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A subjective assessment of alternative mission architectures for the human exploration of Mars at NASA using multicriteria decision making

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Abstract

The primary driver for developing missions to send humans to other planets is to generate significant new scientific knowledge. NASA plans human planetary explorations with an acceptable level of risk consistent with other manned operations. Space exploration risks cannot be completely eliminated. Therefore, an acceptable level of cost, technical, safety, schedule, and political risks and benefits must be established for exploratory missions. This study uses a multicriteria decision model to identify the risks and benefits associated with three alternative mission architecture scenarios for the human exploration of Mars. The three alternatives identified by the Mission Operations Directorate at the Johnson Space Center include split, combo lander, and dual scenarios. The model considers seven phases of the mission: (1) Earth vicinity/departure, (2) Mars transfer, (3) Mars arrival, (4) planetary surface, (5) Mars vicinity/departure, (6) Earth transfer, and (7) Earth arrival. Analytic hierarchy process, subjective probability estimation, and the entropy method are used to capture experts' beliefs concerning the risks and benefits of the three alternative scenarios through a series of sequential, rational, and analytical processes.
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1. Introduction

Three days on the moon in the final Apollo mission in 1972 left astronaut Eugene Cernan exhausted and filthy with rock dust [1]. A 3-year trip to Mars exponentially increases the risks of space travel. Scientist Michael Long [2] suggests a troubling scenario. Imagine a radiation-sick, sleep-deprived

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astronaut stepping on Mars all because of poorly selected mission architecture. Muscles and bones weakened, immune system challenged, he sends out a call to mission control, "Houston we have a problem." Mars is an intriguing and exciting planet with many adventures and discoveries await human explorers. However, human exploration of Mars requires extensive planning because of the complexities of this undertaking. The crew will travel to and from Mars on a relatively fast transit of approximately 6 months and will spend long periods of time (520–580 days) on the surface. Shorter transit times reduce the time spent by the crew in zero gravity, allowing for more time to explore this planet. In addition, a relatively fast transit will reduce the exposure to galactic cosmic radiation and the probability of encountering solar particle events. This study presents a multicriteria decision making (MCDM) model used by the exploration team (ET), a seven-member committee, at the Johnson Space Center to evaluate the risks and benefits associated with three different mission architectures: split mission, combo lander, and dual scenarios.

Split Mission Scenario: In this scenario, the mission is split into two steps: pre-deployment of mission assets to the planet surface, followed by the mission crew. During the assets deployment step, the return habitat/ascent vehicle will be sent to Mars. Upon arriving in a Mars orbit, the return habitat will stay in the orbit while the ascent vehicle lands on Mars and starts producing fuel. After the mission equipment is configured and tested to be viable, the transit habitat/surface habitat vehicle will be sent into Earth orbit. The crew will be transferred to the transit habitat/surface habitat vehicle at a later date. Next, the transit habitat/surface habitat vehicle and the crew will be sent to Mars to land near the ascent vehicle. After the completion of surface exploration, the ascent vehicle will be used to transfer the crew to the return habitat vehicle, which will be orbiting Mars. The return habitat vehicle will be used to return the crew to Earth.

Combo Lander Scenario: In this scenario, the mission assets will travel to and from Mars with the crew. Initially, the transit habitat/surface habitat/ascent vehicle will be launched into Earth's orbit. The crew will be transferred to the transit habitat/surface habitat/ascent vehicle in Earth's orbit at a later date. Next, the transit habitat/surface habitat/ascent vehicle will be sent to Mars with the crew. Upon arriving in a Mars's orbit, the transit habitat vehicle will separate and remain in Mars's orbit while the crew uses the surface habitat/ascent vehicle to land on Mars. After the completion of surface exploration, the ascent vehicle will be used to transfer the crew to the transit habitat vehicle, which will return the crew to Earth.

Dual Scenario: In this scenario, the transit habitat/surface habitat/ascent vehicle/descent vehicle will be launched into Earth's orbit. The crew will be transferred to the transit habitat/surface habitat/ascent vehicle/descent vehicle at a later date. Next, the transit habitat/surface habitat/ascent vehicle/descent vehicle will be sent to Mars with the crew. Upon arriving in Mars's orbit, the transit habitat vehicle will stay in the orbit, the surface habitat vehicle will land on Mars unmanned, and the crew will use the ascent/descent vehicle to land on Mars near the surface habitat. After the completion of surface exploration, the ascent vehicle will be separated and used to transfer the crew to the transit habitat vehicle, which will return the crew to Earth.

Over the last several decades, both intuitive and analytical models have been developed to assist decision makers (DMs) in solving multicriteria decision problems. However, intuitive models do not present a structured framework, while the analytical models are not intended to capture intuitive preferences. These models have made definitive contributions to MCDM theory, but have not been very successful in practice at integrating intuitive preferences of multiple DMs into a structured and analytical framework. The model presented in this paper is used to capture experts' beliefs concerning the risks and benefits of the three alternative mission architecture scenarios through a series of sequential, rational, and analytical processes.

