

RESEARCH PROJECT MANAGEMENT

Document n°: INDIGO-D5.1

Uncertainty modelling of TRL for LARW, DHEP and integrated technologies

Issue date: **A01 – 1/10/2025**

Revision History Table

Version n°	Issue Date	Reason for change
A01	1/10/2025	First version

Date of Issue: **1st October 2025**

Uncertainty modelling of TRL for LARW, DHEP and integrated technologies

Project:

101096055

INtegration and Digital demonstration of low-
emission aIrcraft technoloGies and airport Op-
erations

Acronym:

INDIGO

Work package:

WP5 –
Airframe-propulsion
optimal integration under
uncertainty

Deliverable:

D5.1



INDIGO project has received funding from the European Climate, Infrastructure and Environment Executive Agency (CINEA) under the Horizon Europe programme under grant agreement No 101096055.

Contents

1	Introduction	5
2	Objective and methodology	6
2.1	Technology Readiness Level	6
2.2	Dempster-Shafer theory	7
2.2.1	Dempster's rule of combination	10
2.3	Multi-objective risk assessment	11
3	INDIGO design as a function of available energy density	12
3.1	Top-tier battery cell energy density outlook	13
3.2	The Maximum Theoretical Specific Energy (MTSE)	14
3.3	Dempster-Shafer theory masses definition	15
3.4	Dempster-Shafer theory belief and plausibility computation	18
4	Risk assesment results	20
5	Conclusions	28

1 Introduction

The INDIGO project aims to reduce the impact of noise and pollution in airport areas. Therefore, efforts are being made to develop a medium-range hybrid aircraft with distributed propulsion, in which the outermost propellers use electric propulsion [4].

The development of such a hybrid aircraft configuration for medium-range civil transportation is hindered by technological constraints that are not currently met, including the low Energy Density (ED) of batteries compared to aviation fuel, the excessive weight of electric components, challenges in thermal management and safety, stringent certification requirements, and the lack of supporting infrastructure. Hence, the success of INDIGO's hybrid aircraft design depends on technologies currently in development and not yet readily available. Consequently, the designer must rely on the fact that the critical technological constraints will be met in the near future. Therefore, the designer must choose a timeframe within which the project will be implemented and minimize the risk that the design will not be feasible due to the unavailability of enabling technologies within the identified timeframe. This situation forces the designer to make critical decisions amid uncertainty, considering several factors:

1. The future timeframe for physically building and testing the project.
2. The achievable level of performance within that timeframe for key enabling technologies that are crucial to making the new project competitive.
3. The acceptable level of risk for the project.

To better organize the ideas, we will focus on a single aspect of a key enabling technology: the energy density of rechargeable batteries, which is one of the most critical factors in ensuring the competitive performance of a hybrid aircraft.

The impact of battery energy density on the empty weight and, consequently, on the performance of a hybrid aircraft is immediate, significantly affecting its design. Therefore, the designer must choose the aircraft configuration while considering conflicting factors:

1. An energy density high enough to achieve a hybridization factor that ensures a low environmental impact aircraft, but with the risk of not being immediately available at the required TRL within the aircraft construction schedule and deployment framework timeframe.
2. A battery technology likely to be available when the aircraft is built, but with an energy density that doesn't guarantee a high enough hybridization factor to make the hybrid aircraft sufficiently competitive with traditional solutions.

Suppose we need to work with a future aircraft architecture that provides a specified level of environmental performance in the near future, e.g., when it is deployed. In that case, it becomes essential to calculate the risks associated with choosing a given energy density. Given that the analysis of future technologies always involves a level of uncertainty and risk, this work aims to provide designers with a tool based on imprecise probabilities (Dempster-Shafer theory) to enable them to reliably assess the aircraft pollution and noise impact in terms of both risk and design profitability in probabilistic terms.

