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A Simplified Reliability Model for Mars Rover Landing Systems Using Monte Carlo Simulation and Reduced Gradient Optimization

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Abstract

Planetary landing operations are among the most critical phases of interplanetary missions due to the interaction of atmospheric uncertainties, vehicle dynamics, aerodynamic deceleration, autonomous control, and subsystem performance. This paper presents a reliability assessment of a simplified Entry, Descent, and Landing (EDL) model inspired by the Mars 2020 Perseverance rover mission. The model is based on the vertical equilibrium between aerodynamic drag, gravitational force, and retro-propulsion thrust. Reliability is evaluated using two complementary approaches: Monte Carlo Simulation (MCS) and Generalized Reduced Gradient (GRG) optimization. The performance function represents the balance between decelerating forces and the force driving the vehicle toward the planetary surface. Uncertain variables are modeled using normal and non-normal distributions, including Gumbel distributions for selected aerodynamic parameters. Results show good agreement between GRG and MCS, with reliability indices of $\boldsymbol{\beta \approx 0.34}$–$\mathbf{0.37}$ and failure probabilities of approximately **35**–$\mathbf{37\%}$. Sensitivity analyses indicate limited influence of distribution type, computational platform, and sample size, while the removal of retro-propulsion leads to near-certain failure. The framework provides a transparent approach for preliminary reliability studies of planetary landing systems.

Keywords: Reliability analysis, Planetary landing, Mars Perseverance rover, Monte Carlo simulation

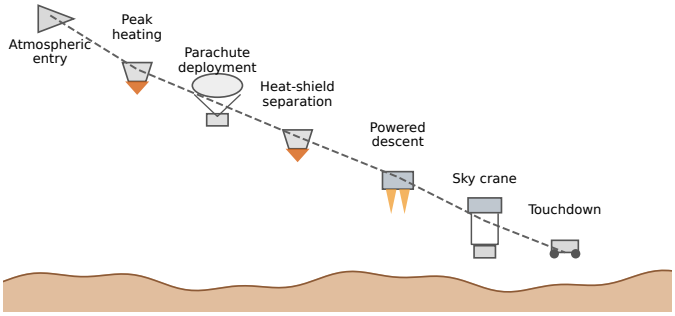


Fig. 1: Schematic representation of the EDL sequence for a Mars rover mission

1 Introduction

Planetary exploration missions are among the most demanding aerospace engineering applications. Spacecraft must operate under strict mass, energy, thermal, communication, and autonomy constraints while facing uncertain environments. Among all mission phases, Entry, Descent and Landing (EDL) is particularly critical, requiring a rapid sequence of atmospheric entry, aerodynamic deceleration, parachute deployment, powered descent, navigation, and touchdown. Because communication delays between Earth and Mars prevent real-time intervention, the entire process must be executed autonomously within a few minutes.

The Mars 2020 Perseverance mission illustrates these challenges. During EDL, the spacecraft had to dissipate a large amount of kinetic energy and transition from hypersonic entry to a safe landing on the Martian surface. Building on the Curiosity mission heritage, Perseverance incorporated improvements such as terrain-relative navigation and a range-trigger strategy to reduce landing uncertainty [1, 2]. The EDL sequence is shown schematically in Figure 1.

The difficulty of landing on Mars is evidenced by failures such as the Mars Climate Orbiter and Schiaparelli missions, in which modeling, navigation, control, or system-level uncertainties contributed to mission loss. These cases highlight the need to explicitly account for uncertainties in atmospheric conditions, vehicle dynamics, subsystem performance, and control actions, rather than relying solely on deterministic analyses.

Reliability analysis provides a framework for quantifying such uncertainties. Failure is defined through a limit-state function, whose negative values indicate unsatisfactory performance. Failure probabilities can be estimated using Monte Carlo Simulation (MCS) or optimization-based methods that identify the most probable failure point [3–5]. Widely applied in structural and mechanical engineering, these methods are increasingly relevant to aerospace systems.

