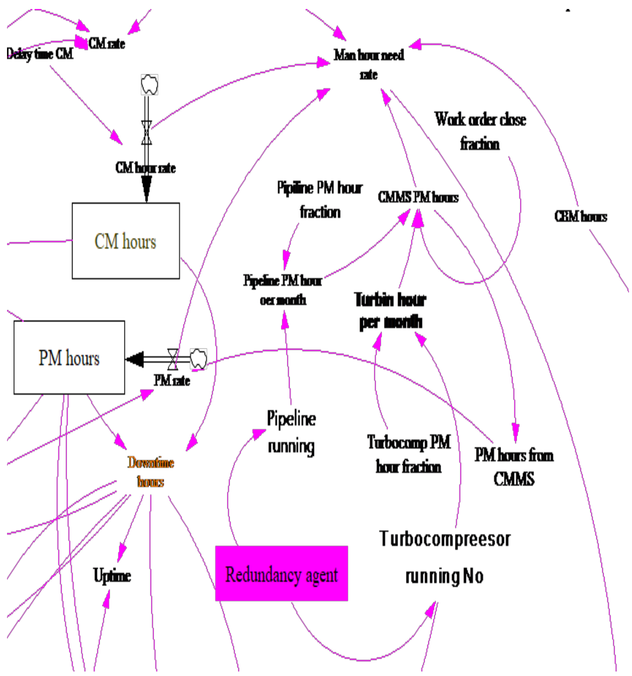

Figure 12. Redundancy and the relationships affecting reliability

3. Results of running model

In the qualitative part of the present study, the data were reviewed and their meanings were searched while taking notes. These notes were obtained from the study of more than 50 papers and books that were recorded in Maxqda 2020 software in addition to the manual method.

At this stage, parts of the texts that were conceptualized for the research questions were selected and labeled. At first, 491 open codes were identified at this stage[1]. By interpreting the open initial codes, the themes were identified again and the extracted codes were placed in the form of selective codes. The open and selective codes identified were categorized into 254 themes. By re-examining and further refining the themes, it was attempted to make have comprehensive and on-repetitive themes. As shown in Table 2, at this stage, 18 organizing themes and two structural and behavioral global themes were extracted.

An appropriate combination of non-fragile components can be a good predictor of reliability. To determine which variables can be a good predictor of reliability; Stepwise multiple regression method was used for six important criteria. The results of statistical analysis of this test are summarized in figures 13-15 and Table 3. Three learning, redundancy and exploratory discussion variables explain 69.4% of the variance of reliability and therefore, have been selected as the most influential antifragility factors and entered into the dynamic model of reliability assessment.

