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A Bayesian Networks Approach to Reliability Analysis of a Launch Vehicle Liquid Propellant Engine

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This paper presents an extension of Bayesian networks (BN) applied to reliability analysis of an open cycle gas generator liquid propellant engine (OGLE) of launch vehicles. There are several methods for system reliability analysis such as RBD, FTA, FMEA, Markov Chains, etc. But for complex systems such as a Launch Vehicle (LV), they are not all efficiently applicable due to failure dependencies between components, computational complexity and state space explosion problems. Thus, to overcome these problems, the BN modeling is preferred for OGLE reliability analysis. In this algorithm, first, the functional models of OGLE are constructed based on expert knowledge and experiments involving system and subsystems interactions. Then, failure modes are derived through performing FMEA. Furthermore, by using modeling properties of Bayesian networks, a constructional model for failure propagation is obtained based on the acquired functional model and FMEA. Finally, by allocating quantitative properties to the Bayesian model and its inference, the reliability of OGLE is obtained. The results are verified using the Monte Carlo simulation results. Comparing the values obtained from the two applied methods shows the high accuracy and efficiency of the introduced algorithm for reliability analysis of OGLE and other complex systems with dependant failure modes in LV.

INTRODUCTION

A typical task for the reliability analyst is to give inputs to a decision problem. An example can be to examine the effect that environmental conditions have on a component's time to failure and give this as input to a maintenance optimization problem. Due to the uncertainty of the quantities in such studies and random fluctuations, the end result should be a statistical model describing a set of random variables. This model must be mathematically sound and, at the same time, easy to understand for the decision- maker.

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Furthermore, the model must be represented in such a way that the quantities we are interested in can be calculated efficiently. In a statistical setting, the numbers we would like to find are either conditional probabilities (*e.g.*, the probability that a component will survive for more than one year in a given environment), or deduced numbers (for instance, the expected life-length of a component). All these requirements have led to an increased focus, among reliability analysts, on flexible modeling frameworks like Bayesian network (BN) models [1]. Assessing the risk of engine failure can be difficult, especially for new vehicles that have had relatively few launch attempts. One approach to estimating the risk of launch vehicle (LV) engine failure is simply to use the actual past frequency of failure of that particular engine as an estimate of its failure probability. However, one can place little confidence on the results of this type of analysis unless there is a long history of launch attempts for the vehicle in question. When this is the case, two other approaches can be considered. The first is to use Bayesian probability (see Refs. 2–7). Bayesian updating has been used in a number of cases, for example updating the probability that a nuclear attack is underway given evidence from a warning system [8] or computing the chance of a failure of the space shuttle based on past near misses [9]. The second approach to the assessment of the likelihood of an LV failure in a given launch is to use probabilistic risk analysis (PRA). This requires decomposition of the LV into subsystems and components, assessment of the probability of failure of each component or subsystem and then computation of the probability of failure of the whole system based on fault tree and event tree analyses. Application of this approach and associated tools in the aerospace field have been well developed in the literature [2][10;11].

Reliability is defined as "the probability that an item (component, subsystem, system) will perform a required function under stated conditions for a stated period of time"[12]. Then, reliability of a launch vehicle is the probability that a vehicle will complete its mission successfully. This metric can also be referred to as the probability of loss of mission by subtracting the success probability from one.

In the realm of PRA, there exists a variety of methodologies for modeling and analyzing systems. Fault Trees (FTs) are inevitably the most widely used models for reliability analysis. FTs are popular because they are easy to use, present the designer with an intuitive high-level abstraction of the system and can be efficiently solved using techniques such as Binary Decision Diagrams. However, traditional (or static) fault trees cannot handle sequential and functional dependencies between components. However, RBD and static FT are inherently modular because they map system components to events in their diagram or tree. Consequently, a number of dynamic methodologies have been developed to overcome this lack of modeling power. Markov Chains (MCs) and their extensions have proven to be a versatile tool for modeling complex dynamic component behavior. They have been extensively used for dependability analysis of dynamic systems and many tools have adopted, directly or indirectly (*i.e.* a higher level model is translated into a MC), MCs as their formalism. However, MCs present two main shortcomings: manually generating a MC describing the system's behavior is a daunting and an error prone task. For this reason, a class of tools such as the Galileo tool [13] provides a higher level description of a system model which is then automatically converted into a MC. In fact, in most cases, only a set of particular component behavior and dependencies is needed to model any kind of system. Any dependability tool ought to have a comprehensive and complete set of components' behaviors and dependencies (generically called constructs). Secondly, MCs are faced with the infamous state space explosion problem [14] where the states to be generated grow exponentially with the number of components included in the system [15].

M. Bouissou and his colleagues extended traditional fault trees by combining fault trees and Markov processes into a new formalism called Boolean logic Driven Markov Processes (BDMP) [16]. The BDMP formalism allows the analyst to define complex dynamic models by associating a particular Markov process to the leaf nodes (*i.e.* the system components) of the FT. In Ref. [16], the authors provide a set of predefined Markov processes an analyst can use to model a wide variety of systems. Embedding Markov processes into FT nodes makes BDMP suitable for dynamic system modeling and nearly as easy to use as traditional FTs.

The objective of this work is to provide a useful tool for reliability analysis of OGLE and decomposition of this system into suitable subsystems and components. We propose an OGLE BN reliability modeling and address the problems and issues mentioned above.

IMPORTANCE OF LV ENGINE RELIABILITY ANALYSIS

The most critical subsystem in any launch vehicle is the propulsion subsystem (Figure 1). Obviously, an engine failure has catastrophic consequences for LVs. During the past few decades, a number of LV failures have occurred, the most notable of which was the loss of the Space Shuttle Challenger due to engine failure at lift-off in 1986.

