



Orijinal Araştırma / Original Research

RELIABILITY ANALYSIS OF A DRAGLINE USING FAULT TREE ANALYSIS

HATA AĞACI ANALİZİ İLE ÇEKME KEPÇELİ YERKAZARIN GÜVENİLİRLİK ANALİZİ

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ABSTRACT

Draglines, as massive and expensive stripping machines, are highly utilized in open cast mining to remove overburden. Reliabilities and availabilities of draglines play a critical role to sustain the continuity of overburden stripping and, hence, coal productions. Thorough understanding of the system and its components is required in order to accomplish high levels of availability and it can be achieved with an in depth reliability analysis. This study presents component-based reliability analysis of a walking dragline being operated in an open cast coal mine in Turkey. The main objective of the study is to understand the effects of each component or subsystem of a dragline on its reliability which will further provide insight into optimized maintenance schedule. The results of the study revealed that the system is expected to fail in 37.9 hours, most probably due to a failure in the rotation component of the movement subsystem. Dragging rope is predicted to have the highest contribution to number of failures within a year, but the motors and generators will cause the longest downtime if failed. Reliability importance (RI) values were also found to be useful to decide which components need attention at certain time intervals.

ÖZ

Anahtar Sözcükler:

Çekme kepçeli yerkazlar,
Güvenilirlik,
Hata ağacı analizi,
Bakım onarım.

Çekme kepçeli yerkazlar, açık ocak kömür madenlerinde örtükazı işleminde kullanılan büyük ve pahalı maden makineleridir. Bu yerkazların güvenilirliği ve kullanılabilirliği, örtükazı işlemlerinin sürekliliğinde ve dolayısıyla kömür üretiminde önemli bir rol oynamaktadır. Yüksek seviyede kullanılabilirliği sağlamak için sistemin ve bileşenlerin kapsamlı bir şekilde anlaşılması gerekir ve bu kapsamlı bir güvenilirlik analizi ile başarılabilir. Bu çalışma, Türkiye'de açık ocak olarak işletilen bir kömür madeninde kullanılan bir çekme kepçeli yerkazarın bileşene dayalı güvenilirlik analizini sunmaktadır. Çalışmanın temel amacı, bu yerkazarın her bir bileşeninin ve alt sisteminin, sistem güvenilirliği üzerindeki etkilerini anlamak ve böylece optimize edilmiş bakım çizelgesine ilişkin daha fazla bilgi sağlamaktır. Sonuçlara göre, yerkazarın hareket alt sisteminin dönüş bileşeni arıza ihtimali en yüksek bileşen olarak belirlenmiştir ve yerkazarın 37.9 saatte arızalanacağı öngörülmüştür. Çekiş halatı ise bir yıl içinde arıza sayısına en fazla katkıda bulunacak bileşen olacağı tahmin edilmiş, ancak motorlar ve jeneratörler arıza halinde en uzun kesintilere neden olmaları beklenmektedir. Güvenilirlik önem (RI) değerlerinin, belirli zaman aralıklarında hangi bileşenlere dikkat edilmesi gerektiğine karar vermek için yararlı olduğu saptanmıştır.

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INTRODUCTION

Draglines, as massive and expensive stripping machines, are highly utilized in open cast mining to remove overburden. Unexpected breakdown of the dragline results in delayed stripping and deferred coal production and increased maintenance costs. The draglines are composed of several subsystems or components which need to be maintained and available for the whole system to be available. Therefore, the reliabilities of each subcomponent significantly affects the whole system reliability. The reliability of the dragline can be increased by regular maintenance and renewal but since these operations also have a cost, the optimum frequency should be determined. In order to determine the intervals for maintenance and repair, the change in the reliability of the dragline with time should be observed and a suitable distribution should be provided.

The objective of the study is to construct a reliability model with the help of fault tree analysis in order to determine the roles of different components in the dragline's overall reliability. The scope of this study is the development of a reliability model of a dragline considering both the system and the sub-units using statistical modeling software and characterization of the system with fault tree analysis which is an analytical technique used to analyze a system to determine all the credible ways in which a single undesired event (top event) can occur.

The research methodology essentially entails five steps: (i) collection of failure data from the mine and classification of the failure data and calculations to find times between failures and failure times, (ii) determination of the subsystems and their components considering expert opinion and determination of probability distributions of the failure data for each subsystem using the computer software Weibull 7, (iii) reliability modeling of the subsystems, determining the change in reliability through time for the components reliability estimation, (iv) implementing Fault Tree Analysis (FTA) to combine subsystem reliabilities and determining the reliability of the whole system, and (v) determination of critical components which require immediate maintenance.

Following the introductory chapter, section 2 comprehensively presents the implementation of the research methodology. Section 3 provides a case study to show the application of the developed model on one of the operating draglines in Turkey. Section 4 presents the main conclusions drawn from

the study and recommendations for future studies in this research domain.