2. Theoretical justifications

Roy [3] argues that solving MCDM problems is not searching for some kind of optimal solution, but rather helping DMs master the (often complex) data involved in their problems and advance towards an acceptable solution. As often happens in applied mathematics, the development of multicriteria models is dictated by real-life problems. Therefore, it is not surprising that methods have appeared in a rather diffuse way, without any clear general methodology or basic theory [4]. The model presented here has evolved in an attempt to solve a complex space exploration problem at the Johnson Space Center. It is a unique MCDM model with several features:

(i) Traditionally, MCDM frameworks fall into three categories: the multiobjective value analysis [5], the outranking method [4], and the interactive methods [6]. The selection of a framework depends on the type of the problem, the type of the choices (continuous or discrete), the type of measurement scales, the type of importance weights, the type of dependency among the criteria, and the type of uncertainty [4]. We show how the integration of several mathematically sound techniques can reduce some of the difficulties in the selection of an appropriate framework. Rather than molding the problem to fit into a framework, we integrate several techniques into a framework to address problem requirements.

(ii) Finding the "best" MCDM framework is an elusive goal that may never be reached [7]. Pardalos and Hearn [8] have argued that one of the major issues for future research in MCDM is to explore ways of combining criteria aggregation methodologies to enable the development of models that consider the DM's preferential system in complex problems. Belton and Stewart [9] also argue the need for integrating frameworks in MCDM. Our model has solved a complex and judgmental multicriteria space exploration problem by suitably combining a set of well-known and proven techniques in MCDM. This integration allows for the objective data and subjective judgments to be used side by side in a mathematically sound decision model.

(iii) We have developed an alternative approach to traditional analytic hierarchy process (AHP) problem structuring where hierarchies of decision criteria and alternatives are used to solve MCDM problems. Our framework integrates AHP preferences of decision criteria with the probability scores and entropy information. This structured framework aggregates the intuitive preferences of multiple DMs to assess the overall performance of alternative scenarios using a weighted sum model [7].

(iv) The generic nature of the model allows for subjective evaluation of a finite number of decision alternatives on a finite number of performance criteria by a group of DMs. The mathematical and computational properties of the model are applicable to a wide range of real-world decision-making problems in MCDM.

3. The procedure and mathematical notations

The model described here is a multicriteria decision model that integrates a series of intuitive and analytical methods including AHP, subjective probabilities, and the entropy method to enhance the DMs' intuition in evaluating three mission architecture scenarios for the human exploration of Mars. To formulate an algebraic model, let S^m be the overall mission architecture score of the mth scenario ($m=1,2,\ldots,M$), W_i the importance weight of the ith mission phase ($i=1,2,\ldots,I$), F_{ij} the importance weight of the jth criterion for the ith mission phase ($i=1,2,\ldots,I$ and $j=1,2,\ldots,J$), β_{ij} the impact factor of the jth criterion for the ith mission phase ($i=1,2,\ldots,I$ and $j=1,2,\ldots,J$). $\beta=-1$ is assigned to *risky criteria* and $\beta=+1$ is assigned to *beneficial criteria*, P_{ij}^m the probability of accomplishment of the jth criterion (event) for the ith mission phase under the mth scenario ($m=1,2,\ldots,M$; $i=1,2,\ldots,I$; and $j=1,2,\ldots,J$), I the number of mission phases, J the number of criteria for the ith mission phase and M the number of mission architecture scenarios.

Given the above notations, the overall score of the mth mission architecture scenario is

$$S^m=\sum_{i=1}^{I} W_i\left(\sum_{j=1}^{J} F_{ij}\beta_{ij}(P_{ij}^m)\right) \tag{1}$$

where

$$\beta_{ij}=-1 \text{ or} +1,$$

$$0\leqslant P_{ij}^m\leqslant 1,$$

$$0\leqslant W_i\leqslant 1,$$

$$\sum_{i1=}^{1} W_i=1,$$

$$0\leqslant F_{ij}\leqslant 1,$$

$$\sum_{j=1}^{J} F_{ij}=1.$$

The proposed framework consists of five distinct steps.

(i) *The ET identified mission phases and determined their importance weight with AHP*: In this step, the ET conducted multiple interviews with many technical experts in many disciplines and held brainstorming sessions to identify the mission phases necessary for the human exploration of Mars. Based on these interviews and sessions, the team identified seven phases of the Mars mission: Earth vicinity/departure, Mars transfer, Mars arrival, planetary surface, Mars vicinity/departure, Earth transfer, and Earth arrival. Next, each ET member used AHP to determine his/her importance weight of the various mission phases by making trade-offs among them. A group mean mission phase vector was generated from these individual preferences and used in the model presented earlier.

The importance weights of the mission phases could have been elicited by other weighting procedures. The simplest way is weighting them directly by point allocation. Other value theory-based weighting methods include SMART and SMARTER [10,11], SWING [12], and AHP [13,14]. In SMART, ten points are given to the least important criterion. Then, more points are given to the other criteria, depending on their relative importance. In SMARTER, the weights are elicited with the centroid method of Solymosi and Dombi [15]. The SWING method is similar, but the procedure starts from the most important criteria, keeping it as the reference.