2 Objective and methodology

The aim of this work is to propose a methodology for analyzing emerging or developing technologies that enables a risk-benefit assessment. This approach considers, even roughly, development trends and the potential for maturation, which could lead them to reach a level of development safe for adoption in innovative designs to be implemented in the near future.

Starting from this premise, it is necessary to identify the appropriate performance indicators and predictive methodologies that enable this analysis to be conducted successfully.

Regarding the performance indicator, we decided to propose the Technology Readiness Level (TRL), a system for assessing technological maturity on a scale of 1 to 9. NASA originally developed it and is widely used by various American and European agencies, including the European Space Agency [7] and the European Commission [3].

To obtain the risk-benefit assessment, we select an appropriate TRL value that enables the technology for our design, and we use a predictive approach to estimate the (imprecise) probability of reaching the required TRL within a specific time frame.

The predictive approach must recognize that forecasting TRL development over time involves extrapolations and expert judgments, which are inherently imprecise and sometimes contradictory. Therefore, we chose to use the Dempster-Shafer theory of imprecise probability [5, 6, 2], which, despite some computational complexity, effectively manages uncertain probabilities caused by epistemic uncertainty. This theory also facilitates combining imprecise probability distributions created by different experts, even when they contain limited contradictions.

In summary, by utilizing these two key ingredients, we develop a process that enables a systematic evaluation of the trade-off between the technological potential and associated risks of a given technology, thereby supporting strategic decision-making. This methodology will then be applied in the selection of energy storage solutions for INDIGO hybrid-electric innovative aircraft.

For the sake of clarity, we will first shortly explain the basic ideas of TRL and Dempster-Shafer theory in two subsections before introducing the proposed methodology.

2.1 Technology Readiness Level

For the sake of completeness, we report below the TRL table currently adopted by the European Union¹ in Table 2.

¹"Technology readiness levels (TRL); Extract from Part 19 - Commission Decision C(2014)4995", ec.europa.eu. 2014.

TRL	European Union definition
1	Basic principles observed
2	Technology concept formulated
3	Experimental proof of concept
4	Technology validated in lab
5	Technology validated in relevant environment (industrially relevant environment in the case of key enabling technologies)
6	Technology demonstrated in relevant environment (industrially relevant environment in the case of key enabling technologies)
7	System prototype demonstration in operational environment
8	System complete and qualified
9	Actual system proven in operational environment (competitive manufacturing in the case of key enabling technologies; or in space)

Table 2: TRL definition according to ESA and European Union.

The focus in this report is on the $TRL \geq 9$.

2.2 Dempster-Shafer theory

When making a forecast, we are inherently dealing with *imprecise probabilities*. In this context, the Dempster-Shafer Theory (DST) [5, 6, 2] is a mathematical model often used to handle uncertainty and incomplete information. DST, unlike traditional probability theory, assigns an estimate, known as **mass**, to subsets of possible outcomes. The masses, rather than just a single specific *precise probability*, allow the calculation of a plausible interval within which the event is likely to occur, bounded by upper and lower bounds called **belief** and **plausibility**, that represent the lowest and highest bounds of the probability that the event will happen. The masses are usually determined after collecting and analyzing experts' opinions. A decisive advantage of this method is that it enables the combination of evidence from multiple sources to produce a certainty range that reflects uncertainty and insufficient information.

In summary, the key elements of DST are:

- **Discernment Frame:** The set of all possible outcomes or hypotheses of a problem.
- **Mass Function:** A function that assigns a “mass” value (a kind of “degree of belief”) to each element of the discernment frame.
- **Belief:** The sum of the masses of all proper subsets of an event, representing the total support for a conclusion.
- **Plausibility:** Derived from the belief in the negation of an event, plausibility provides an upper bound on the probability of an event.

- **Certainty Interval:** DST uses a belief-plausibility interval to show a range of possible beliefs, instead of a single value.

Figure 1 illustrates graphically the relationship between belief and plausibility, as well as the connection between plausibility and the belief in the negation of an event.