1. RESEARCH METHODOLOGY

1.1. Data Classification and Preliminary Analysis

The failure data usually consists of; description of the failure, time of failure and time of repair. The values required for the reliability analysis are the time between failure (TBF) and time to repair (TTR) data. Prior to calculating those values, failure data should be classified into components and sub-units. Machines are mechanical and electrical systems operating with the coordination of many components carrying out different functions. Classification can differ in terms of extent, meaning a component can be selected as the motor of the machine as a whole or the motor itself can be classified into several components such as pistons, bearing, shaft etc. This classification depends on the scope of the analysis.

After decomposing the system into components, TBF and TTR values are calculated for each component for statistical analysis. TBF values should be calculated, keeping in mind that the component is not working for the whole period between two component failures. Other component failures in between should be taken into account for the calculations. TTR values are simple and basically the time it takes for the component to start working again. After preparing the data sets, they should be checked for trends and dependencies.

Monotonic increase or decrease in TBF data suggest the component to be in non-stationary state, meaning the component is either in wear-out or infant mortality state. Non-stationary failure data can be modelled using non-homogenous Poisson process. The data should also be examined for correlation. Stationary but correlated data can be modeled using branching Poisson process. If the data are independent and identically distributed (i.i.d.), meaning there is no evidence of trend and data dependency, the reliabilities can be modelled using best-fit distributions (Barabady and Kumar, 2008).

In order to check data sets for trends, run charts are practical tools. The data sets can be examined for possible trends such as mixtures, oscillations, trends, and clustering. The data can be considered trend free with p-values below 5%, rejecting the hypothesis of the presence of men-

tioned anomalies. Figure 1. shows a sample run chart for a sample data set. The run chart is constructed using Minitab 17 software. A run is defined as succession of similar events proceeded and followed by a different event. In Figure 1., two type of runs are investigated; about median and up/down. One counts the runs of above and below the median value, and the other counts increasing and decreasing sequences. The p-values show that there are no apparent signs of clustering, mixtures, trends or oscillations (p-values > 0.05). Pearson’s correlation coefficient can be used to check for linear correlations between two data sets. However, non-linear correlations shouldn’t be neglected and checked via graphical methods.

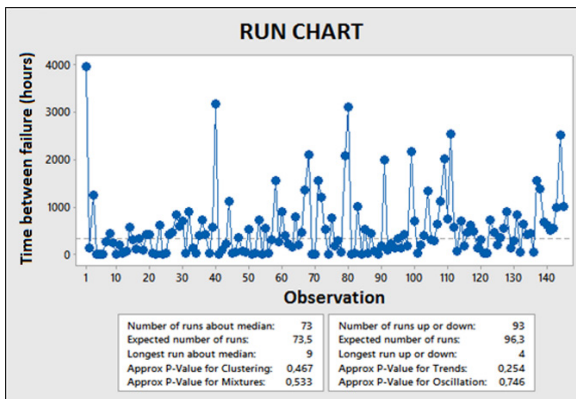


Figure 1. Run chart of a sample dataset

In order to see if the component is in its stationary period, cumulative TBF plots can be examined. If the component is in its useful life period (stationary), the plot is expected to be a straight line. Figure 2. is the cumulative TBF plot of the same sample failure data that shows a stationary behavior.

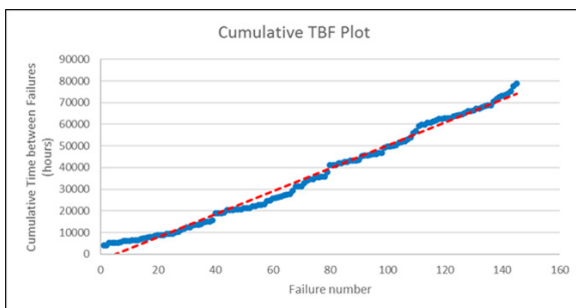


Figure 2. Cumulative TBF plot of a sample dataset

1.2. Reliability Assessment using Fault Tree Analysis

Reliability assessment starts with determining the failure and repair behavior of components and representing those behaviors with a statistical model. After checking the data for trends and dependencies, the process that defines the data best is selected. In the scope of this paper, data is assumed to be i.i.d. and best-fit probability distributions are determined. There are various computer softwares that will aid in fitting a distribution and Weibull ++7 is used in this paper. Each component should be assigned two distributions; one for TBF data and one for TTR data.

Failure distribution assignments for TBF data start to give us some information about the component reliabilities. A useful information to obtain from a failure distribution is the mean life time. This value is the expectation of the TBF distribution and gives the estimated time for that component to work without failure. The distributions also give the change in component reliabilities with time. Component reliabilities after a certain time of operation can be determined. From the distributions assigned to TTR data gives the mean time it takes for the component to continue operation after a failure.