We chose to employ AHP for eliciting the importance weights of the phases. AHP uses a series of pairwise comparisons. Saaty [14] argues that a DM naturally finds it easier to compare two things than to compare all the items in a list. AHP also evaluates the consistency of the DMs and allows for the revision of their responses. AHP has been applied to many diverse decisions because of the intuitive nature of the process and its power in resolving the complexity in a judgmental problem. A comprehensive list of the major applications of AHP, along with a description of the method and its axioms, can be found in Saaty [13,14], Weiss and Rao [16] and Zahedi [17]. AHP has proven to be a popular technique for determining weights in multicriteria problems (Shim [18] and Zahedi [17]). The importance of AHP and the use of pairwise comparisons in decision making are best illustrated in the more than 1000 references cited in [14]. A mathematical summary of AHP is presented in Appendix A.

Schoemaker and Waid [19] have compared several commonly used multicriteria decision making techniques, including AHP, multiple regression, and the multiattribute utility approach of Keeney and Raiffa [5]. These methods differ in several ways. First, they require different types of judgments; second, they require different response modes; and third, they have different domains of applications. Schoemaker and Waid [19] show that all three methods produce similar results, but each has advantages over the others under certain circumstances. In this study, AHP was employed because it does not assume consistency among preferences, while the construction of a utility function by the multiattribute utility approach requires a transitive preference relation. In addition, AHP produces more detailed information on pairwise comparisons, and it is applicable to nonmeasurable criteria, such as "loss of crew during direct entry" or "problems with rendezvous and docking." Thus, AHP is preferred to multiple regression for qualitative criteria because these criteria do not allow for an easy derivation of measurable attributes. For repetitious decision-making situations, a multiattribute utility approach is supposed to be more advantageous. However, an individual's utility function changes over time and has to be re-evaluated periodically. Thus, the multiple attribute utility approach does operationally do better than AHP.

AHP has been a controversial technique in the Operations Research community. Harker and Vargas [20] show that AHP does have an axiomatic foundation, the cardinal measurement of preferences is fully represented by the eigenvector method, and the principles of hierarchical composition and rank reversal are valid. On the other hand, Dyer [21,22] has questioned the theoretical basis underlying AHP and argues that it can lead to preference reversals based on the alternative set being analyzed. In response, Saaty [23] contends that rank reversal is a positive feature when new reference points are introduced. In this study, in order to avoid the controversial rank reversal, we use the geometric aggregation rule.

Each ET member used Expert Choice [24], an AHP-based software, individually to perform the necessary pairwise comparisons. When the consistency ratio was unacceptable, the team member was informed that the pairwise comparisons were logically inconsistent and was asked to revise his/her Expert Choice judgments.

An average of the ET members' importance weight for each mission phase, W_i, was calculated at the end of this step. As it is shown in Table 1, Earth arrival was perceived as the most important phase of the mission with a mean of 0.232, followed by Mars arrival (0.192), and planetary surface (0.151).

(ii) *The ET identified the criteria to be considered within each mission phase and determined their importance weights with AHP*: The ET conducted additional interviews and brainstorming

Table 1
Mission architecture phases and their average importance weight (W_i)

Mission phase	Weight
1. Earth vicinity/departure	0.099
2. Mars transfer	0.086
3. Mars arrival	0.192
4. Planetary surface	0.151
5. Mars vicinity/departure	0.111
6. Earth transfer	0.129
7. Earth arrival	0.232

sessions and identified a set of criteria within each mission phase to be used in the evaluation process. We defined criteria in event-driven terms such as “stranded crew on Mars” or “loss of payload.” In addition, the ET had to decide whether a criterion should be considered as a *risk* or *benefit* by assigning an impact factor, β_{ij}. $\beta = -1$ was assigned to a risky criterion, while $\beta = +1$ was assigned to a beneficial criterion. Once the criteria and their impacts were identified, each team member used AHP individually and identified his/her importance weight of each criterion, w_{ij}. Once again if consistency ratio were unacceptable, the individual was asked to revise his/her weight. At the end of this step, a group mean criteria vector, w_{ij}, was generated based on the ET importance weight of each criterion in each mission phase. Table 2 shows the criteria chosen by the ET for the mission phases along with their impacts.

(iii) *The ET identified probabilities of occurrence of each criterion for each mission phase and all mission architecture scenarios*: Subjective probabilities are commonly used in multicriteria decision making because they require no historical data [25–27]. Some researchers conclude that the difficulty of obtaining relevant historical information on which to base probabilities inhibits their use. However, probabilistic phrases such as “possible,” “likely,” “certain,” etc. provide an opportunity to elicit the required information verbally and then convert these verbal phrases into numeric probabilities [28]. Other commonly used approaches include reasoning [29], scenario construction [25] and cross-impact analysis [30]. Merkhofer [31] and Spetzler and Stael von Holstein [32] review probability elicitation procedures that are used in practice.