Since the engine is such a significant driver of launch vehicle reliability, it must be separated from the propulsion subsystem and calculated at the component level. Throughout the history of launch vehicles, engines have been one of the leading causes of launch vehicle failure. Figure 1 shows the leading subsystem and component contributors to unreliability of an LV.

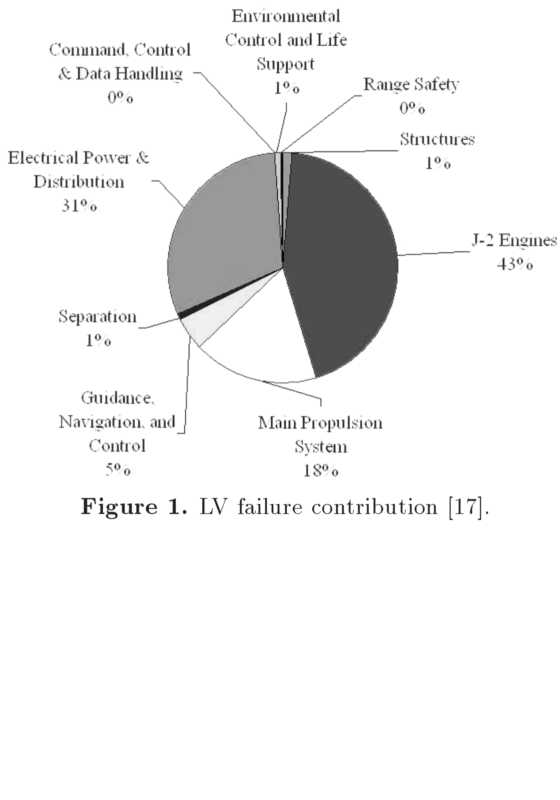

Figure 1. LV failure contribution [17].

As seen, engine unreliability is the leading cause of unreliability for this LV.

THE BASICS AND THEORY OF BAYESIAN NETWORKS

K. Pearson, an early, pre-eminent statistician, argued that the only proper goal of scientific investigation was to provide descriptions of experience in a mathematical form [18]. The history of BNs in reliability can (at least) be traced back to Barlow (1988) and Almond (1992) [1].

A Bayesian network is essentially a directed acyclic graph and consists of a set V of nodes and a set E of edges that connect some pairs of nodes together with the associated conditional probability distributions. This graphical model is an interaction between probability theory and graph theory that provides an effective tool for dealing with a large class of problems containing uncertainty and complexity. In BN modeling, the prior probabilities that are the probability distributions over variables space X before obtaining any relevant data are the basic data provided for computations. The prior probability is related to background information, modeling assumptions or simply a function introduced for mathematical convenience. These probabilities are updated simultaneously just as new evidence is observed. However, the graph helps to indicate independence structures that enable the probability distribution to be decomposed into smaller pieces [18].

In this work, we call the nodes with no input)root nodes[, the nodes that are directly connected and entered into node x1 'parent nodes of x1' and those directly connected and outcome from node x2 'children nodes of x2', respectively.

The direct dependencies between the variables are represented by directed edges between the corresponding nodes and the conditional probabilities for each variable are stored in tables attached to the dependent nodes. A complex model is built by combining simpler parts, an idea known as modularity [18]. However, in this work, we have specifically utilized the result of the FMEA analysis of an OGLE in addition to using expert knowledge and a casual approach to build the topology of BN.

After building BN graph topology and specifying conditional probability tables (CPTs) (obtained from prior observed evidences) to the nodes, making inference from BN can be started. The first step for inference is to derive joint probability function governing the space of variables. Then, by marginalizing each variable, their marginal pdf can be obtained. The step by step algorithm for BN inference made in this work is illustrated in Figure 2.

Finally, information about the observed value of a variable is propagated through the network to update the probability distributions over other variables that are not observed directly.

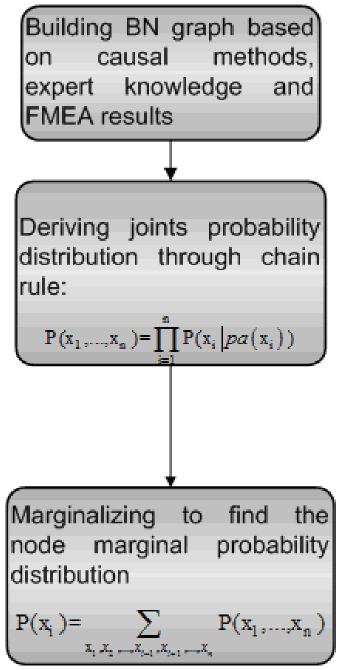

Figure 2. BN inference algorithm.

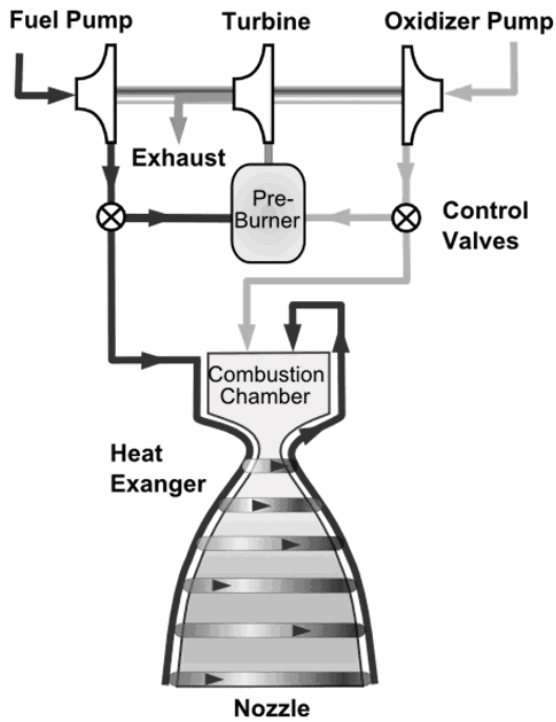

Figure 3. schematic flow paths for gas generator cycles [21].