This paper presents a reliability assessment of a simplified planetary landing system inspired by the Perseverance rover. The model describes the vertical force equilibrium during the final descent phase, considering aerodynamic drag, Martian gravity,

and retro-propulsion. Based on a previous study by Silva and Silva [6], the work is reformulated here as a concise scientific paper with improved figures, a clearer reliability framework, and a sensitivity analysis. Rather than reproducing NASA's full EDL architecture, the objective is to demonstrate how reliability methods can identify critical assumptions and dominant subsystems in a simplified model.

The main contributions are: (i) a compact performance-function formulation for planetary landing; (ii) a comparison between MCS and GRG optimization for reliability estimation; (iii) an evaluation of normal and non-normal probabilistic models; (iv) an analysis of Monte Carlo convergence and computational-platform effects; and (v) the identification of retro-propulsion as the dominant critical subsystem in the simplified model.

2 Reliability formulation of the landing problem

2.1 Performance function

The final descent phase can be idealized by a vertical force balance. The forces that contribute to reducing the downward motion of the vehicle are the aerodynamic drag D and the retro-propulsion thrust E. The force that drives the vehicle toward the surface is the weight W under Martian gravity. The performance function is defined as

$$F = D - W + E. \tag{1}$$

The aerodynamic drag is modeled by the classical quadratic expression

$$D = \frac{1}{2}\rho S V^2 C_d, \tag{2}$$

where ρ is the atmospheric density, S is the effective projected parachute area, V is the descent velocity, and C_d is the drag coefficient. Substituting Eq. (2) into Eq. (1) yields

$$F(\boldsymbol{X}) = \frac{1}{2}\rho S V^2 C_d - W + E. \tag{3}$$

The corresponding vector of random variables is

$$\boldsymbol{X} = \{X_1, X_2, X_3, X_4, X_5, X_6\}^T = \{\rho, S, V, C_d, W, E\}^T. \tag{4}$$

The failure criterion is defined such that $F(\boldsymbol{X}) > 0$ corresponds to a safe descent condition, $F(\boldsymbol{X}) = 0$ represents the limit-state condition, and $F(\boldsymbol{X}) < 0$ indicates failure. Figure 2 summarizes the physical interpretation of the model.

2.2 Random variables

The numerical values adopted for the random variables are presented in Table 1. These values follow the source study and are used here as a didactic probabilistic model

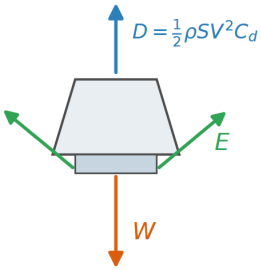


Fig. 2: Simplified force model adopted for the reliability formulation

Table 1: Random variables adopted in the simplified landing reliability model.

Variable	Description	Unit	Mean	Standard deviation
X_1	Atmospheric density, ρ	kg/m^3	0.014555	0.000011
X_2	Parachute projected area, S	m^2	363.05	1.82
X_3	Descent velocity, V	m/s	0.75	0.00375
X_4	Drag coefficient, C_d	–	1.072	0.050
X_5	Weight on Mars, W	N	3792.5	19.0
X_6	Retro-propulsion force, E	N	3800.0	19.0

rather than as a full mission-certified dataset. Each variable is characterized by a mean value, standard deviation, and coefficient of variation.

Two probabilistic models are considered. The first assumes normal distributions for all variables. In the second, the descent velocity X_3 and drag coefficient X_4 follow Gumbel minimum and Gumbel maximum distributions, respectively, while the remaining variables remain normal. This comparison evaluates the sensitivity of the reliability estimates to the modeling of extreme aerodynamic quantities. Figure 3 illustrates the adopted probability models.