One of the most common distributions used in lifetime distributions in reliability engineering is the Weibull distribution. Due to its versatility, it can take on other distributions’ characteristics. and can be with 2 or 3 parameters. 2 parameter Weibull distributions contain the scale and shape parameters that determine the life characteristics. The cumulative density function of a Weibull distribution can be defined as (Reliasoft, 2015);

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^\beta} \tag{1}$$

The cumulative density function is the same function used to calculate the failure probability, and the reliability is given as 1 – F(t).

3-parameter Weibull distribution has a location parameter in addition to those of 2-parameter Weibull distribution and it has a cumulative distribution function of (Reliasoft, 2015):

$$F(t) = 1 - e^{-\left(\frac{t-\gamma}{\eta-\gamma}\right)^\beta} \tag{2}$$

In Equation 2, β is the shape parameter, η is the scale parameter, γ is the location parameter and t is time.

Lower shape parameters ($\beta < 1$) suggest that the failure frequency is high at start and decreases continuously which is similar to an exponential distribution which occurs when β equals to one. Shape parameters greater than one suggest that the failure frequency increases to maximum and then decreases with time.

The scale parameter is an estimate of the mean and gives the time when the failure probability is 63.2%. The location parameter in the 3-parameter Weibull distribution suggests that no failure occurs before a certain time. In other words, a location parameter greater than one indicates that the curve does not start from the origin, but starts from the right-hand side. In Figure 3a and 3b, the effect of shape and scale parameters can be seen.

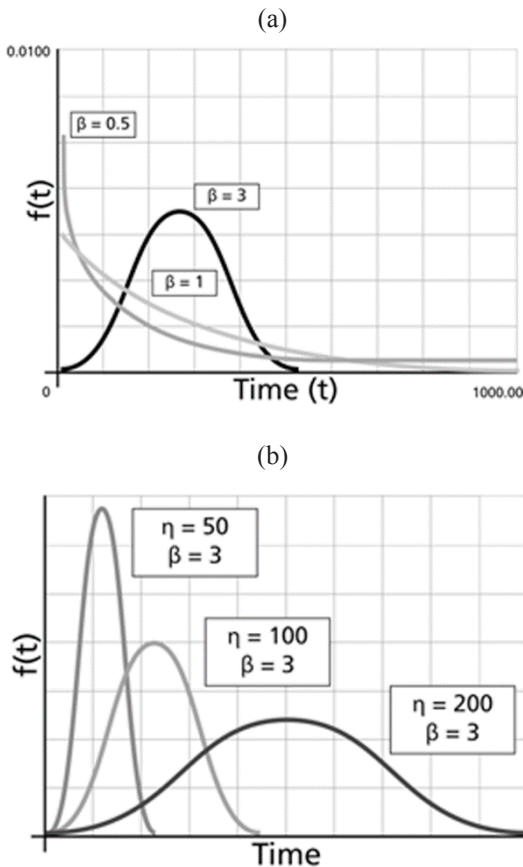


Figure 3. Effect of Shape (a) and Scale (b) parameters on Weibull pdf (Reliasoft, 2015)

Another widely used distribution is exponential distribution which suggests a failure behavior starting with high failure frequency and decreasing

continuously. The exponential distribution has one parameter which is the failure rate (λ) which is the inverse of mean. There can also be 2-parameter Exponential distributions where the other parameter is the location parameter similar to the one in the Weibull distribution which shifts the curves t_0 location to the right or left. The failure probability from an exponential distribution is calculated as (Reliasoft, 2015);

$$F(t) = 1 - e^{-\lambda t} \tag{3}$$

After determining component failure distributions, fault tree analysis (FTA) is the graphical tool that aids in bringing the components together. FTA is an analytical technique for analyzing the system in terms of different component failures leading to system failure which is called top event. FTA is a top to down, failure oriented symbolic logic model used to determine the probability of system failure by identifying failure paths leading to it (Ericson II, 1997).

The system at hand should be constructed carefully and thoroughly where every possible cause for system failure should be taken into account. Components can cause system failures with various ways. In order to represent component roles in system operability, different logic operators are used in fault tree construction:

- OR gate: occurrence of at least one input is enough for the output to occur.
- AND gate: all input events must occur for the output event to occur.
- Exclusive OR gate: only one input should occur for the output event to occur.
- Priority AND gate: all input events must occur in a specific sequence for the output to occur.
- Inhibit gate: inputs must occur and a condition should be satisfied for the output event to occur.

With these in mind, the fault tree is constructed with component failures as basic events, leading up to the top event which is the system failure. Events and gates are represented with different symbols and some of them can be seen in Figure 4.