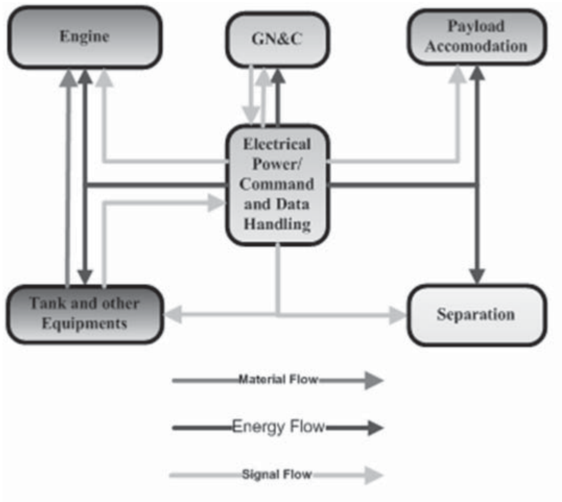

Figure 4. Engine and other launch vehicle subsystems relationship.

OGLE SPECIFICATIONS

An OGLE utilizes the chemical combustion energy to propel a vehicle forward. The main purpose of OGLE design is reliability growth under the condition of design constraints to achieve the mission success. The reliability analysis of this system depends on engine concepts including pressure-fed and pump-fed. The first one is the most simple and reliable, but the second one enables us to get higher specific impulse. The goal of this paper is pump-fed engine reliability analysis. There are three categories of pump-fed engines: gas generator cycle (also called pre-burner sometimes), staged combustion cycle and expander cycle.

These concepts are the most common turbine drive cycles for pump-fed, liquid-propellant engines [19; 20]. The schematic flow paths for gas generator cycles are illustrated in Figure 3. Also, the single-shaft turbo-pump arrangement (*i.e.* a turbine driving both fuel and oxidizer pump is mounted on the same shaft) is shown for a basic cycle in Figure 3 to keep the schematics as simple as possible.

The considered engine has ten components: fuel diaphragm valve, oxidizer diaphragm valve, fuel pump, oxidizer pump, starter, turbine, gas generator (pre burner), fuel cut-off valve, oxidizer cut-off valve and thrust chamber.

Engine interaction with other launch vehicle subsystems and also OGLE functional flow diagram have been derived by authors for a typical LV and shown in Figures 4 and 5, respectively. In Figure 4, as shown, the liquid propellant engine is related to two launch vehicle subsystems: electrical power/command & data handling and tank & other equipment.

As seen in Figure 5, after the tanks are charged, an electrical signal is sent from the propellant tanks to the electrical power/command & data handling. Then, the electrical power/command and data handling sends an electrical command to the solid propellant starter, oxidizer and fuel diaphragm valves. Thus, the engine turbo-pump starts working and the gas generator enters the engine cycle and the solid propellant starter gets out of the cycle in less than 2 seconds. After the engine burning time is elapsed, the electrical command is sent to the propellant tanks by the electrical power/command & data handling subsystem to eliminate the ullage pressure over the oxidizer and fuel tanks. Consequently, the electrical command is sent to the oxidizer and fuel cut-off valves by the electrical power/command & data handling subsystem to cut off the fuel and oxidizer flow to the gas generator and thrust chamber. By performing this sequence, the engine cuts off.

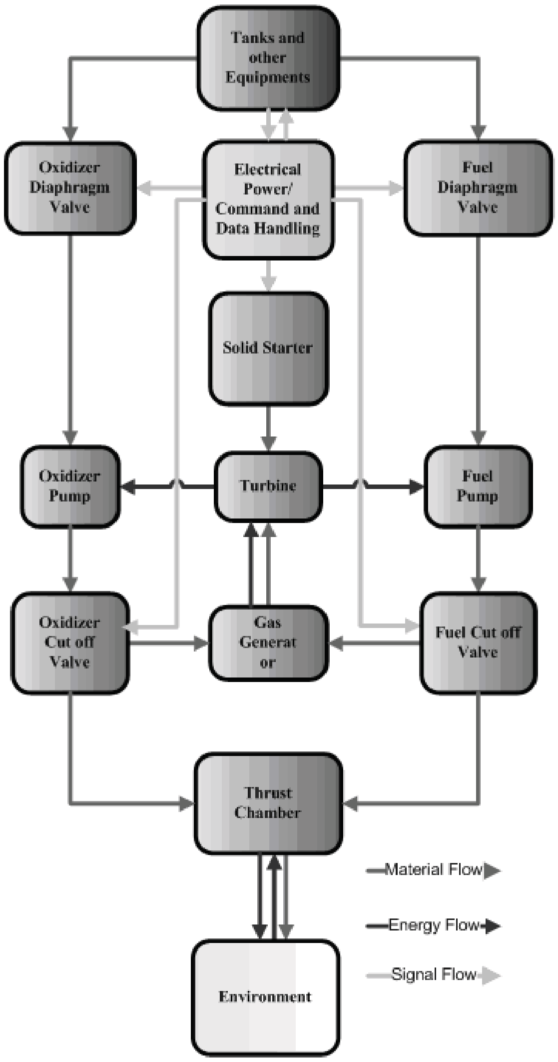

Figure 5. OGLE functional flow diagram.

FAILURE MODE AND EFFECTS ANALYSIS

Failure mode and effects analysis (FMEA) is a systematic analytical method on reliability used in the phases of conceptual design and system engineering.

This method helps to raise potential failure modes in the process of conceptual design to production. Analysis is further made on raised failure modes so as to identify weak points of design and production in early developing process. A shortened period for product development and reduced risk of product in the mission operation can be achieved in conceptual design through FMEA methodology. OGLE failure modes and effects are derived by applying this methodology. As an example, the FMEA chart of the Oxidizer Diaphragm Valve (ODV) is shown in Table 1. These results show that the components have different roles and scores in reliability analysis. Here, FMEA is employed to recognize any critical component.