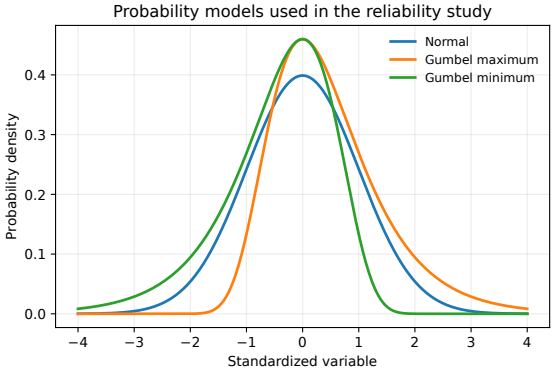


Fig. 3: Comparison between normal, Gumbel maximum and minimum distributions

For normally distributed variables, the transformation between a physical variable X_i and the corresponding reduced variable Y_i is

$$X_i = \mu_i + \sigma_i Y_i, \tag{5}$$

where μ_i and σ_i are the mean and standard deviation of X_i. Equivalently,

$$Y_i = \frac{X_i - \mu_i}{\sigma_i}. \tag{6}$$

This transformation allows the reliability problem to be expressed in the standard normal space for optimization-based reliability calculations.

3 Reliability methods

3.1 Monte Carlo Simulation

Monte Carlo Simulation estimates the probability of failure by generating a set of random samples of the vector $\boldsymbol{X}$ and evaluating the performance function for each sample. Given N simulations, the failure probability is estimated as

$$\widehat{P}_f = \frac{N_f}{N}, \tag{7}$$

where N_f is the number of samples for which $F(\boldsymbol{X}) < 0$. The reliability index associated with the simulated values of the performance function may also be approximated by

$$\beta \approx \frac{\mu_F}{\sigma_F}, \tag{8}$$

where μ_F and σ_F are the sample mean and standard deviation of $F(\boldsymbol{X})$, respectively.

MCS is conceptually simple and robust, although its computational cost increases for very small failure probabilities. In the present study, it provides an adequate basis for comparing modeling assumptions and sample sizes.

3.2 Reduced gradient reliability optimization

The Generalized Reduced Gradient (GRG) method is used to determine the point on the failure surface closest to the origin, defining the reliability index. The optimization problem is formulated as

$$\begin{aligned} \min_{\boldsymbol{Y}} \quad & \beta(\boldsymbol{Y}) = \sqrt{\boldsymbol{Y}^T \boldsymbol{Y}} \\ \text{s.t.} \quad & F(\boldsymbol{Y}) = 0 \end{aligned} \tag{9}$$

The optimal point is the Most Probable Point (MPP) of failure in the reduced space, as shown schematically in Figure 4. Once β is obtained, a first-order estimate of the probability of failure can be written as

$$P_f \approx \Phi(-\beta), \tag{10}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

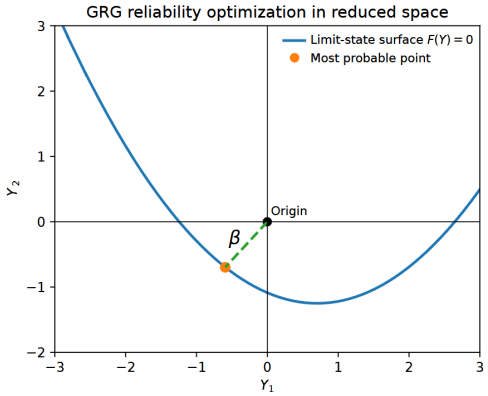


Fig. 4: Optimization interpretation of the reliability index

The GRG formulation provides a complementary perspective to MCS. While MCS evaluates many possible realizations of the random variables, GRG searches directly for the critical point of the limit-state surface. Agreement between these two approaches increases confidence in the numerical implementation and in the qualitative interpretation of the results.

4 Numerical results

4.1 Case A: landing model without retro-propulsion

To assess the importance of retro-propulsion, the first experiment sets $E = 0$, yielding

$$F = \frac{1}{2}\rho S V^2 C_d - W. \tag{11}$$

The corresponding results are shown in Table 2.

Table 2: Reliability results for the simplified model without retro-propulsion

Method	Reliability index β	Probability of failure P_f
GRG optimization	-200	100%
Monte Carlo Simulation	-210	100%

The negative reliability indices indicate that aerodynamic drag alone is insufficient to ensure a safe landing, highlighting the critical role of retro-propulsion in the EDL architecture.

4.2 Case B: normal probability model with retro-propulsion

The second experiment considers active retro-propulsion and normally distributed variables. The results are presented in Table 3.