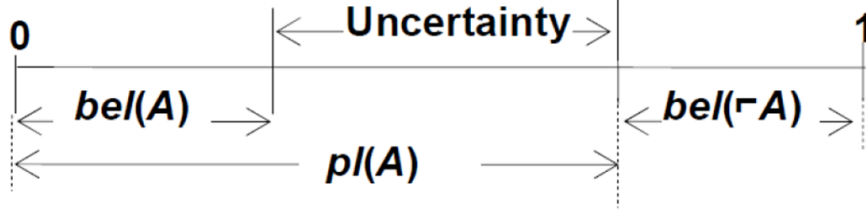


Figure 1: Uncertainty interval definition.

For the sake of completeness, we report from [9] the formal definitions of DST in the sections below.

Let X be the universe: the set representing all possible states of a system under consideration. The power set

$$2^X$$

is the set of all subsets of X , including the empty set $\emptyset$. For example, if:

$$X = \{a, b\}$$

then

$$2^X = \{\emptyset, \{a\}, \{b\}, X\}$$

The elements of the power set can be taken to represent propositions concerning the actual state of the system, by containing all and only the states in which the proposition is true.

The theory of evidence assigns a belief mass to each element of the power set. Formally, a function

$$m : 2^X \rightarrow [0, 1]$$

is called a 'basic belief assignment' (BBA) when it possesses two properties. First, the mass of the empty set is zero:

$$m(\emptyset) = 0.$$

Second, the masses of all the members of the power set add up to a total of 1:

$$\sum_{A \in 2^X} m(A) = 1$$

The mass $m(A)$ of A , a given member of the power set, expresses the proportion of all relevant and available evidence that supports the claim that the actual state belongs to A but to no particular subset of A . The value of $m(A)$ pertains only to the set A and makes no additional claims about any subsets of A , each of which has, by definition, its own mass.

From the mass assignments, the upper and lower bounds of a probability interval can be defined. This interval contains the precise probability of a set of interest (in the

classical sense), and is bounded by two non-additive continuous measures called **belief** (or **support**) and **plausibility**:

$$\text{bel}(A) \leq P(A) \leq \text{pl}(A)$$

The belief $\text{bel}(A)$ for a set A is defined as the sum of all the masses of subsets of the set of interest:

$$\text{bel}(A) = \sum_{B|B \subseteq A} m(B) \quad (1)$$

The plausibility $\text{pl}(A)$ is the sum of all the masses of the sets B that intersect the set of interest A :

$$\text{pl}(A) = \sum_{B|B \cap A \neq \emptyset} m(B) \quad (2)$$

The two measures are related to each other as follows:

$$\text{pl}(A) = 1 - \text{bel}(\bar{A})$$

And conversely, for finite A , given the belief measure $\text{bel}(B)$ for all subsets B of A , we can find the masses $m(A)$ with the following inverse function:

$$m(A) = \sum_{B|B \subseteq A} (-1)^{|A-B|} \text{bel}(B)$$

where $|A - B|$ is the difference of the cardinalities of the two sets.

It follows from the last two equations that, for a finite set X , one needs to know only one of the three (mass, belief, or plausibility) to deduce the other two; though one may need to know the values for many sets in order to calculate one of the other values for a particular set. In the case of an infinite X , there can be well-defined belief and plausibility functions but no well-defined mass function.

Going back to a more practical exposition, let's summarize how the DST works:

- **Problem Definition:** A discernment framework is established that lists all possible events or hypotheses.
- **Mass Assignment:** For each potential outcome, a belief mass is assigned based on the available evidence.
- **Belief and Plausibility Calculation:** Belief and plausibility values are calculated for the various hypotheses.
- **Evidence Combination:** When multiple sources of evidence exist, the values are combined using the Dempster-Shafer rule to update the belief.