Here, mission failure is defined as failure of the engine to produce the required thrust during the specified time to fulfill the mission objectives. Mission failures can be classified as catastrophic, premature shut-down, and deferred.

Catastrophic failure (Criticality I): An uncontained failure in which the effects propagate beyond the physical envelope of the engine system, with sufficient energy potential likely to propagate failure to adjacent systems. It is important to assess and discriminate this type of failure from a premature shut-down for crew safety in manned vehicles and for mission success in multi-engine unmanned vehicles (if engine-out is a

Table 1. FMECA of Oxidizer Diaphragm Valve (ODV).

Identification number	Item/ functional identification	Function	Failure modes and causes	Mission Phase/ Operational mode	Failure Effects			Failure Detection method	Compensation provisions	Severity class	Possible Cause
					Local Effects	Next Higher Level	End Effects				
1	ODV	Opening	Internal leak; premature opening	prelaunch	Accumulation of oxidizer in main combustion chamber prior to start signal; possible hard start	Hard start; may damage engine	Possible launch delay	CC injector pressure and temperature monitors; ODV D/S skin temp,; ODV position monitor	Leak and functional check during prelaunch preparations; Prelaunch purges; controller	3	Contamination on seat; damaged seat seal; premature open signal
2	ODV	Closing	Fail closed	prelaunch	Engines fails to start	None	Possible launch delay	ODV position monitor	functional check during prelaunch preparations	3	Loss of pneumatics; mechanical restriction to actuator/valve motion
3	ODV	opening	Restricted flow; partially opened valve	During launch	Reduced Lox flow to MCC, MR upset, reduced performance	May cause premature cutoff	Possible loss of mission	ODV position monitor; MR monitor	functional check during prelaunch preparations	2	Contamination; mechanical restriction to actuator/valve motion
4	ODV	Passing flow	External Leak	During launch	Loss of Oxidizer to main combustion chamber, injector and ASI.	LOX impinging on adjacent hardware may cause secondary failure	Possible loss of mission	Engine LOX flow monitor: ODV D/S skin temperature	Proof and leak test at build plus leak test prelaunch	2	Material or manufacturing defect; seal damage or loss of seal retention
5	ODV	opening	Fails open/ leaks	prelaunch	LOX accumulation in injector, hard start and off-MR operation. High MR transient at shutdown,	Possible combustion chamber/ injector burnout	Possible loss of vehicle/ mission	CC injector pressure and temperature monitors; ODV position monitor	Close vehicle prevalve. Fail safe closing spring	1	Internal leak from contamination on seat or damaged seat; loss of pneumatic pressure to close;

viable mode of operation). Premature shut-down (Criticality II): A failure in which the effects are contained and degrade the performance to an extend to trigger an engine shut-down. In multi-engine vehicles with an 'engine-out' potential, the discrimination between catastrophic failure and premature shut-down plays an important role in the criteria for vehicle mission success.

Deferred failure (Criticality III): A failure causing general slow-acting and minor performance degradation in which continued operation of the engine is a consideration. Action to cope with the failure will be deferred to allow analysis by the pilot or an automatic logic and to decide whether corrective action can be taken or an abort sequence should be initiated [19]. A typical example is when the diaphragm valve (of fuel or oxidizer) remains closed and only postpones the launch but the same scenario might occur for the cut-off valve (of fuel or oxidizer) when it remains open. This process leads to engine explosion due to the accumulation of fuel or oxidizer in the combustion chamber.

In this paper, by FMEA, the dependency points between failure modes are derived and used to build a BN model qualitative part.

BN MODELING OF LV ENGINE

As mentioned before, a BN is made up of a qualitative and a quantitative part.

The first step to start the modeling is building the constructional graph (qualitative part). To this end, the main nodes should be defined. For OGLE BN analysis, in this work, we have selected11 main nodes whose titles are listed in Table 2.

For each one of these nodes, two states are defined: true expressing the state of correct working and false expressing the state of failing. The causal relationship between these nodes is illustrated in Figure 6.

As can be seen, the starter, fuel diaphragm valve, oxidizer diaphragm valve, fuel cutoff valve and oxidizer cutoff valve are all root nodes and the others are descendants of these roots. Failure flow propagates through the coded relationship in the graph from a failed node to other nodes of the network until it reaches the engine node.

On the other hand, to define the quantitative part, we should inevitably supply marginal probability tables (MPTs) for all root nodes and CPTs for all descendant nodes. Contents of these tables are gained from expert knowledge and the results of the related tests. For example, the CPT of the turbine node is available in Table 3.

Based on the causal relationship in the above BN, the most critical node of the graph is thrust chamber node.

Table 2. main nodes defined in BN.

	Node Title	symbol
1	Solid Starter	SS
2	Oxidizer Diaphragm Valve	ODV
3	Fuel Diaphragm Valve	FDV
4	Gas Generator	GG
5	Turbine	T
6	Oxidizer Pump	OP
7	Fuel Pump	FP
8	Oxidizer Cutoff Valve	OCV
9	Fuel Cutoff Valve	FCV
10	Thrust Chamber	TC
11	Engine	E

MODEL SOLVING AND INFERENCE THE RELIABILITY VALUES

The next step to calculate the reliability value of the OGLE is making inference from the BN model. Here, we use an accurate method to make inference from the model. The step by step algorithm of the exact inference is shown in Figure 3. As you can see, in this method, the joint probability distribution governing the BN variables is derived first. Then, by marginalizing this joint function with respect to each variable, the marginal probability distribution is obtained.