Table 3: Reliability results with active retro-propulsion and normal distributions

Method	Reliability index β	Probability of failure P_f
GRG optimization	0.34	37%
Monte Carlo Simulation, 1,000 samples	0.37	35%

The results show that both reliability methods provide similar safety margin estimates. Although the predicted failure probability is high, it reflects the simplified model and approximate data, making it more suitable for sensitivity analysis than for mission-level reliability assessment.

4.3 Case C: non-normal probability model

The third experiment adopts Gumbel distributions for velocity and drag coefficient, introducing asymmetry and extreme-value effects into the probabilistic model. The results are presented in Table 4.

Table 4: Reliability results considering selected non-normal distributions

Method	Reliability index β	Probability of failure P_f
GRG optimization	0.34	37%
Monte Carlo Simulation, 10,000 samples	0.36	37%
Monte Carlo Simulation, Python, 100,000 samples	0.34	37%

The non-normal model yields a failure probability similar to the normal model, indicating that the distribution choice has limited influence on the reliability estimate. The main factor is the balance between braking forces and the weight term.

Figure 5 compares the reliability indices and probabilities of failure obtained in the active retro-propulsion scenarios.

4.4 Monte Carlo convergence

The source study used different numbers of samples in the MCS calculations: 1,000 samples in the initial Excel implementation, 10,000 samples in the refined Excel calculation, and 100,000 samples in the Python implementation. The corresponding probabilities of failure are shown in Figure 6.

The probability of failure remains within a narrow interval, from approximately 35% to 37%. Therefore, increasing the number of samples by two orders of magnitude did not change the engineering interpretation of the result. This behavior is expected

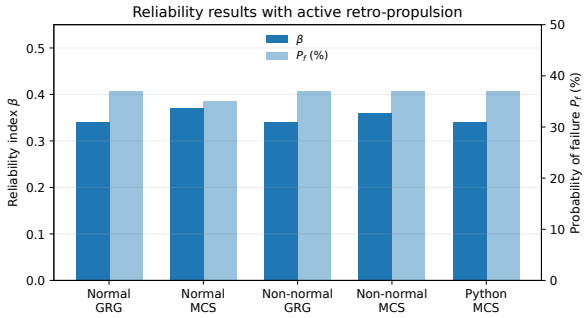


Fig. 5: Comparison of reliability results obtained with active retro-propulsion

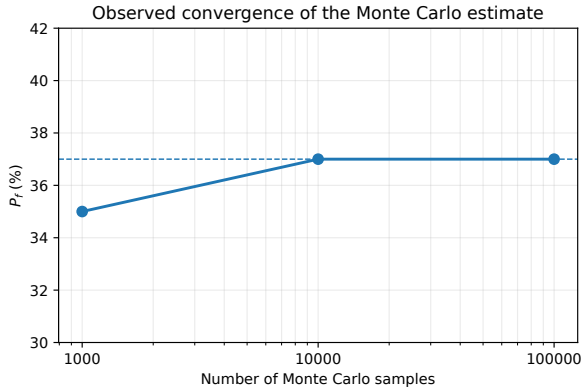


Fig. 6: Observed convergence of the Monte Carlo probability of failure estimate for the simplified landing model

because the probability of failure is relatively large. For rare-event probabilities, much larger sample sizes or variance-reduction techniques would be necessary.

5 Sensitivity analysis of critical subsystems

A central objective of the paper is to determine which modeling assumptions significantly affect the reliability estimate. Table 5 summarizes the main sensitivity observations.

Figure 7 provides a graphical ranking of these effects. The removal of retro-propulsion produces a drastic change in the estimated probability of failure, while the other modifications produce only minor changes.

This result is important from a systems engineering perspective. A subsystem is critical not only because it contributes to nominal performance, but because its degradation or absence can move the entire system from a marginally safe or feasible state to a practically certain failure state. In the simplified performance function, retro-propulsion plays exactly this role. Figure 8 summarizes this interpretation.