This study utilized verbal probabilistic scales with probabilistic phrases, such as “possible,” “likely,” and “certain” to elicit the required information. These verbal probabilistic phrases were then converted into numeric probabilities using a numerical scale [28]. Alternatively, the ET could have used numeric probabilities rather than the probabilistic phrases. The probabilities associated with the decision criteria are assumed to be binomial. Binomial probabilities are commonly used in MCDM so that the decision maker can simplify the problem by analyzing possible outcomes as either occurring or not occurring. For example, Schoemaker [25] illustrated the assignment of binomial probabilities to events such as “Dow Jones Industrial Average falling below 1500 mark by 1990” or “Election of a Democrat as US president by 1990.” Vickers [27] assigned binomial probabilities to events such as “Japanese car manufacturers gain at least 30% of the European market share” and “The incorporation of East Europe into Europe by 1993” in order to examine the future of European automobile industry. The main motivation for using binomial probabilities is to reduce the complexity of the model

Table 2
Mission phase criteria (events) with their impact (β_{ij}) and average subjective weight (w_{ij})

Criteria	Impact	Weight
1. *Earth vicinity/departure*		
EV1: TMI miss due to problems with vehicles	−1	0.068
EV2: Loss of vehicle due to problems with TMI	−1	0.216
EV3: Loss of crew due to problem with TMI	−1	0.439
EV4: Post-TMI Earth-return abort options	+1	0.153
EV5: Resource availability for full operations support for all exploration vehicles during near Earth operation	+1	0.068
EV6: Unplanned shuttle mission to fix problem on MTV	−1	0.056
2. *Mars transfer*		
MT1: Need to perform nonsurface contingency EVA (Challenging EVA suit design implications)	−1	0.205
MT2: Adequate in situ crew skill development (Computer-based proficiency training and failure simulations)	+1	0.214
MT3: Support crew activities (physical/mental health maintenance, protection from solar flare/proton events)	+1	0.186
MT4: Ability of the crew/vehicle to resolve serious systems problems without the help of the MCC	+1	0.325
MT5: Art. Gravity not being used (no spin-up), resulting in deconditioned crew	−1	0.069
3. *Mars arrival*		
MA1: Errors in the post-insertion orbit plane or altitude	−1	0.073
MA2: Extended Mars vicinity phase	−1	0.105
MA3: Errors in aerocapture leading to loss of crew	−1	0.482
MA4: NO GO for surface descent	−1	0.079
MA5: Crew forced to perform strenuous activities during CAP	−1	0.046
MA6: Injury to crew during CAP	−1	0.088
MA7: Descent problem to cause crew to abort back to Mars orbit	−1	0.127
4. *Planetary surface*		
PS1: Needing contingency surface EVA to restore ascent capability	−1	0.128
PS2: Stranded crew on Mars	−1	0.528
PS3: Bad weather or other anomaly which could delay ascent, and even require extra EVAs to return to hab	−1	0.099
PS4: Early surface mission termination and ascent to Mars orbit	−1	0.122
PS5: Meet surface mission constraints and schedule	+1	0.044
PS6: Meet Go/No-Go criteria for EVA	+1	0.079
5. *Mars vicinity/departure*		
MV1: NO-GO for ascent	−1	0.176
MV2: NO-GO for TEI	−1	0.150
MV3: Crew stranded in Mars orbit	−1	0.437
MV4: Ascent to lower-than-desired orbit, requiring the return vehicle coming to rescue	−1	0.129
MV5: Problems with rendezvous and docking	−1	0.077
MV6: Problems with transferring items to return vehicle	−1	0.030

Table 2 (*continued*)

Criteria	Impact	Weight
6. *Earth transfer*		
ET1: Need to perform nonsurface contingency EVA	−1	0.390
ET2: Crew's ability to meet their physical fitness activities	+1	0.261
ET3: Art. Gravity not being used (no spin-up), resulting in deconditioned crew	−1	0.084
ET4: Problems with MCCs	−1	0.264
7. *Earth arrival*		
EA1: Loss of payload	−1	0.037
EA2: Loss of crew during direct entry	−1	0.342
EA3: Loss of crew during Earth orbit insertion and shuttle recovery	−1	0.333
EA4: Address planetary protection issues	+1	0.108
EA5: Problem ditching the NTR stage	−1	0.086
EA6: Deconditioned crew having trouble during contingency recovery operations	−1	0.093

and allow ET members to analyze event-driven criteria. Each team member assigned a probability of occurrence to each criterion for each mission phase under each mission architecture scenario, P_{ij}^m. Next, a group average of these probabilities was generated from the individual probability judgments. Table 3 shows the average probabilities of occurrence of mission phase criteria for the ET collectively.

(iv) *The entropy method was used to revise the importance weight of the criteria identified by the ET in step* ii: The entropy method is a commonly used method for calibrating the weights assigned to different decision criteria in MCDM [33,34]. A criterion does not influence the final choice much when all the alternatives have similar value for that criterion. The entropy concept suggests that if a criterion's values are the same, the criterion can be eliminated from further consideration. Alternately, the weight assigned to a criterion can be smaller if all alternatives have similar values for a criterion. On the other hand, when the differences between a criterion's values across particular alternatives are greater, the criterion is viewed as more important. The entropy concept has been shown to be particularly useful to investigate contrasts between sets of data.

The entropy method was used to revise the ET weight for each criterion (w_{ij}) developed in step ii based on the information provided by the probabilities of occurrence. An Excel-based program and the average probabilities presented in Table 3 were used to perform all the necessary calculations. Each criterion is an information source. The more the information revealed by a criterion, the more relevant the criterion is. Hwang and Yoon [33] and Zeleny [34] argue that this intrinsic information must be used together with the initial weight assigned to various criteria by the DM. In other words, the overall importance weight of a criterion, F_{ij}, is directly related to the intrinsic weight, f_{ij}, reflecting average intrinsic information developed by a set of mission architecture scenarios, and the subjective weight, w_{ij}, rendered by the ET member. The probabilities of occurrence were used to measure this average intrinsic information.