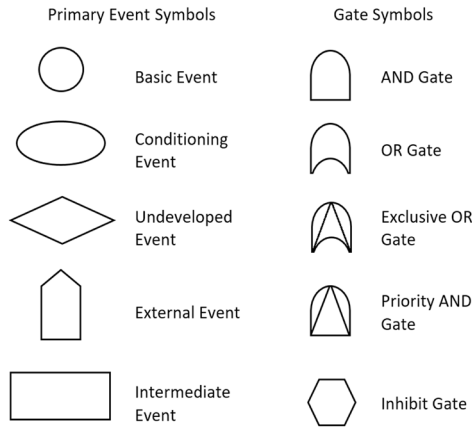


Figure 4. Symbols used for operators in Fault Tree Analysis (Vesely et al., 1981)

AND gate represents a parallel system where OR gate represents a series configuration. Figure 5a and 5b shows the fault tree representations of simple series and parallel systems and reliability of the systems can be calculated accordingly.

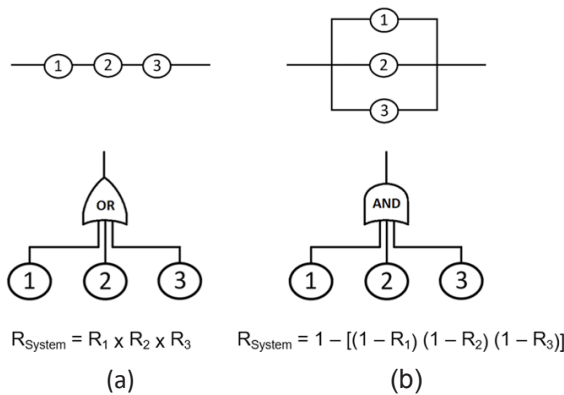


Figure 5. Fault tree representations and reliability calculations of simple series (a) and parallel (b) configurations

The knowledge and expertise of the analyst is crucial for fault tree analysis so it is difficult to define how to construct a fault tree. Fault tree requires detailed analysis and may require comprehensive assumptions, but other than those, the main steps can be listed as (Öktem, 2006);

- Determining the Top Event: The undesired event to be analyzed is chosen.
- Combining the Known Causes: Existing faulty states and failure events are determined with the available knowledge. Even though the failure list can be lacking, it is important for the fault tree construction.

- Construction of Fault Tree: Independent events that may cause the top event are determined. These events are connected with an OR gate and the construction continues from top to bottom trying to find other failure causes.
- Revision, Addition and Testing: Fault tree construction is a trial and error process no failure causes should be overlooked.
- Evaluation of the Results: The completed fault tree is evaluated according to the purpose of the analysis. The evaluation can include various stages: listing minimum cut sets, grading minimum cut sets, and calculation of probabilities etc.

After constructing the fault tree for the whole system, system reliability can be calculated and analyzed. In addition to obtaining system reliability characteristics, importance factors are other important outputs. Those factors determine the components that have the highest influence on system reliability at a given time. This information can be put into good use in terms of preventive maintenance. Birnbaum's Importance measure is one of the commonly used factors and calculated as the partial derivative (Reliasoft, 2017);

$$I(t) = \frac{\partial R_s(t)}{\partial R_i(t)} \tag{4}$$

where $I(t)$ is the importance value, $R_s(t)$ and $R_i(t)$ are the system's and i^{th} component's reliabilities at time "t". Since it is a time dependent value, most important components may vary at different time intervals.

1.3. Simulation

Until now, the analyses are done using only the TBF data and the time it takes to repair different components is not taken into account. A component may have high reliability but its repair may take a considerable time. In order to see the effect of repair times, obtained TTR data distributions are introduced to the fault tree and the system is simulated for a period of time. The availability simulation gives important information about the component contributions to system failures and downtimes. There are two results obtained from the simulation that are important for maintenance planning and they are: Failure Criticality Index (FCI) and Operational Criticality Index (OCI).

They are calculated as;

$$I_k^{FCI}(t) = \frac{\text{Number of System Downing Failures Caused by Component } k \text{ in } (0,t)}{\text{Number of System Failures in } (0,t)} \quad (5)$$

$$I_k^{OCI}(t) = \frac{\text{Total down time of comp when system down in } (0,t)}{\text{Total system down time in } (0,t)} \quad (6)$$

FCI value is the percentage of a components failures in a time interval to total number of system failures in that time interval. Only the number of failures are considered without the influence of downtime. Other parameter is OCI which is defined as the percentage of a component’s down time over the system downtime. Both these values should be considered in determination of critical components.

Another issue that should be kept in mind is that repair efficiencies may vary from component to component. In other words, some components may be replaced and brought back to as-good-as-new condition where other components may be repaired to its condition right before the failure (as-bad-as-old). There is a parameter called “Restoration Factor” to be entered for the simulation that governs the reliability of the component after it is repaired.