In Table 3, an example of DST computation results is reported, again taken from reference [9]. We are looking through a variety of detector systems at a single faraway signal light, which can only be colored in one of three colors (red, yellow, or green). The uncertainty comes from the fact that, in some cases, the observer, while perceiving a light, cannot distinguish its color or can exclude at least one color but remains unsure about the other two.

	Hypotheses	Mass	Belief	Plausibility
1	Null	0	0	0
2	Red	0.24	0.24	0.45
3	Green	0.16	0.16	0.37
4	Yellow	0.33	0.33	0.57
5	Red or green	0.03	0.43	0.67
6	Red or yellow	0.06	0.63	0.84
7	Green or yellow	0.06	0.55	0.76
8	Any Θ	0.12	1.00	1.00

Table 3: Example of D-S theory calculations.

The table, and in particular the assignment of basic probabilities, allows us to highlight the difference between the imprecise probabilities of DST and classical probabilities. In the mass assignment space of DST, events like “Red or Yellow” are modeled as distinct entities in the probability space. In classical probability theory, the event “Red or Yellow” would be considered the union of the events “Red” and “Yellow,” and, according to the axioms of probability, $P(\text{Red or Yellow}) \geq P(\text{Yellow})$, and $P(\text{Any}) = 1$, where Any refers to Red, Yellow, or Green. In DST, the mass assigned to Any refers to the proportion of evidence that cannot be assigned to any of the other states, which here means evidence that indicates the presence of a light but says nothing about its color. In this example, the proportion of evidence showing that the light is Red or Green is assigned a mass of 0.05. DST allows us to extract the evidence value of these observations. Furthermore, in DST, the empty set is considered massless, which means that the light signal system exists, and we are examining its possible states, rather than speculating on its existence.

In the following, we will apply the DST framework to estimate the probability range that a battery technology characterized by a specific E_d will be available within a particular year, at least in the prototypical state ($\text{TRL} \geq 7$). Mass will provide us with the probability of this specific event occurring, based on expert opinion, while belief and plausibility will give us the minimum and maximum probabilities, respectively, of this event occurring.

2.2.1 Dempster’s rule of combination

Dempster’s rule of combination is useful when you want to combine two independent sets of probability mass assignments in specific situations. This rule derives a common shared belief between multiple sources and ignores *all* the conflicting (non-shared) beliefs through a normalization factor. Specifically, the combination (called the **joint mass**) is calculated from two sets of masses m_1 and m_2 as follows:

$$m_{1,2}(\emptyset) = 0$$

$$m_{1,2}(A) = (m_1 \oplus m_2)(A) = \frac{1}{1 - K} \sum_{B \cap C = A \neq \emptyset} m_1(B)m_2(C) \quad (3)$$

where

$$K = \sum_{B \cap C = \emptyset} m_1(B)m_2(C). \quad (4)$$

K is a measure of the amount of conflict between the two mass sets [9].

In this work, given the Dempster-Shafer theory masses for the same hypothesis in two different years, Dempster's rule of combination will be used to combine the opinions of more than one expert (see Sec. 3.4).

2.3 Multi-objective risk assessment

To estimate the likelihood that a specific technology with a certain performance level will achieve the required level of technological maturity within a given year, a risk index must be developed. This risk index should then be correlated with the associated technology performance level for each subsequent year, enabling a systematic trade-off between technological potential and risks. This approach supports strategic decisions in selecting enabling technology options for cutting-edge designs. By measuring maturity risk across different technologies with various performance levels, this method provides a structured decision-support tool for engineers and industries, helping to facilitate a safe adoption plan for advanced technologies.

We illustrate the details of the proposed multi-objective approach using the scheme in Fig. 2, which displays the construction of the performance-likelihood trade-off plan for a specific upcoming year.