The greater the difference between the probabilities of a criterion for a set of mission architecture scenarios, the larger is the contrast intensity of the criterion, and the greater is the amount of information transmitted by that criterion. Assume that vector $p_{ij} = (p_{ij}^1, \ldots, p_{ij}^q)$ characterizes the set

Table 3
Group average of the probabilities of occurrence (P_{ij}^{m})

Criteria	SPLIT (%)	COMBO (%)	DUAL (%)
1. *Earth vicinity/departure*			
EV1	32.86	45.71	47.14
EV2	28.57	31.43	27.14
EV3	12.86	22.86	34.29
EV4	47.14	38.57	50.00
EV5	48.57	35.71	41.43
EV6	21.43	41.43	30.00
2. *Mars transfer*			
MT1	37.14	38.57	50.00
MT2	77.14	72.86	71.43
MT3	77.14	70.00	81.43
MT4	70.00	62.86	65.71
MT5	78.57	80.00	70.00
3. *Mars arrival*			
MA1	24.29	25.71	31.43
MA2	34.29	30.00	27.14
MA3	37.14	32.86	34.29
MA4	24.29	25.71	28.57
MA5	31.43	30.00	32.86
MA6	25.71	24.29	24.29
MA7	27.14	21.43	20.00
4. *Planetary surface*			
PS1	32.86	37.14	41.43
PS2	22.86	25.71	28.57
PS3	34.29	37.14	38.57
PS4	30.00	28.57	35.71
PS5	58.57	55.71	54.29
PS6	61.43	54.29	61.43
5. *Mars vicinity/departure*			
MV1	32.86	30.00	22.86
MV2	24.29	28.57	34.29
MV3	27.14	24.29	25.71
MV4	22.86	25.71	20.00
MV5	25.71	20.00	40.00
MV6	30.00	27.14	20.00
6. *Earth transfer*			
ET1	41.43	42.86	44.29
ET2	74.29	60.00	57.14
ET3	52.86	60.00	57.14
ET4	24.29	27.14	24.29
7. *Earth arrival*			
EA1	27.14	21.43	15.71
EA2	12.86	27.14	37.14
EA3	18.57	22.86	24.29
EA4	84.29	57.14	58.57
EA5	27.14	31.43	40.00
EA6	50.00	42.86	78.57

P in terms of the jth criterion for the ith mission phase:

$$P_{ij} = \sum_{m=1}^{M} p_{ij}^{m} \quad (i = 1, 2, \ldots, I;\; j = 1, 2, \ldots, J;\; m = 1, 2, \ldots, M).$$

Then, the entropy measure of the jth criterion for the ith mission phase is

$$e(p_{ij}) = -K \sum_{m=1}^{M} \frac{p_{ij}^{m}}{P_{ij}} \ln \frac{p_{ij}^{m}}{P_{ij}}, \tag{2}$$

where $K > 0$, ln is the natural logarithm, $0 \leqslant p_{ij}^{m} \leqslant 1$, and $e(p_{ij}) \geqslant 0$. When all p_{ij}^{m} are equal for a given i and j, then $p_{ij}^{m}/P_{ij} = 1/M$, and $e(p_{ij})$ assuming its maximum value, which is $e_{\max} = \ln M$. By setting $K = 1/e_{\max}$, $0 \leqslant e(p_{ij}) \leqslant 1$ can be achieved. This normalization is necessary for meaningful comparisons. In addition, total entropy is defined as

$$E = \sum_{j=1}^{J} e(p_{ij}).$$

The smaller $e(p_{ij})$ is, the more information is transmitted by the jth criterion for the ith mission phase and the larger $e(p_{ij})$, the less information is transmitted. When $e(p_{ij}) = e_{\max} = \ln M$, the jth criterion of the ith mission phase is not transmitting any useful information. The intrinsic weight of the jth criterion of the ith phase is calculated as

$$f_{ij} = \frac{1}{I - E}\,[1 - e(p_{ij})]. \tag{3}$$

Because f_{ij} is inversely related to $e(p_{ij})$, $1 - e(p_{ij})$, is used instead of $e(p_{ij})$ and normalized to make sure $0 \leqslant f_{ij} \leqslant 1$ and

$$\sum_{j=1}^{J} f_{ij} = 1.$$

The greater the difference between the probabilities of occurrences, p_{ij}^{m}, the larger is the value of f_{ij}, and hence, the more important is the jth criterion for the ith mission phase. When all the probabilities of occurrence, p_{ij}^{m}, are equal, then $f_{ij} = 0$. In order to calculate the overall importance weight of the jth criterion for the ith mission phase, F_{ij}, the intrinsic weight, f_{ij}, is multiplied by the subjective weight, w_{ij}, and then the product is normalized:

$$F_{ij} = \frac{f_{ij} w_{ij}}{\sum_{j=1}^{J} f_{ij} w_{ij}}. \tag{4}$$

The overall importance weight of all criteria, F_{ij}, along with the intrinsic weights, f_{ij}, and the subjective weights, w_{ij}, for the ET are presented in Table 4.