However, to find the joint probability function from the developed BN, we use the chain rule, which is the generalized form of the Bayesian theory. By using this rule, we have:

$$P(x_1, ..., x_n) = \Pi_{i=1}^{n} P(x_i|pa(x_i)) \quad (1)$$

where, x_i is ith variable(node), $pa(x_i)$ are x_i's parent nodes and $P(x_1, ..., x_n)$ is probability joint function. Then, the joint probability function for the defined variables is:

$$\begin{aligned}&P(SS, ODV, FDV, GG, T, OP, FP, OCV, FCV, TC, E)\\&= P(SS|pa(SS)).P(ODV|pa(ODV))\\&.P(FDV|pa(FDV)).P(GG|pa(GG)).P(T|pa(T))\\&.P(OP|pa(OP)).P(FP|pa(FP)).P(OCV|pa(OCV))\\&.P(FDV|pa(FCV)).P(TC|pa(TC)).P(E|pa(E)) \quad (2)\end{aligned}$$

By substituting parent variables in the above equation, the joint probability distribution governing the OGLE

Table 3. CPT of turbine node.

	Solid starter	Gas Generator	True%	False%
1	True	True	95	5
2	True	False	0	100
3	False	True	0	100
4	False	False	0	100

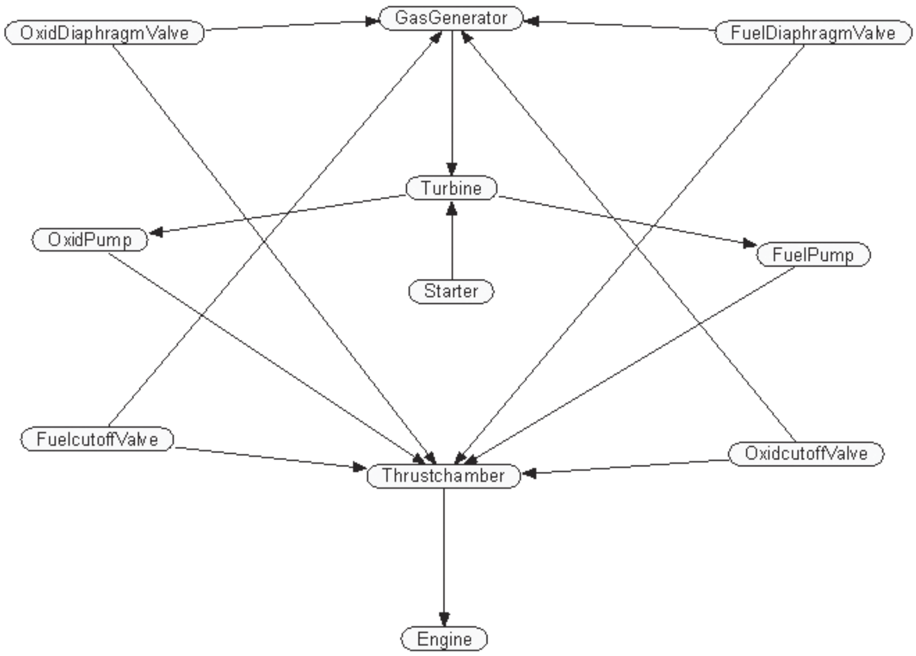

Figure 6. Launch vehicle OGLE BN.

variables is obtained:

$$P(SS, ODV, FDV, GG, T, OP, FP, OCV, FCV, TC, E) = P(SS).P(ODV).P(FDV).P(PP|ODV, FDV, OCV, FCV).P(GG|ODV, FDV, OCV, FCV).P(T|SS, GG) .P(OP|T).P(FP|T).P(OCV).P(FDV) .P(TC|ODV, FDV, OCV, FCV, OP, FP).P(E|TC) \quad (3)$$

Now, by marginalizing Eq. 3 with respect to each variable, the related marginal probability distribution is determined. Here, for example, we introduce the approach for turbine node.

Since the variables are discrete, we use sequential summations with respect to all states of all variables except the variable whose marginal probability distribution is found. Then, we have:

$$P(T) = \sum_{all\ variables\ except\ T} P(SS, ODV, FDV, GG, T, OP, FP, OCV, FCV, TC, E) = \sum_{SS}\sum_{ODV}\sum_{FDV}\sum_{GG}\sum_{OP}\sum_{FP}\sum_{OCV}\sum_{FCV}\sum_{TC}\sum_{E} P(SS, ODV, FDV, GG, T, OP, FP, OCV, FCV, TC, E) \quad (4)$$

Eqtionua 4, unlike its simple form, converts to a large expression after expansion that needs many sequential multiplication and summation operations. By substituting joint probability distribution from Eq. 2 into the above expression, Eq. 4 can be rewritten as follow:

$$P(T) = \sum_{SS}\sum_{ODV}\sum_{FDV}\sum_{GG}\sum_{OP}\sum_{FP}\sum_{OCV}\sum_{FCV}\sum_{TC}\sum_{E} P(SS|pa(SS)).P(ODV).P(FDV).P(PP|ODV, FDV, OCV, FCV).P(GG|ODV, FDV, OCV, FCV) .P(T|SS, GG).P(OP|T).P(FP|T).P(OCV).P(FDV) .P(TC|ODV, FDV, OCV, FCV, OP, FP).P(E|TC) \quad (5)$$

For simplification and calculation of Eq. 5, we have used the following steps: 1. take out all the unrelated expressions and put them out of the innermost summation, 2. do the innermost summation to obtain the new expression, 3. enter the new expression into the multiplication.

These steps should be followed iteratively until no summation remains in the last expression.

By performing this iterative sequential approach, the marginal probability of turbine to work correctly according to CPT of Table 3 is obtained to be equal to 90.8marginal probability value of correct working for all the other nodes can be inferred. The results are shown on each node in Figure 7.