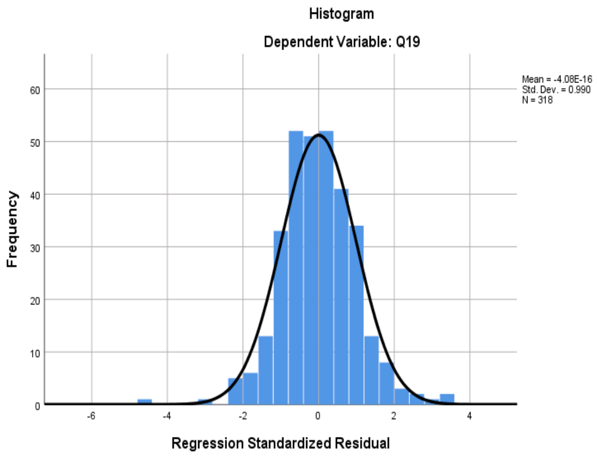

Figure13. Depenent variable histogram

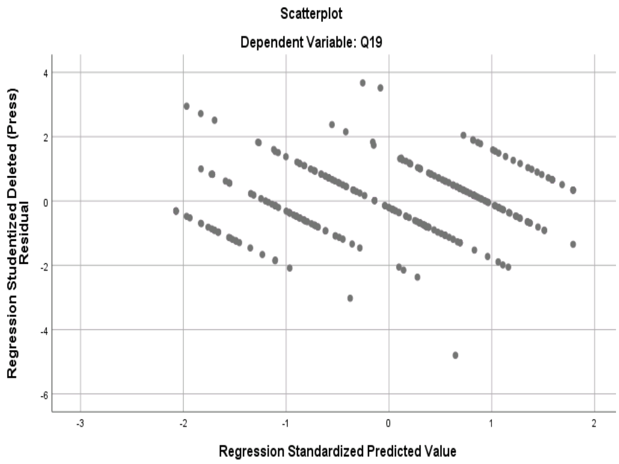

Figure 14. dependent variables scattplot

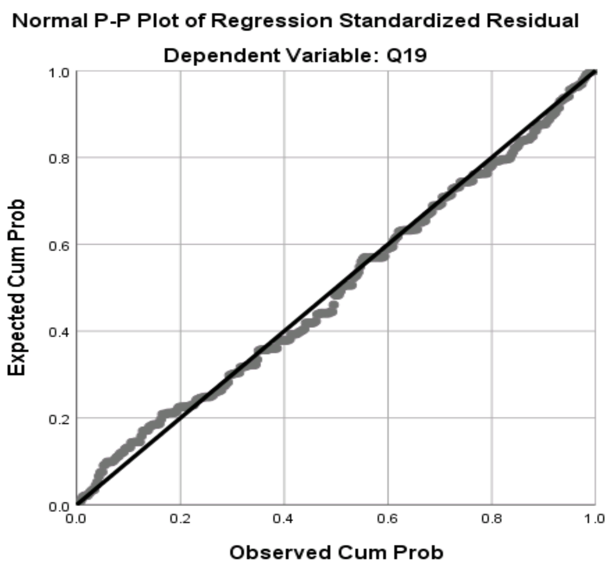

Figure 15. Normal P plot of regression standard residual

1. Selective Codes

Table 2. Final modified themes of antifragility

Basic	Organizing	global
The system facing the environmental stress with learning processes uses the existing mistakes and become stronger. 85 cases.	Learning and growth	Behavioral components
In facing the environmental uncertainties, the system has more ascending movement more than descending movement. 12 cases.	Asymmetry	
For antifragility, the smaller components should be designed as they will be destroyed for the survival of the main system. 19 cases.	Creative-based panarchy of antifragility	
The unplanned results can create new structures in some cases in the system. 12 cases	Emergence approaches	
The simple rules that the system learns over the time to face with the problems. 4 cases.	Heuristic	
Non-interference of low-experienced experts in the affairs can increase the system performance. 5 cases.	Experience and specialization	
It causes that the organizations have better performance in the face of threats. 8 cases.	Resilience	
Anti-fragility is defined as a part of agility activities of the system. 4 cases.	Agility	
Full elimination of negative factors is harmful for the system. 12 cases.	Hormesis	
The system ability in recognition of black swans helps its anti-fragility. 16 cases	Unknown risks	
The risk management considers the important issues in short and long-term periods. 6 cases.	Barbell strategy	
Unfragile organizations have high entropy but this feature cannot degrade them because they are based on some layers. 3 cases.	Entropy	Structural components
Unfragile organizations have flexible and multi-sectional structure. The balance between the limitations and degree of freedom has required optimization conditions for a system. 26 cases.	Flexibility and operational adjustment with the connection and freedom degree of system	
Redundancy makes the system sustainable and in unfragility, it is considered investment. In the long-term, redundancy has many benefits to optimization for an organization. 11 cases.	Redundancy	
High reliability is necessary for system but they don't become unfragile. Fragility is controlled by high reliability. 2 cases.	High reliability	
The increase of system entry has not the same output increase.	Non-linearity	
There are many different environments that their work rules can not be defined clearly and maximum participation is required (participation system). 9 cases.	Transparent procedures	
The higher the number of system elements, their higher its complexity. 10 cases.	Complexity	

The results show that all three components of exploratory discussions, redundancy and learning affect the reliability of the system and the effect of redundancy is higher than the other components. The initial model in which no antifragile criterion is entered is called original and the final model, with the simultaneous effect of entering antifragility criteria into the model is called antifragile reliability.