(v) *The model is used to provide a consensus ranking of the mission architecture scenarios*: The overall score of each mission architecture scenario (S^m) is calculated using the importance weight of mission phases (W_i), the overall weight of the criteria (F_{ij}), the impact factor of the criteria (β_{ij}), and the probabilities of occurrence of the criteria for different scenarios (P_{ij}^{m}). A Microsoft Excel program based on the model presented earlier was used to perform all necessary calculations. Mission architecture scenarios with higher overall scores are preferred to scenarios with lower overall scores.

Table 4
The overall importance weight of mission phase criteria (F_{ij})

Criteria	Subjective weight (w_{ij}) (%)	Intrinsic weight (f_{ij}) (%)	Overall weight (F_{ij}) (%)
1. *Earth vicinity/departure*			
EV1	6.83	9.05	2.30
EV2	21.59	1.38	1.11
EV3	43.86	53.45	87.22
EV4	15.33	4.35	2.48
EV5	6.79	5.81	1.47
EV6	5.61	25.95	5.42
2. *Mars transfer*			
MT1	20.53	64.06	67.41
MT2	21.40	3.76	4.12
MT3	18.63	13.46	12.85
MT4	32.54	6.84	11.42
MT5	6.90	11.88	4.20
3. *Mars arrival*			
MA1	7.34	25.85	15.75
MA2	10.49	18.82	16.37
MA3	48.19	5.33	21.29
MA4	7.89	9.37	6.13
MA5	4.57	2.81	1.07
MA6	8.83	1.50	1.10
MA7	12.70	36.34	38.29
4. *Planetary surface*			
PS1	12.84	26.72	15.89
PS2	52.76	24.77	60.52
PS3	9.90	7.14	3.27
PS4	12.21	28.46	16.10
PS5	4.43	3.01	0.62
PS6	7.86	9.91	3.60
5. *Mars vicinity/departure*			
MV1	17.64	13.38	23.90
MV2	15.04	11.90	18.12
MV3	43.71	1.24	5.47
MV4	12.94	6.27	8.21
MV5	7.66	50.64	39.26
MV6	3.00	16.58	5.04
6. *Earth transfer*			
ET1	39.04	3.75	6.04
ET2	26.13	68.37	73.71
ET3	8.39	13.64	4.72
ET4	26.44	14.24	15.53
7. *Earth arrival*			
EA1	3.73	13.65	2.43
EA2	34.21	45.81	74.95
EA3	33.27	3.57	5.69
EA4	10.84	9.60	4.98
EA5	8.61	7.42	3.06
EA6	9.33	19.96	8.90

The overall scores were calculated according to the ET consensus values. In this study, "consensus" was assumed to mean collective opinion. Consensus was achieved by averaging the subjective weights of the mission phases and their respective criteria and probabilities. Table 5 shows mission scenarios and their overall score for the ET. As is shown, given the goal of maximizing the overall score, the split scenario with an overall score of (-0.109) is the optimal choice, followed by the combo lander scenario (-0.158) and the dual scenario (-0.212). While all these scores are negative, one must realize that they are used for comparison purposes. In addition, we are assessing risks and factors that mitigate those risks. On the whole, there remains certain amount of risk in any space exploration and that is precisely what these negative numbers are revealing.

Although individual and group decision making are interrelated, there are no unique and compelling solutions to group choice problems [35]. Dyer and Forman [36] discuss several approaches to combining individual preferences into a joint representation of the group's preferences. Using the simple average method, mission architecture scenarios were ranked according to their average overall scores of the individual ET member. Table 6 presents individual overall scores for each ET member, assuming total independence and no integration of data throughout the process. Split Scenario was the first choice for all ET members, with the exception of team members D and G. An overall mean of the individual scores revealed results similar to the overall group scores presented in Table 5. While this is a simple solution, it may not be necessarily desirable.

Beck and Lin [37] have proposed yet another straightforward method, the maximize agreement heuristic, for approximating the optimal consensus rankings of a group of decision makers. The maximize agreement heuristic is easy to implement and provides excellent consensus ranking solutions [38]. Given the rankings provided by individual ET members from the overall scores in Table 6, we used the maximize agreement heuristic and found exactly the same consensus ordering that reflected the collective ET agreement. In summary, the overall synthesis of results from the three aggregation methods suggests the Split Scenario as the most attractive mission architecture scenario, followed by the Combo Lander and Dual Scenarios.

4. Practical implications

Advances in computer technology and availability of data have made MCDM more complex and more useful than ever. While intuition and simple rules are still favorite decision-making methods, they may be dangerously inaccurate for complex decision problems. The model presented here can help DMs improve their decision quality when they are confronted with complex decision problems. Our model ensures consistency and completeness of the required information and synthesizes a vast amount of information using a manageable and easy to understand structure, while incorporating the use of human intuition and subjective analysis skills.

The analytical processes in our model help a DM decompose complex MCDM problems into manageable steps, making this model accessible to a wide variety of DMs and situations. We use AHP, subjective probabilities, the entropy method, and MAH to help DMs crystallize their thoughts and reduce the inconsistencies associated with MCDM. Although technical details of the model may be beyond the reach of some DMs, the basic concepts are not difficult to understand or implement. As such, the DMs can use available analytical tools and techniques with some assistance from the experts [26].