However, the goal is to determine the reliability of the OGLE. According to definition, reliability is the probability that an item will perform a required

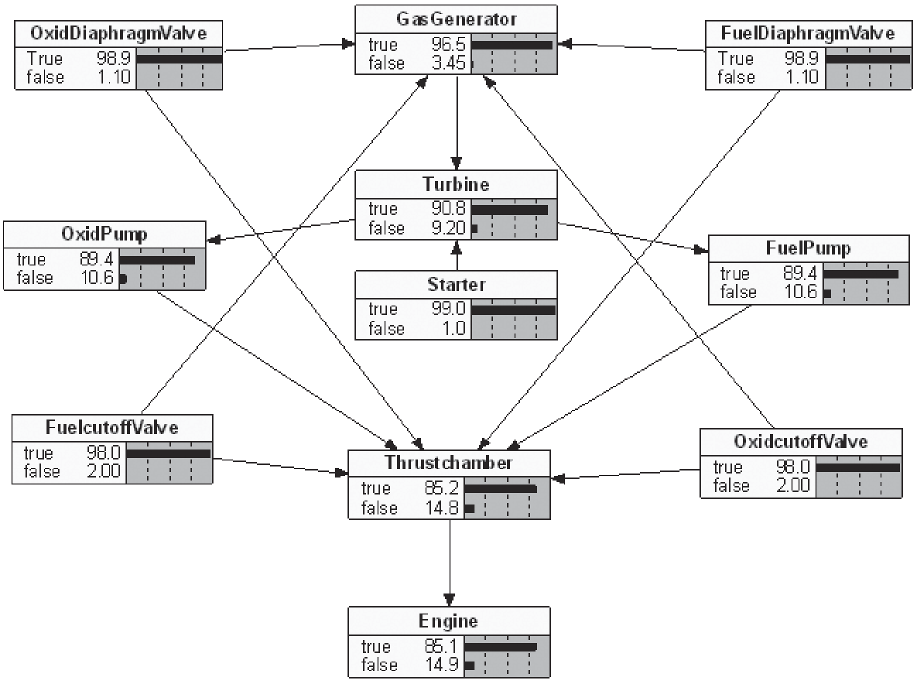

Figure 7. inferred BN model of typical launch vehicle OGLE.

function without failure under stated conditions for a period of time. On the other hand, considering the known bathtub curve diagram in Figure 8, since the OGLE passes the primary infant mortalities (red region) through acceptance tests, it is used in its service life (green region). Then, the failure rate change with respect to time is so tiny. Furthermore, since the launch vehicle is multistage, the burn time of these engines is so short (less than 400 sec.) and can be neglected. Then, from the engineering point of view, we can assume that the reliability of the OGLE is independent of time and we consider the probability of its correct working as the reliability of LV OGLE.

Then, the probability of being in true state is the reliability of the OGLE and is equal to 85.1

This analysis is important since it has calculated the time independent reliability value. Also, through this analysis, the reliability of the main components

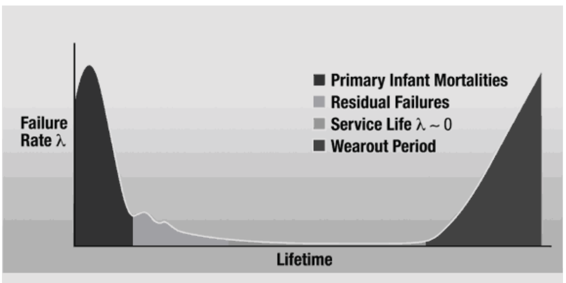

Figure 8. bathtub curve [17].

as well as the engine reliability is gained. The main advantage of this type of analysis is that you can monitor the effects of each real-time change in state probabilities on the reliability of the OGLE and its main components; for example, as soon as an evidence of its correct working turns out, it shows that the starter has worked correctly and this evidence is entered into the BN model. In this way, the reliability of the engine changes from 85.1improves. This change in reliability is calculated and observed simultaneously in the BN model (Figure 9). This reliability improvement grows even more by appearance of new evidences, so that by determining the correct working of the oxidizer and fuel diaphragm valves, the reliability of the engine changes from 85.9and improves. This reliability variation for LV engine is a considerable value (Figure 10). It means that about 3failures of this engine is related to the starting function at the beginning of engine[s working and in the case of starting the engine correctly, we can trust this engine 3

BN MODEL VERIFICATION

To verify the developed BN model, the problem has been solved another time with Monte Carlo simulation method [22]. To do this, the gained marginal probabilities for each node have been used as failure weight function. Then, by generating random values, it is determined whether a component has worked correctly or failed. And, finally, the presented causal