2. CASE STUDY

The subject of the case study is a dragline operating in Western Lignite Enterprises (GLİ) owned by Turkish Coal Enterprises (TKİ) in Tunçbilek/ Kütahya since 1970. The failure data since 1998 to 2011 for the dragline is obtained from GLİ. The

data included type of failure, failure definition and explanation, time of failure, and time the failure is fixed. After picking out the duplicate data, there were 1023 failure data for the dragline.

The TTR data for each failure and the TBF data (operational time) are calculated considering that the dragline works 21 hours a day. Before the TBF are calculated, the dragline is decomposed into its components and they are listed in Table 1.

As seen in Table 1, even though the most number of failures occur in the dragging unit taking up 27% of all failures with 281 failures, the downtime due to the failures in the machinery house is 7,805 hours which is more than 50% of the total down time.

Following the classification of the data, TBF values are calculated for each component and checked for randomness. There were no apparent trends in the data sets so they are modeled by their best-fit distributions. Distributions of each component of each subsystem were determined using the Weibull ++7 software (Reliasoft, 2011a). Since boom component does not have sufficient failure data, it was omitted in the analysis. Most of the components were found to have a Weibull distribution as their best-fit failure distributions with one having exponential distribution. The failure distributions of the rigging components can be seen in Table 2. Using the determined distributions, reliability plots of the components are generated and the reliability vs. time plot of the same components are presented in Figure 6.

Table 1. Dragline components and summary of subsystem failure data

SUBSYSTEM	Components	# of failures	Down Time (hrs)
Dragging	Rope, Chain, Socket, Ringbolt, Control	281	1,491.58
Hoisting	Rope, Brake, Socket, Control	101	1,229.83
Rigging	Rope, Ringbolt, Socket, Pulley	182	380.25
Bucket	Chain, Pins, Bucket Main Body, Ringbolt, Teeth	182	653.50
Boom	Boom	10	99.00
Movement	Rotation, Walking, Warning	121	2,307.70
Machinery House	Motors, Generators, Lubrication	146	7,805.11
	TOTAL	1,023	13,948.52

Table 2. Distribution parameters of components of rigging subsystem

Component	Distribution	Distribution Constants	
Rope	Weibull-3P	β	1.66
		η	663.91
		γ	-6.92
Socket	Weibull-3P	β	0.95
		η	2,553.02
		γ	-28.73
Pulley	Weibull-2P	β	1.054
		η	1,232.87
Ringbolt	Weibull-3P	β	0.63
		η	3,348.66
		γ	82.74

From the plot it is observed that the rope has the lowest reliability among rigging components. Also, until around 1200 hours, socket is the most reliable component and gives its place to the ringbolt after 1200 hours.

Another parameter obtained from the distributions is the mean life estimations. Mean life estimations are calculated for all components and the 10 components with the lowest mean life estimations are listed in Table 3.

Table 3. Ten components with lowest estimated mean lives

Component	Mean Life Time (hr)
Dragging Rope	567
Rigging Rope	587
Dragging Chain	908
Bucket Pin	950
Lubrication	968
Dragging Ringbolt	1048
Bucket Teeth	1125
Movement Warning	1157
Hoisting Rope	1179
Bucket Ringbolt	1197

After determining the failure probability density functions, they are introduced to the fault tree. Top event, which is the undesired event, is determined and that is the failure of the dragline for this case. The relations of the components are then represented in the fault tree by using gates. Dragline components are connected in series (OR Gate) since any failure in a component results in the halt of the whole system. There is also a "Voting Gate" in the bucket subsystem and it is a special kind of OR gate where output occurs when more than a specific number of input events occur. BlockSim 7 (Reliasoft, 2011b) is used for the fault tree analy-

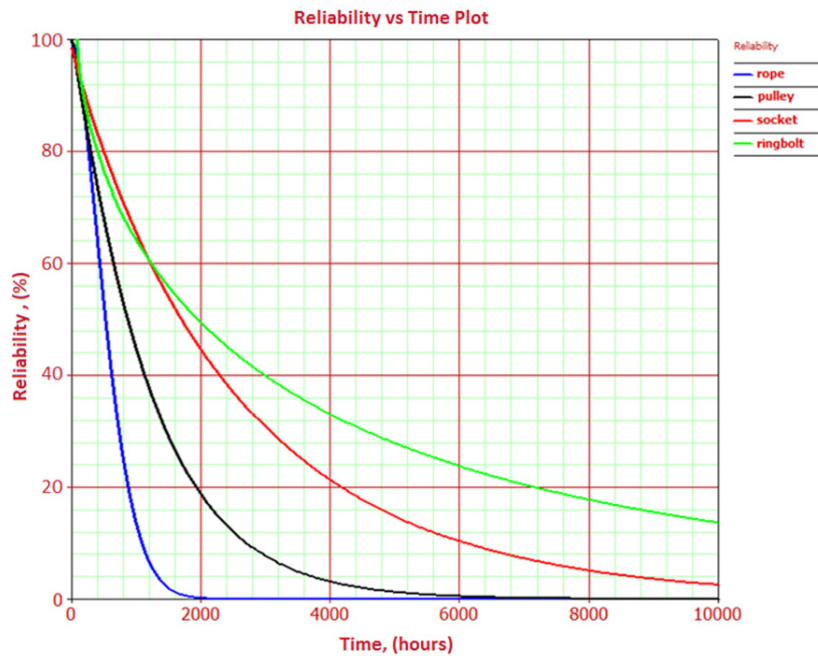


Figure 6. Reliability curves of rigging components

sis in this paper. In Figure 7., the fault tree representation of the dragging subsystem can be seen and the reliability of the subsystems are expressed as Equation 7-12.