Table 5
Mission scenarios and their overall score (S^m) for the ET

Misson phase	Mission phase importance weight (%)	Criteria	Impact I β_{ij}	Subjective weight (w_{ij}) (%)	Intrinsic weight (f_{ij}) (%)	Overall weight (F_{ij}) (%)	SPLIT scenario (%)	COMBO scenario (%)	DUAL (scenario) (%)
EV	9.91	EV1	−1	6.83	9.05	2.30	32.86	45.71	47.14
		EV2	−1	21.59	1.38	1.11	28.57	31.43	27.14
		EV3	−1	43.86	53.45	87.22	12.86	22.86	34.29
		EV4	+1	15.33	4.35	2.48	47.14	38.57	50.00
		EV5	+1	6.79	5.81	1.47	48.57	35.71	41.43
		EV6	−1	5.61	25.95	5.42	21.43	41.43	30.00
MT	8.56	MT1	−1	20.53	64.06	67.41	37.14	38.57	50.00
		MT2	+1	21.40	3.76	4.12	77.14	72.86	71.43
		MT3	+1	18.63	13.46	12.85	77.14	70.00	81.43
		MT4	+1	32.54	6.84	11.42	70.00	62.86	65.71
		MT5	−1	6.90	11.88	4.20	78.57	80.00	70.00
MA	19.20	MA1	−1	7.34	25.85	15.75	24.29	25.71	31.43
		MA2	−1	10.49	18.82	16.37	34.29	30.00	27.14
		MA3	−1	48.19	5.33	21.29	37.14	32.86	34.29
		MA4	−1	7.89	9.37	6.13	24.29	25.71	28.57
		MA5	−1	4.57	2.81	1.07	31.43	30.00	32.86
		MA6	−1	8.83	1.50	1.10	25.71	24.29	24.29
		MA7	−1	12.70	36.34	38.29	27.14	21.43	20.00
PS	15.14	PS1	−1	12.84	26.72	15.89	32.86	37.14	41.43
		PS2	−1	52.76	24.77	60.52	22.86	25.71	28.57
		PS3	−1	9.90	7.14	3.27	34.29	37.14	38.57
		PS4	−1	12.21	28.46	16.10	30.00	28.57	35.71
		PS5	+1	4.43	3.01	0.62	58.57	55.71	54.29
		PS6	+1	7.86	9.91	3.60	61.43	54.29	61.43
MV	11.07	MV1	−1	17.64	13.38	23.90	32.86	30.00	22.86
		MV2	−1	15.04	11.90	18.12	24.29	28.57	34.29
		MV3	−1	43.71	1.24	5.47	27.14	24.29	25.71
		MV4	−1	12.94	6.27	8.21	22.86	25.71	20.00
		MV5	−1	7.66	50.64	39.26	25.71	20.00	40.00
		MV6	−1	3.00	16.58	5.04	30.00	27.14	20.00
ET	12.91	ET1	−1	39.04	3.75	6.04	41.43	42.86	44.29
		ET2	+1	26.13	68.37	73.71	74.29	60.00	57.14
		ET3	−1	8.39	13.64	4.72	52.86	60.00	57.14
		ET4	−1	26.44	14.24	15.53	24.29	27.14	24.29
EA	23.20	EA1	−1	3.73	13.65	2.43	27.14	21.43	15.71
		EA2	−1	34.21	45.81	74.95	12.86	27.14	37.14
		EA3	−1	33.27	3.57	5.69	18.57	22.86	24.29
		EA4	+1	10.84	9.60	4.98	84.29	57.14	58.57
		EA5	−1	8.61	7.42	3.06	27.14	31.43	40.00
		EA6	−1	9.33	19.96	8.90	50.00	42.86	78.57
				Overall Group Score			−0.109	−0.158	−0.212

Table 6
Mission scenarios and their overall score (S^m) for the ET members

Exploration team member	SPLIT score	COMBO score	DUAL score
A	−0.251	−0.353	−0.414
B	−0.165	−0.222	−0.231
C	−0.122	−0.128	−0.169
D	−0.093	−0.074	−0.116
E	−0.087	−0.139	−0.163
F	−0.088	−0.183	−0.194
G	−0.142	−0.120	−0.139
Overall ET mean	−0.106	−0.129	−0.156

The structured framework presented in this study has some obvious attractive features:

(i) There are no limits to the number of alternatives and the number of criteria that can be considered.
(ii) The information requirements of the model are stratified into a hierarchy (mission phases and their respective criteria) that simplifies information input and allows DMs to focus on a small area of the large problem. This process is also useful for seeking input from different experts or levels of management in the organization.
(iii) Inconsistencies are inevitable when dealing with subjective information from different DMs. The built-in inconsistency checking mechanism of AHP helps to identify inconsistencies in judgments at very early stages of the computation process.
(iv) Decision relevant information about the alternatives is transmitted through their risks and benefits. Traditionally, the problem is: Can the differences in the importance of risks and benefits be captured fully by their weights, or are they better reflected in their probabilities of occurrence? Our methodology helps bridge the two concepts by enabling DMs to assess the relative weight of different risks and benefits by the richness of their probability range. The more divergent the probability range of a risk or benefit, the more information is emitted by it, and the more important it becomes in influencing the final choice.
(v) This approach can be implemented very easily on a PC because software packages for AHP such as Expert Choice are readily available and the use of our framework in an interactive format requires only some additional coding. Our current implementation does not have an automatic interface with Expert Choice.
(vi) This model can be used in an interactive mode to deal with sensitivity analysis, giving DMs a tool to evaluate alternatives in widely varied scenarios.