Table 3. Summary of stepwise multiple regression analysis results

Durbin-Watson	Estimation standard error	Adjusted R^2	R^2	R	Model
1.973	0.72572	0.582	0.583	0.764[a]	First step
	0.63277	0.673	0.675	0.822[b]	Second step
	0.61184	0.694	0.697	0.835[c]	Third step
	0.60472	0.701	0.705	0.840[d]	Fourth step
	0.59967	0.706	0.711	0.843[e]	Fifth step
	0.59683	0.709	0.715	0.845[f]	Sixth step
Learning and growth			0.675	0.822b	Predictors in the first step
Learning and growth, redundancy			0.675	0.822b	Predictors in the second step
Learning and growth, redundancy, transparent procedures and exploratory discussions			0.675	0.822b	Predictors in the third step
Learning and growth, redundancy, transparent procedures and exploratory discussions, high reliability			0.675	0.822b	Predictors in the fourth step
Learning and growth, redundancy, transparent procedures and exploratory discussions, high reliability, Barbell strategy			0.675	0.822b	Predictors in the fifth step
Learning and growth, redundancy, transparent procedures and exploratory discussions, high reliability, Barbell strategy, Panarchy creativity-based fragility.			0.675	0.822b	Predictors in the sixth step
Dependent variable: Reliability					

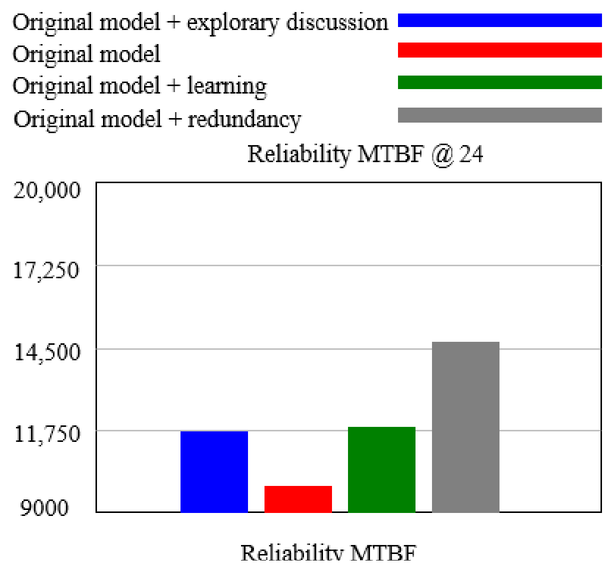

Figure16 . Column diagram of reliability and impact of antifragility components

The results show that after redundancy, which has a significant effect on reliability, the learning component has a higher impact on reliability compared to exploratory discussions. The results are shown based on Figure 16.

4. Model validation

Validation of dynamic models is more based on confirming the structure and ensuring its design and does not have the zero and one aspect [226].

Various methods are used to validate dynamic models [Sterman, 2018, 2000]. Some tests are so important in confirming the method that they can be considered mandatory [Barlas and Carpenter, 1990]. The first test that can be stated is the confirmation of the model structure, which is derived from qualitative judgments.

To confirm the structure, the present model has been investigated by maintenance experts in Gas Transmission Company-zone 10, and managers and experts have emphasized the comprehensiveness of the model structure.

In the next method, the dimensional validation test of the model was evaluated and confirmed. State and rate variables must have dimensional compatibility and the variables with no significance in the model are eliminated. This can be done well using the software. By performing this test, no error has occurred in the model and the simulated model was run and confirmed.

Another test was done in this study that was examining the model boundary conditions. In this test, very small or very high extreme values, the variables are entered into the model and their effect on the model and the model response is evaluated. In case of failure rates entering the system become zero, not only the reliability of the maintenance system increases up to maximum operating hours, but also it makes emergency repair hours zero.

To perform this test, the time period of the model is extended to 24 months and the result is confirmed based on the output of the model shown in Figure 17.