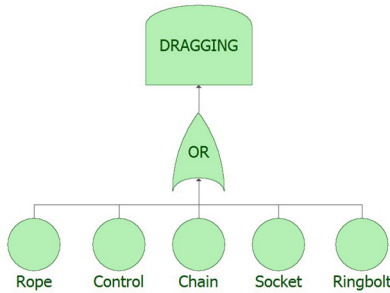


Figure 7. Fault tree representation of dragging subsystem

$$R_{dragging} = R_{rope} \times R_{control} \times R_{chain} \times R_{ringbolt} \times R_{socket} \quad (7)$$

$$R_{bucket} = R_{chain} \times R_{pin} \times R_{bucket\ main\ body} \times R_{ringbolt} \times (5R_{tooth}^4 - 4R_{tooth}^5) \quad (8)$$

$$R_{hoisting} = R_{rope} \times R_{brakes} \times R_{socket} \times R_{control} \quad (9)$$

$$R_{rigging} = R_{rope} \times R_{socket} \times R_{pulley} \times R_{ringbolt} \quad (10)$$

$$R_{movement} = R_{rotation} \times R_{walking} \times R_{warning} \quad (11)$$

$$R_{machinery\ house} = R_{lubrication} \times R_{generators} \times R_{motors} \quad (12)$$

The bucket teeth are connected by a Voting Gate that suggest the system failure occur if more than one tooth fails. The plot of subsystem reliabilities can be seen in Figure 8. It is observed that the bucket subsystem has the lowest reliability where hoisting is the most reliable. However, there are some changes in the ranking at different time intervals.

Finally, all subsystems are connected to construct the system fault tree. The final fault tree of the dragline system is given in Figure 9. Final fault tree

is then used to determine system reliability, system mean life and component importance factors.

As a result of the fault tree analysis, the mean life estimation of the dragline was found to be 37.9 hours. At 37.9 hours of operation, using Birnbaum’s measure, five most important components are shown in Figure 10. Rotation component of the movement subsystem was found to have the highest reliability importance (RI). These values can be calculated for different time intervals to determine the components to be maintained. For example, although the hoisting brakes are not shown in Figure 10 among the 5 most important components, at 100 hours, it becomes the third most important component which is caused by different reliability behavior of components. Some of the component reliabilities decrease more rapidly with time.