5. Conclusion and future research directions

The model presented in this study decomposes an MCDM problem into clearly defined components in which all alternatives, criteria, weights, and probabilities are depicted. Next, objective information and subjective judgments of experts are integrated by utilizing several methods of problem structuring and information processing. This study was not intended to replace human judgment in mission architecture evaluation at NASA. In fact, human judgment has provided the basic input to this study. The model helped the ET think systematically about the complex mission architecture selection problem. It also helped improve the quality of resulting decisions by using a structured framework. Objective data on the characteristics of most scenarios were limited because of inherent uncertainties in space exploration. However, experienced ET members were reasonably confident in providing estimates of values for these characteristics as a substitute for objective data. This study combined these subjective values numerically and provided an overall score for each mission architecture scenario. It is important to realize that human beings are imperfect information processors, and their judgments and preferences about uncertainty can be limited. An awareness of human cognitive limitations is critical in developing the necessary judgmental inputs. Also, the use of experts in the field is essential to the success of this model, since only subject-matter experts have the necessary estimates of values for the characteristics of the problem's scenarios.

Furthermore, the effectiveness of our model relies heavily on the DMs' cognitive abilities to provide valid judgments. We consider subjective estimation of probabilities and weights since there is not enough empirical evidence in space exploration. Because these judgments can be influenced by DMs' individual biases, they should be used with caution. As with all the other decision calculus models, it is vital that the researchers and practicing managers remain aware of the limits of subjective estimates used in these models. When empirical analysis is feasible and makes economic sense, it should be preferred [39]. This model should not be used to plug-in numbers and crank-out solutions. Potentially, DMs can make bad judgments with this model as they do with any framework. Such judgments can generate misleading results and, ultimately, poor decisions.

Finally, our methodology only addresses some of the problems inherent in the MCDM. Quantification of all risks and benefits is a difficult task. Storing information generated during a session for use in future sessions along with information on actual performance of the selected alternative, can facilitate the process of learning from past mistakes. This may be done by interfacing our methodology with knowledge-based systems for fine-tuning weights and subjective probabilities by inductive reasoning. Neural networks may be another avenue for developing knowledge-based models in this area.

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Appendix A. Mathematical summary of AHP

Assume team member i believes that $c_1, c_2, \ldots, c_I$ are the I mission phases that contribute to the overall mission architecture selection problem. The team member's next task is to assess the relative importance of these mission phases with AHP by comparing each possible pair of mission phases c_j, c_k and indicating which phase is more important and by how much.

These judgments are represented by an $I \times I$ matrix:

$$A = (a_{jk}) \quad (j, k = 1, 2, \ldots, I)$$

if c_j is judged to be of equal importance as c_k, then $a_{jk} = 1$,
if c_j is judged to be more important than c_k, then $a_{jk} > 1$,
if c_j is judged to be less important than c_k, then $a_{jk} < 1$,

$$a_{jk} = 1/a_{kj}, \quad a_{jk} \neq 0.$$

Thus, matrix A is a reciprocal matrix so that the entry a_{jk} is the inverse of the entry a_{kj}. a_{jk} reflects the relative importance of c_j compared with mission phase c_k. For example, $a_{12} = 1.25$ indicates that c_1 was 1.25 times as important as c_2.

The vector w representing the relative weights of each of the I *mission phases* was found by computing the normalized eigenvector corresponding to the maximum eigenvalue of matrix A. An eigenvalue of A is defined as λ which satisfies the following matrix equation:

$$Aw = \lambda w.$$

Saaty has shown that the best estimate of w is the one associated with the maximum eigenvalue ($\lambda_{\max}$) of the matrix A. Because the sum of the weights should be equal to 1.00, the normalized eigenvector is used. Saaty's algorithm for obtaining this w is incorporated in the software Expert Choice (2000) utilized in this study.

One of the advantages of AHP is that it assesses the consistency of the team member's pairwise comparisons. Saaty suggests a measure of consistency for the pairwise comparisons. When an individual's judgments are perfectly consistent, the maximum eigenvalue ($\lambda_{\max}$) equals the number of mission phases that are compared (I). Typically, the responses are not perfectly consistent, and $\lambda_{\max}$ is greater than I. The larger the $\lambda_{\max}$, the greater is the degree of inconsistency. Saaty defines consistency index (CI) as $(\lambda_{\max} - I)/(I - 1)$ and provides a random index (RI) table for matrices of order 3–10 (see table below). This RI is based on a simulation of a large number of randomly generated weights. Saaty recommends the calculation of a consistency ratio (CR) that is the ratio of CI to RI for the same order matrix. A CR of 0.10 or less is considered acceptable. When the CR is unacceptable, individuals are alerted to that fact and requested to revise their weights to make them more consistent.

n	3	4	5	6	7	8	9	10
RI	0.58	0.90	1.12	1.32	1.41	1.45	1.49	1.51

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