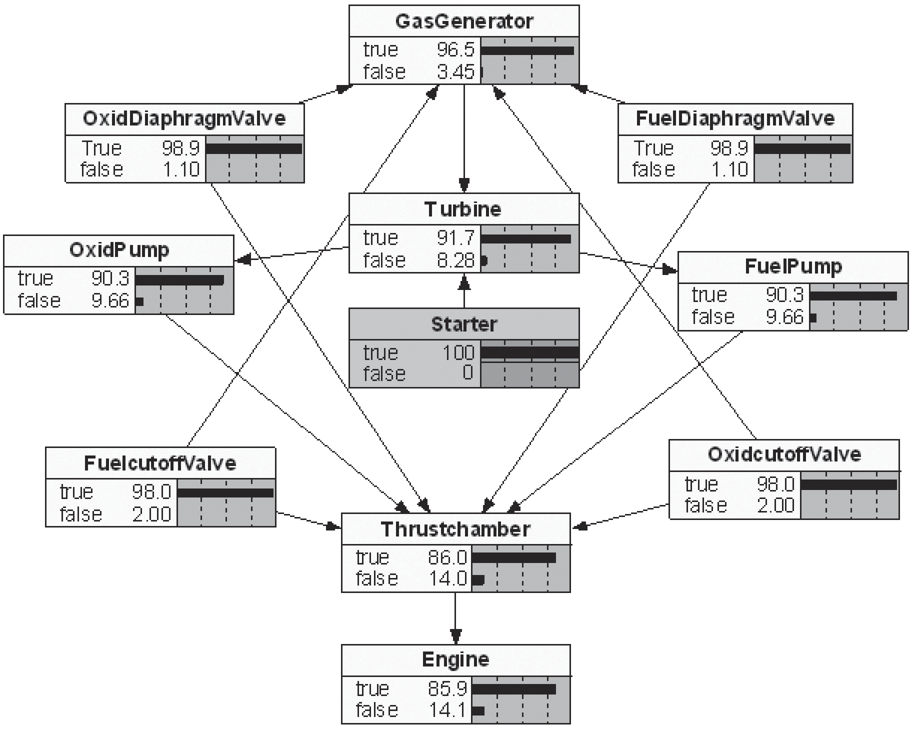

Figure 9. OGLE reliability change with respect to new evidence of starter correct working.

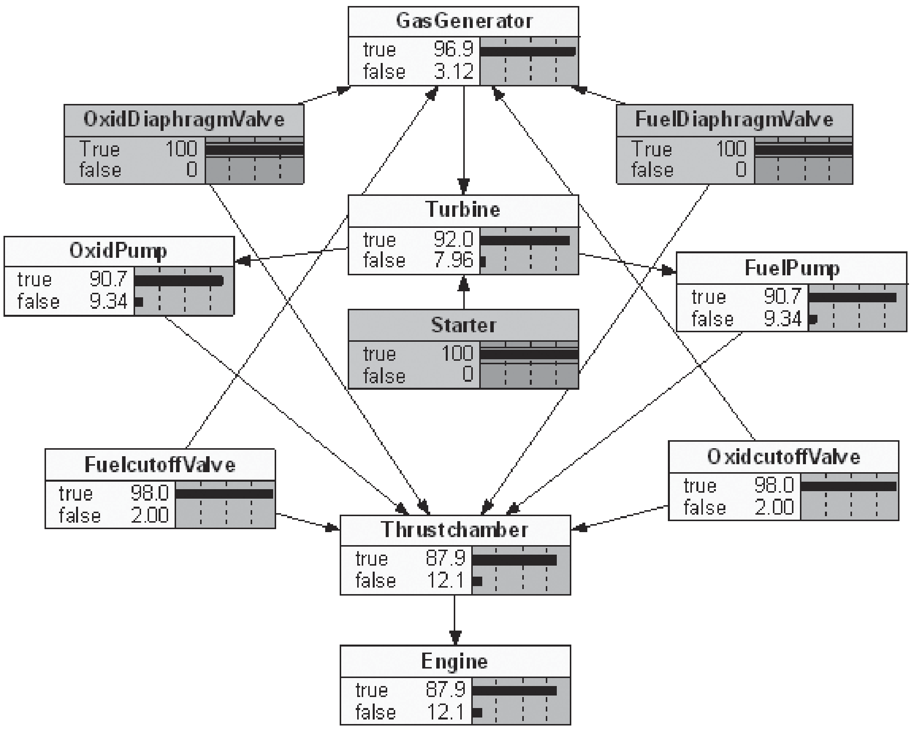

Figure 10. OGLE reliability change with respect to new evidence of correct working of fuel and oxidizer diaphragm valves beyond starter.

Table 4. reliability compare of two methods.

	BN model %	Monte Carlo Simulation			Diff. %
		Converged value	Mean%	Sdv	
Before engine starts	85.1	84.79	84.59	0.009	0.31
After starting	87.9	87.13	85.75	0.02	0.77
Reliability improvement after starting	+2.8	1.16	1.36	—-	—-

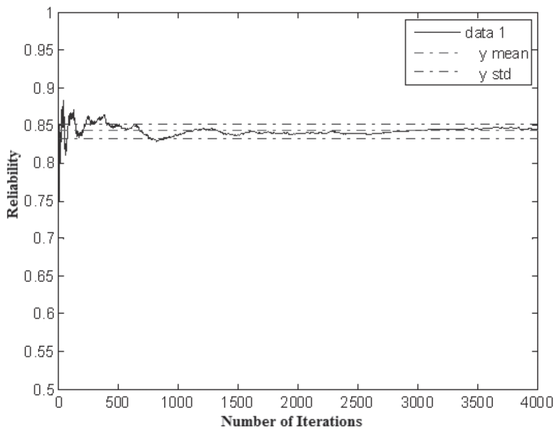

Figure 11. reliability value versus number of iterations.

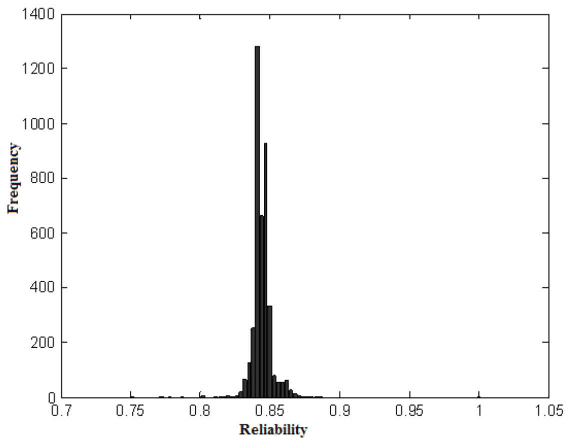

Figure 12. reliability frequency graph obtained in a 4000 iteration simulation.

relationship in BN model is used to apply the effect of a component failure on other components. Verification of the developed BN algorithm to reliability analysis of the OGLE was performed by Monte Carlo simulation because both of these methods are based on modeling the functional relationship between components. In this way, the developed algorithm[s claim to predict the failure or correct working of an OGLE can be verified by simulating the functional relationship (interaction) between components. By running the simulation iteratively until its convergence, the reliability value of the OGLE is obtained. In this work, to take these steps, a Matlab code has been developed and run for 4000 iterates. The reliability value versus number of iterations has been plotted in Figure 11 and, as you can see, the graph is converged to 84.79

Also, the reliability frequency obtained in iterative simulation is plotted in Figure 12 and, as you can see, the obtained distribution is symmetric with a low standard deviation that shows the accuracy of the simulation.