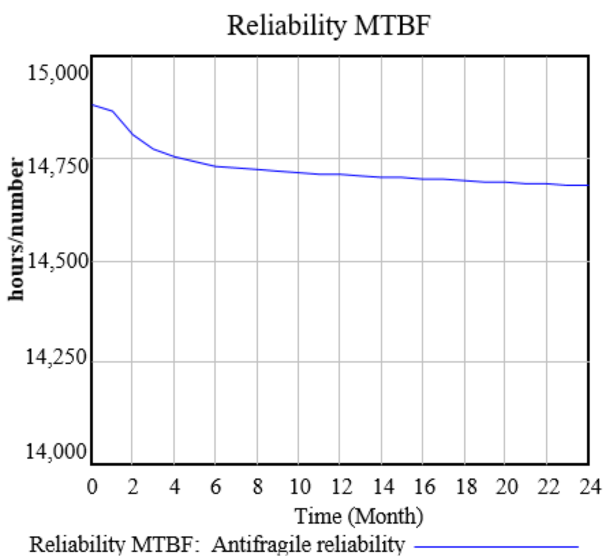

Figure 17. Test of the limit condition of increasing the time interval

On the other hand, since the reliability of the system is determined based on working hours and the number of stops, the model response can be investigating by setting the stops to zero. At this stage, the system response is as expected and confirmed, which is shown in Figure 18 of the test result.

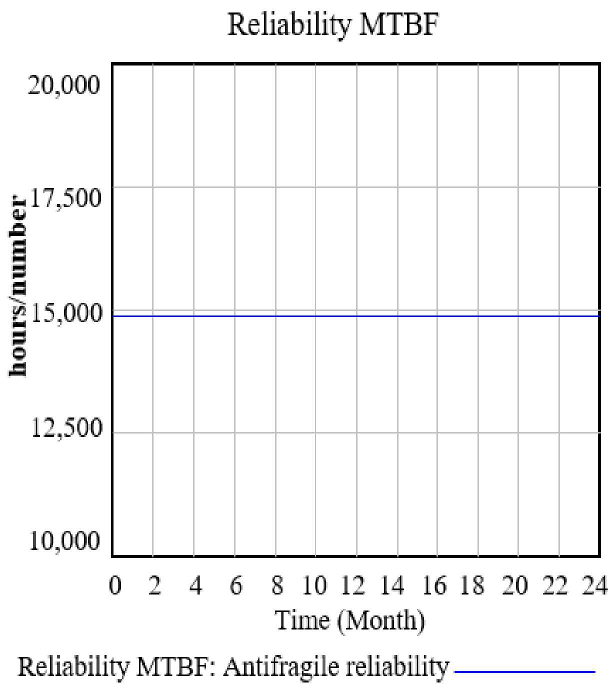

Figure 18 . Zero stops and failures in the limit test and reliability

Sensitivity analysis is used for the overall evaluation of the model functioning. The method is to identify the variables on which the model relies heavily. It is then examined whether this sensitivity and significance exist in the real environment. With a few changes, the system response is examined and various work policies are extracted.

Validity of policy content, determine the validity of policy content is the last step in model validation. Increasing system redundancy has been the policy under investigation at this stage. In increasing redundancy, the experts expect to improve the system reliability, and as shown in Figure 19, the present model explains this well and the sensitivity test of the redundancy policy is approved.

On the other hand, with the increase of redundancy and increasing reserved machineries, it is expected that the working hours of preventive maintenance and repairs will increase, which was also confirmed in the model simulation. Figure 19 depicts this goal.

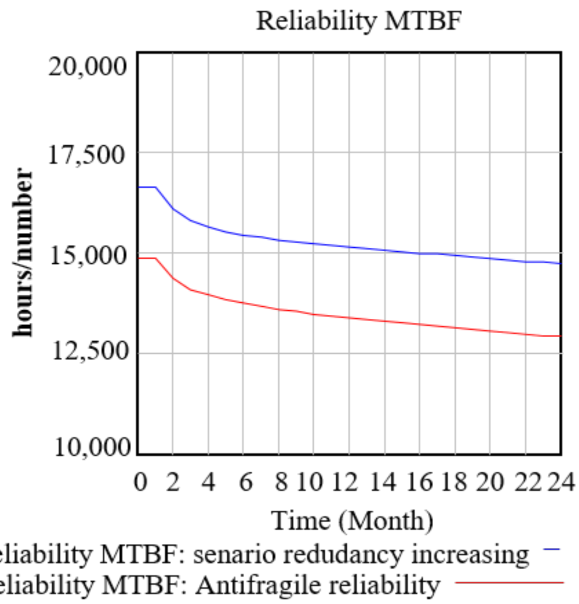

Figure 19. Increasing PM hours in sensitivity test by increasing redundancy

Finally, increasing the number of machineries can lead to higher repair costs than before. Figure 20 shows that the model predicts this goal well.