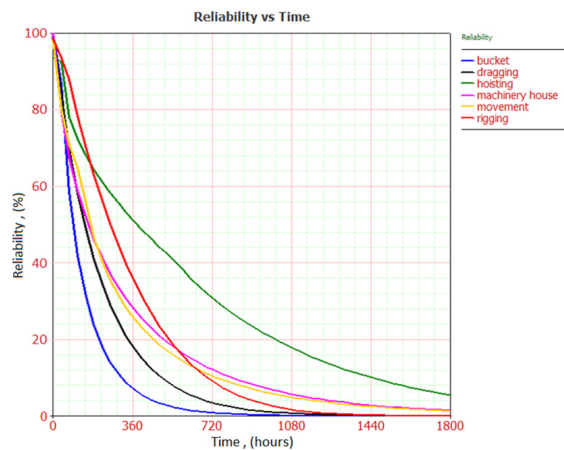


Figure 8. Time varying reliabilities of subsystems

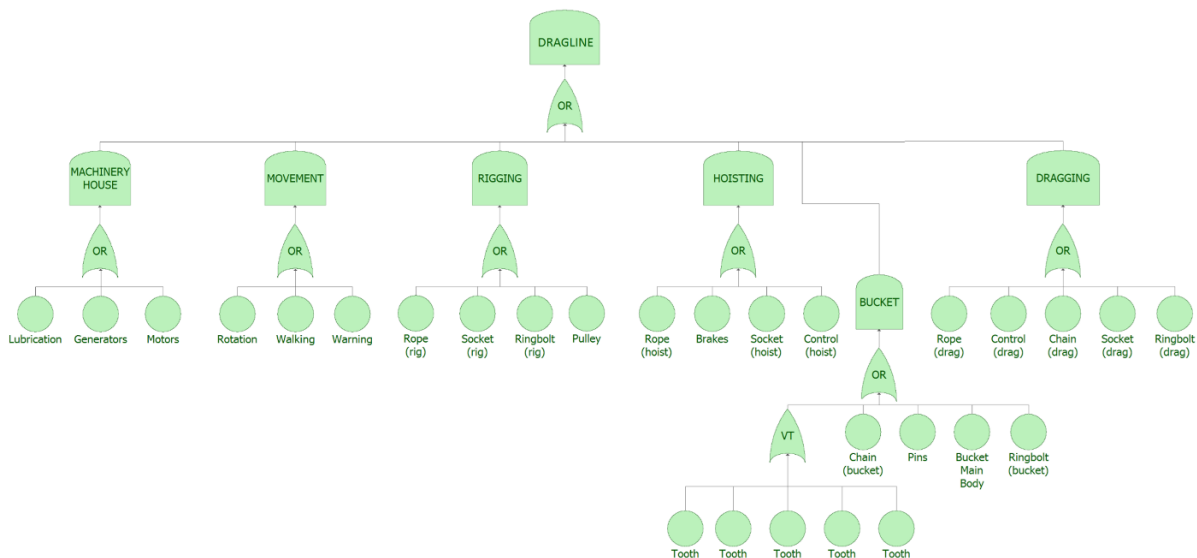


Figure 9. Fault tree representation of the dragline system

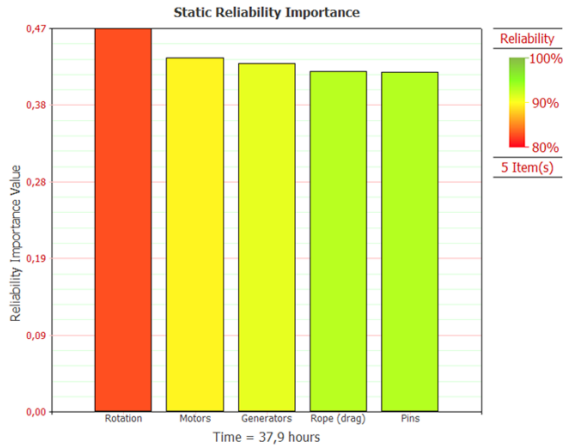


Figure 10. Five components with highest RI values at dragline’s mean life

The final plot of system reliability with respect to time is presented in Figure 11. The reliability of the dragline falls below 60% at around 20 hours. The reason system reliability is not 100% at time t=0 is that there are some components with failure probability functions with positive location parameters (prone to failure at t=0).

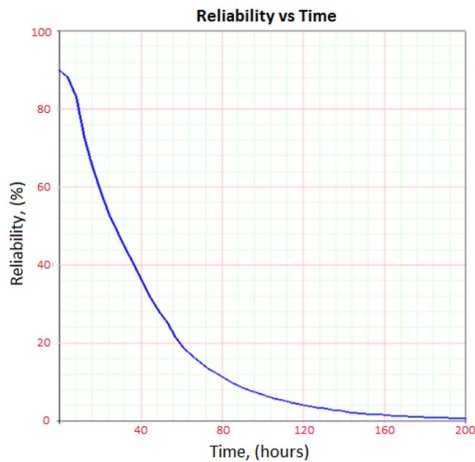


Figure 11. Reliability plot of the dragline

Finally, availability simulation is conducted. As mentioned earlier, machinery house failures take significantly longer to repair and should be taken into consideration. In this sense, analysis similar to time between failure data is conducted for time to repair data. Appropriate distributions are fitted to the repair time data and introduced to the fault tree analysis. Availability simulation is conducted to see the contribution of components to total number of failures (FCI) and total downtime (OCI). Table 4. shows the results of availability simulation for one year of operation (7665 hours). Number of simulations are selected as 2000 and Figure 12 shows a sample simulation showing the

up and down times of selected components and the system.

In the simulation, repair characteristics are assumed as “repaired to as good as new condition” meaning when a failure occurs, the failed component is repaired to its state at t=0. That analysis is not in the scope of this paper, but maintenance characteristics should be considered for an in depth analysis.

Considering number of failures, dragging and rigging ropes cause the most number of system stops. Those two components cause more than 20% of the total number of system failures. However, if we look at downtimes, the motors and generators in the machinery house cause more than 50% of total downtime.