Table 5: Summary of sensitivity results for the simplified landing reliability model

Modified aspect	Reference result	Modified result	Interpretation
GRG versus MCS	$P_f \approx 37\%$	$P_f \approx 35$–37%	The two methods lead to consistent estimates.
Normal versus non-normal distributions	$P_f \approx 37\%$	$P_f \approx 37\%$	The result is not strongly sensitive to the adopted distribution type.
Excel versus Python	$P_f \approx 37\%$	$P_f \approx 37\%$	The computational platform does not change the engineering conclusion.
1,000 versus 100,000 MCS samples	$P_f \approx 35\%$	$P_f \approx 37\%$	The estimate remains stable for this non-rare probability level.
Removal of retro-propulsion	$P_f \approx 37\%$	$P_f \approx 100\%$	Retro-propulsion is the dominant critical subsystem in the simplified model.

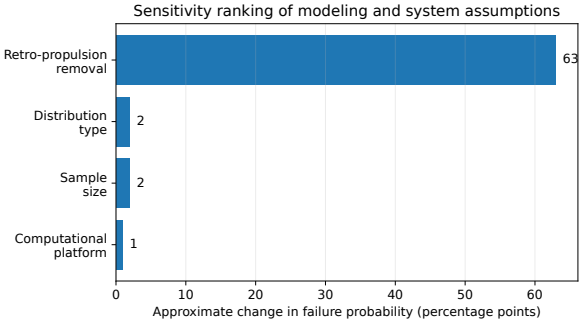


Fig. 7: Sensitivity ranking of modeling and system assumptions

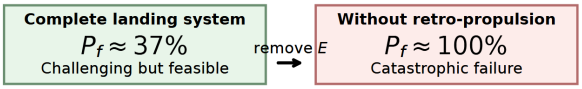


Fig. 8: Mission-critical subsystem interpretation

6 Conclusions and future work

This paper presented a reliability assessment of a simplified planetary landing system inspired by the Mars Perseverance mission. The performance function considered the balance between aerodynamic drag, Martian weight, and retro-propulsion thrust, evaluated using MCS and GRG optimization.

GRG and MCS showed good agreement, yielding $\beta = 0.34$–0.37 and failure probabilities of 35–37% with active retro-propulsion. Variations in probability distributions, Monte Carlo sample sizes, and computational platforms had little influence on the results. Conversely, retro-propulsion was identified as the dominant critical subsystem, with its removal increasing failure probability from approximately 37% to nearly 100%.

These results demonstrate the value of reliability analysis for estimating failure probabilities and identifying critical subsystems and assumptions. The agreement between GRG and MCS also supports their use in preliminary mission studies with limited design information.

Despite its simplified formulation, the framework provides a transparent approach to reliability and sensitivity analysis and critical subsystem identification. Future work should incorporate transient dynamics, correlated variables, subsystem redundancy, atmospheric and sensor uncertainties, guidance-control interactions, and advanced reliability methods for more realistic mission analyses.

Declarations

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Availability of data and material

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Competing interests

The authors declare that they have no competing interests.

Authors Contributions

M.A.S. and V.M.S. conducted the original research. M.A.S. and J.V. wrote the manuscript and prepared the figures and tables. J.V. and M.A.S. reviewed the text.

References

[1] Nelessen, A.: Mars 2020 entry, descent, and landing system overview. In: 2019 IEEE Aerospace Conference, pp. 1–20 (2019)

[2] NASA Mars Exploration Program: Mars 2020 Mission Perseverance Rover: Entry, Descent, and Landing. Online mission documentation (2021)

[3] Hasofer, A.M., Lind, N.C.: Exact and invariant second-moment code format. Journal of the Engineering Mechanics Division **100**(1), 111–121 (1974)

[4] Ditlevsen, O., Madsen, H.O.: Structural Reliability Methods. Wiley, Chichester (1996)

[5] Melchers, R.E.: Structural Reliability Analysis and Prediction, 2nd edn. Wiley, Chichester (1999)

[6] Silva, V.M.d., Silva, M.A.d.: Confiabilidade do pouso em Marte do rover Perseverance. Final research report, PIBIC, Federal University of ABC (2022)