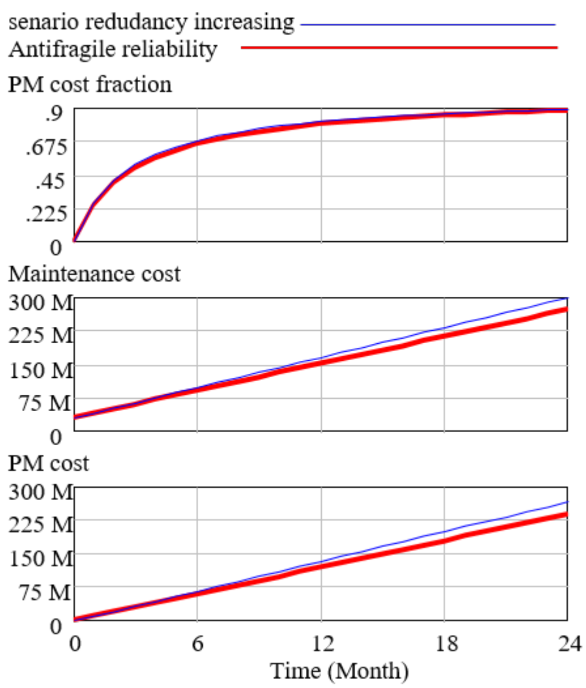

Figure 20. Increasing costs in sensitivity test of increasing redundancy

The utility and fitness test with the audience is also included in the proposed model. Model size, simplicity or complexities of the model are some of the items that are considered important to the audience. The present study has been approved in the zone 10 of operation and applied by the system's audience of the net. Since the researcher himself is experienced in the field of refinery and power plant industry management, he has helped to improve the fit of the model with the audience.

Finally, Monte Carlo sensitivity test is done by changing redundancy factor, failure rate, CBM hours and according to figure 21 the results showed that our model works properly and is valid.

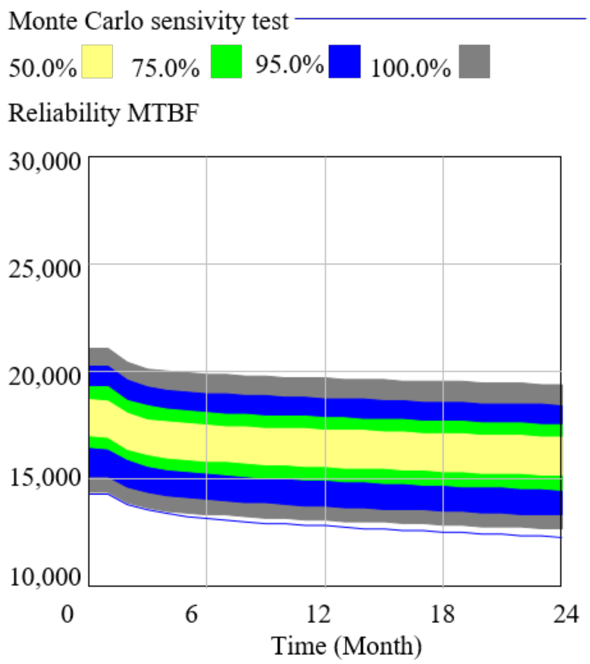

Figure 21- Monte Carlo sensitivity test

5. Discussion

The results show that the antifragility components are effective on the reliability index in gas transmission Company of zone 10. The components of organizing themes in the antifragility approach, learning and growth, have a significant impact on improving reliability. Learning criteria in competitive business scorecard models [Gopal, 1998] and BSC Balanced Scorecard [Kaplan and Norton, 1992] have been identified as one of the important performance evaluation indicators and are consistent with the present study.

The participation of beneficiaries with the exploratory discussions is one of the well-known indicators in the antifragile reliability approach, which is also mentioned in the evaluation charter model [Adams and Neely, 2000].Learning index is a common element of the present research and the mentioned models.