The gained results from the two methods are compared in Table 4. The disparity between the values obtained by the developed BN model and Monte Carlo simulation is just a small difference of 0.31verify the developed model and validate the results obtained for the reliability value of LV OGLEs from this model.

CONCLUSION

In the present paper, we have considered the failure dependencies in an open cycle gas generator liquid propellant engine (OGLE). In an OGLE, the propagation of components failures strongly affects the stochastic behavior as well as the reliability of this complex system. To this end, the functional model of a typical OGLE has been derived (Figure 5) while failure dependency points emerge by means of FMEA. By using these dependency points and BN properties, the failure propagation in an OGLE has been modeled (Figure 6). A comparison between the results obtained by the developed BN approach and Monte Carlo simulation shows the precision and accuracy of the developed algorithm. Thus, this model can be used as a strong useful tool for the reliability analysis of OGLEs of LVs (Table 4).

The developed model is also capable of updating the reliability value of OGLEs real-timely so that by observing the evidence that]engine started_, the reliability value updates from 85.1this algorithm, the reliability of all components as well as that of the engine itself is determined. This algorithm can be used in LV design process, too.

REFERENCES

1. Mittal A., Kassim A., *Bayesian Network Technologies: Applications and Graphical Models*, Chapter 5, Applications of Bayesian Networks in Reliability Analysis, IGI Publishing, (2007).

2. Seth D. Guikema and M. Elisabeth Pate-Cornell, "Bayesian Analysis of Launch Vehicle Success Rates",

JOURNAL OF SPACECRAFT AND ROCKETS, **41(1)**, PP 145-151(2004).

3. Benjamin J.R. and Cornell C.A., *Probability, Statistics, and Decision for Civil Engineers*, McGraw-Hill, (1970).
4. Savage L.J., *The Foundations of Statistics*, Wiley, (1954).
5. Raiffa H. and Schlaifer R., *Applied Statistical Decision Theory*, MIT Press, Boston, (1968).
6. Gallagher M.A., Weir J.D. and True W.D., "Relating Weapon System Test Sizes to War getting Capability", *Military Operations Research*, **3(3)**, PP 5-12(1992).
7. Fries A. and Easterling R.G., "Annual Testing of Strategic Missile Systems", *Proceedings of the American Statistical Association Section on Physical and Engineering Sciences*, PP 132-134(1999).
8. Pat'e-Cornell M.E., and Fischbeck P.S., "Probabilistic Interpretation of Command and Control Signals: Bayesian Updating of the Probability of Nuclear Attack", *Reliability Engineering and System Safety*, **47(1)**, PP 27-36(1995).
9. Kaplan S., "On the Inclusion of Precursor and Near Miss Events in Qualitative Risk Assessments: A Bayesian Point of View and a Space Shuttle Example", *Reliability Engineering and System Safety*, **27(1)**, PP 103-115(1990).
10. Guarro S., Bream B., Rudolph L.K. and Mulvihill R.J., "The Cassini Mission Risk Assessment Framework and Application Techniques", *Reliability Engineering and System Safety*, **49(3)**, PP 293-302(1995).
11. Pat'e-Cornell M.E. and Fischbeck P.S., "PRA as a Management Tool: Organizational Factors and Risk-Based Priorities for the Maintenance of the Tiles of the Space Shuttle Orbiter", *Reliability Engineering and System Safety*, **40(3)**, PP 239-257(1993).
12. Ebeling C.E., "An Introduction to Reliability and Maintainability Engineering", *University of Dayton, MCGraw-Hill*, PP 5-6(1997).
13. Sullivan K.J., Dugan J.B. and Coppit D., "The Galileo fault tree analysis tool", *29th Annual International Symposium on Fault-Tolerant Computing*, (1999).
14. De Souza e Silva E, Ochoa PM., "State space exploration in markov models", *ACM SIGMETRICS Perform Eval Rev*, **20(1)**, (1992).
15. Boudali H. and Dugan J.B., "A discrete-time Bayesian network reliability modeling and analysis framework", *Journal of Reliability Engineering and System Safety*, **87**, PP 337-349(2005).
16. Bouissou M. and Bon JL., "A new formalism that combines advantages of fault-trees and Markov models: Boolean logic driven Markov processes", *Reliability Eng Syst Saf*, **82(2)**, PP 149-63(2003).
17. Krevor Z.C., "A Methodology to Link Cost and Reliability for Launch Vehicle Design", Ph.D. Thesis, School of Aerospace Engineering Georgia Institute of Technology, (2007).
18. Koski T. and Noble J.M., *Bayesian Networks An Introduction*, John Wiley & Sons, Ltd., PP 2-3(2009).
19. Huzel D.K. and Huang D.H., "MODERN ENGINEERING FOR DESIGN OF LIQUID-PROPELLANT ROCKET ENGINES", *Jeanne Godette Series Managing Editor AIAA*, PP 32-40(1992).
20. SUTTON G.P. and BIBLARZ O., *Rocket Propulsion Elements*, Seventh Edition, A Wiley-lnterscience Publication JOHN WILEY & SONS, INC., PP 203-210(2001).
21. Pustonski V., *Introduction to Astronautics*, Tallin university of Technology, (2009).
22. Jun S. Lue, *Monte Carlo strategies in scientific computations*, Department of Statistics, Harvard University, (2001).