Table 4. Simulation results for one year of operation time

SUBSYSTEM	COMPONENT	FCI	OCI
BUCKET	Ringbolt	5,58%	0,86%
	Bucket Main Body	2,35%	1,35%
	Chain	1,11%	0,25%
	Pin	6,60%	0,95%
	Tooth	0,07%	0,01%
	Tooth	0,08%	0,01%
	Tooth	0,08%	0,01%
	Tooth	0,07%	0,01%
	Tooth	0,07%	0,01%
	Socket	1,10%	0,17%
DRAGGING	Ringbolt	5,67%	1,87%
	Rope	10,87%	3,48%
	Chain	6,86%	2,26%
	Control	3,29%	0,50%
HOISTING	Control	0,58%	0,95%
	Rope	4,82%	3,21%
	Brakes	2,36%	0,45%
	Socket	0,71%	0,11%
MOVEMENT	Warning	5,71%	13,87%
	Walking	3,46%	1,02%
	Rotation	5,65%	1,61%
MACHINERY HOUSE	Lubrication	6,28%	0,79%
	Air Conditioning	-	-
	Motors	5,08%	25,88%
	Generators	2,47%	37,61%
RIGGING	Pulley	4,98%	0,86%
	Rope	10,08%	1,25%
	Socket	2,37%	0,37%
	Ringbolt	1,74%	0,27%

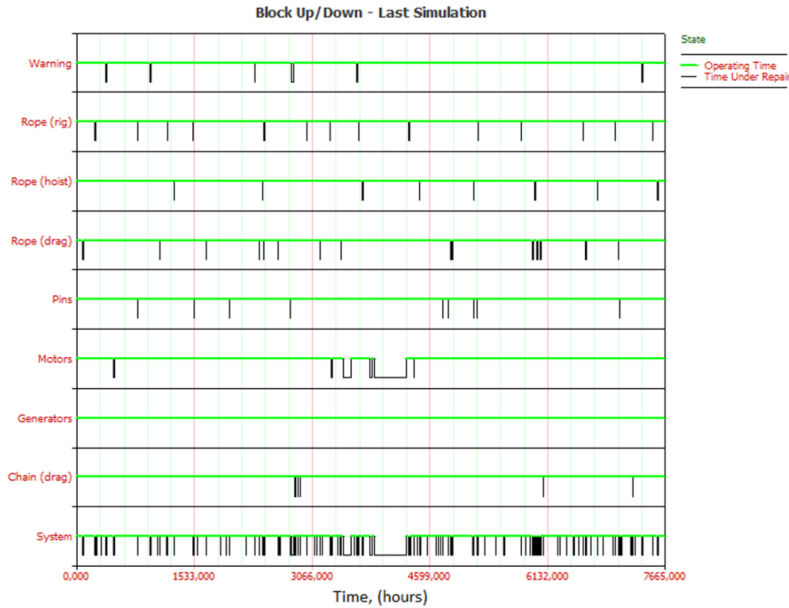


Figure 12. Sample simulation of 7665 hours of operation

CONCLUSIONS AND RECOMMENDATIONS

Fault tree analysis was conducted for a dragline operating in a coal mine in Tunçbilek. The failure data between the years 1998 and 2011 were classified and checked for trends and correlations and then introduced to the software “Weibull ++7” in order to determine their probability distributions and reliability modelling. The obtained distributions were then combined with a constructed fault tree to examine the system reliability model. Finally, the fault tree model is used for simulation of failure behavior and component contributions on system failures. It was determined that the system is expected to fail in 37.9 hours, most probably due to a failure in the rotation component of the movement subsystem. Dragging rope is predicted to have the highest contribution to number of failures within a year, but the motors and generators will cause the longest downtime if failed. Reliability importance (RI) values were also found to be useful to decide which components need attention at certain time intervals.

The results of these analysis would be beneficial in preparing a maintenance plan considering the critical components in terms of both reliabilities and repair times. An adequate maintenance plan will help improve machine availability, thus decreasing the direct and indirect costs caused by unplanned down times of the machinery. Additional analysis can be conducted considering the effect of working conditions on some component specific failures. Finally, optimization of preven-

tive and corrective maintenance intervals can be investigated considering maintenance costs, repair efficiencies and losses in revenue due to breakdowns.

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REFERENCES

- Barabady, J., and Kumar, U. 2008. Reliability analysis of mining equipment: A case study of a Crushing plant at Jajarm Bauxite Mine in Iran. *Reliability Engineering & System Safety*, 647-653.
- Reliasoft Corporation 2015. Life Data Analysis Reference. Retrieved 02 2017 from <http://www.reliawiki.org>
- Ericson II, C. 1997. FTAB - A New Generation Computer Code for Fault Tree Analysis. 15th International System Safety Conference, pp. 437-447.
- Öktem, R. 2006. Hata Ağacı Analizi. In L. H. Ringdahl, *Safety Analysis Principles and Practice in Occupational Safety*. Türk Tabipler Birliği
- Vesely, W., Goldberg, F., Roberts, N., and Haasl, D. 1981. *Fault Tree Handbook*. Washington, D.C.: U.S. Government Printing Office.
- Reliasoft 2011a, Weibull ++7 Software, ReliaSoft Office 7, ReliaSoft Corporation Tucson
- Reliasoft 2011b, Blocksim 7 Software, ReliaSoft Office 7, ReliaSoft Corporation Tucson