The results of the present study on the importance of redundancy are similar to other studies in system reliability [Yadav et al., 2008]. The important point is that in other approaches, redundancy optimization is emphasized, but in antifragility, redundancy optimization is not approved and is not justified by the long-term view of redundancy optimization. Although more studies are needed, preliminary studies on the interruption of the country's gas transmission and the damage caused by gas supply problems to power plants and other social problems confirm the reliability approach of antifragility and emphasis on the lack of necessity of optimization in gas transmission processes.

5. Conclusions

The present study investigates the effect of antifragility approach on the reliability of the maintenance system. Research findings show that the concept of antifragility includes two global, 18 organizing and 254 basic themes. Studies show that among the organizing themes of antifragility, three components of learning and growth, redundancy and exploratory discussions are related to system reliability. After entering these criteria into the dynamic model of maintenance performance evaluation, it was found that all three components have a positive effect on reliability, but the role of redundancy in improving system reliability is more significant than the other two components and learning and exploratory discussion are in the next ranks.

The conclusion that can be made is that reliability heavily depends on invisible factors such as learning from errors and collaborative system. The traditional view of maintenance systems to improve the situation will not be fully effective and the present study provides an opportunity to examine the effect of other antifragility criteria, besides reliability, on other performance evaluation criteria for maintenance systems. Among the limitations of the study is the time-centered and deterministic method of system dynamics, which is an inseparable property of the aforementioned method.

It is suggested that in future researches, the effects of other antifragility variables in a dynamic environment at different time intervals and compare the results. Be integrated to monitor the effects of black swans on the organization's risk management more effectively. Finally, it is recommended that in the design of utilities and lines of pressure optimization, the issue of redundancy beyond the short-term optimization is considered in order that the long-term benefits are not affected by a few short-term benefits.

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ارایه مدل نوینی از نگهداری و تعمیرات پویا با رویکرد شکست ناپذیری در بهبود قابلیت اطمینان (مطالعه موردی: منطقه ده عملیات انتقال گاز ایران)

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چکیـــــده

قابلیت اطمینان یکی از مهم‌ترین شاخص‌های ارزیابی عملکرد در حوزه نگهداری و تعمیرات محسوب می‌شود. تحقیق حاضر که به‌صورت آمیخته انجام‌شده است به دنبال شناسایی مؤلفه‌های شکست‌ناپذیری و بررسی تأثیر آن‌ها بر قابلیت اطمینان سیستم با استفاده از پویایی سیستم‌ها انجام‌شده است. در بخش کیفی تحقیق با استفاده از روش تحلیل مضمون، با مشارکت ۱۰ متخصص خبره سازمانی و دانشگاهی، عوامل شکست‌ناپذیری در قالب ۲۵۴ کد باز، ۱۸ کد سازمان دهنده و دو کد فراگیر با مرور ادبیات تحقیق و استفاده از نرم‌افزار ماکس کیودا[1] نسخه ۲۰۲۰ شناسایی و دسته‌بندی گردید.در ادامه و در بخش کمی تحقیق ارتباط مؤلفه‌های سازمان دهنده شکست‌ناپذیری به روش رگرسیون چندگانه باقابلیت اطمینان سیستم موردبررسی قرار گرفت. سه معیار یادگیری، افزونگی و بحث‌های اکتشافی به‌عنوان عواملی که بیشترین تأثیر بر قابلیت اطمینان سیستم را دارند شناسایی و انتخاب شدند. تأثیر این شاخص‌ها بر قابلیت اطمینان سیستم در محیطی پویا و با استفاده از نرم‌افزار ونسیم نسخه DDS شبیه‌سازی گردید. نتایج بیانگر تأثیر مثبت هر سه معیار یادگیری، افزونگی و بحث‌های اکتشافی در بهبود قابلیت اطمینان سیستم در منطقه ده عملیات انتقال گاز است و شاخص افزونگی بیشترین تأثیر و مؤلفه‌های یادگیری و بحث‌های اکتشافی در رده‌های بعدی تأثیرگذاری در بهبود قابلیت اطمینان سیستم قرار دارند.

واژگان کلیدی: نگهداری و تعمیرات، قابلیت اطمینان، شکست‌ناپذیری، پویایی سیستم، انتقال گاز، تحلیل موضوعی

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