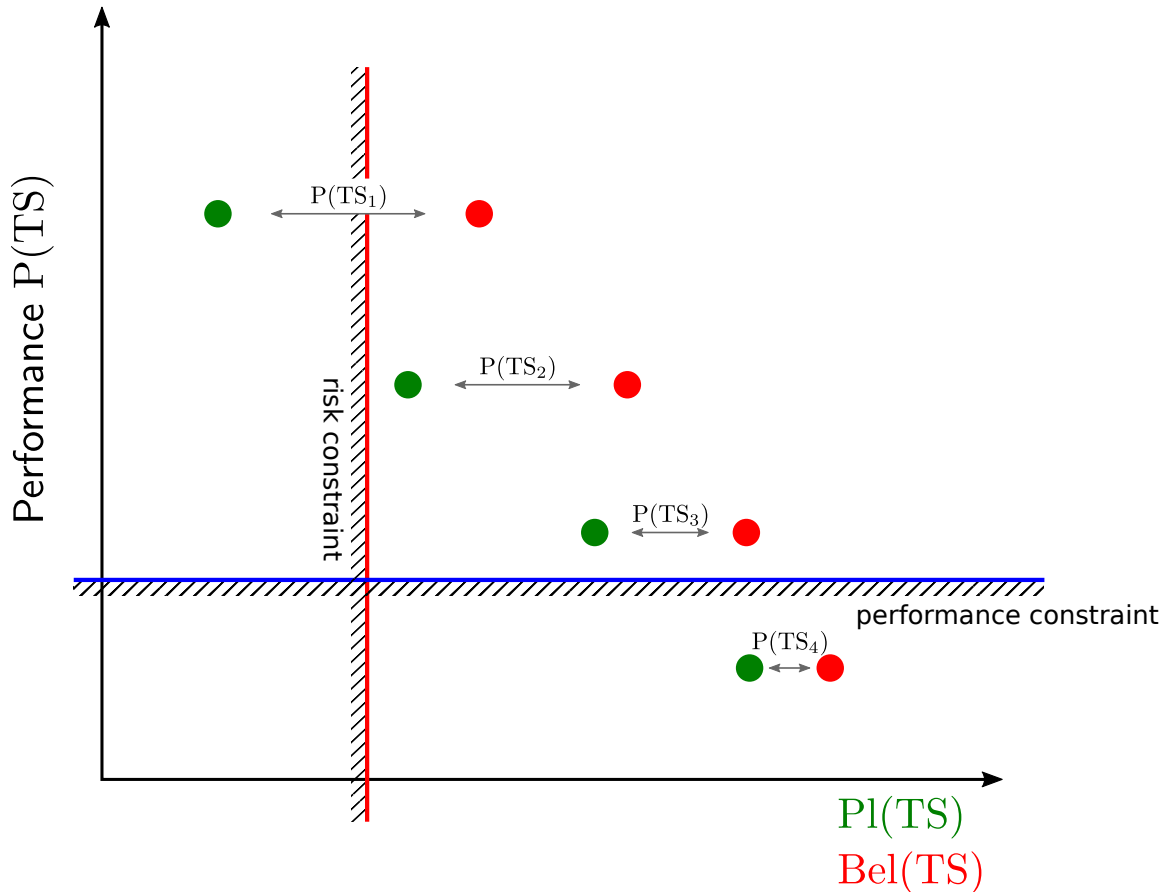


Figure 2: Multi-objective performance imprecise probability map for a given year.

At a specific point in time, belief and plausibility are plotted on the x-axis, while the relative performance level is shown on the y-axis. This visualization allows us to create

a multi-objective map illustrating the tradeoff between performance and imprecise probability. On this map, constraints related to the maximum acceptable risk level (depicted by the red vertical constraint line) and the minimum required performance (depicted by the blue horizontal constraint line) can be added. The maximum acceptable risk level acts as a barrier to the lower acceptable belief and plausibility; the lower these are, the greater the risk of technology adoption. The minimum required performance serves as a design threshold, indicating that technologies with a performance level below this cannot produce acceptable designs. These maps, generated for each technology set and specific year, will help us rank the performance of different enabling technology sets based on risk and performance, thereby identifying the most promising technologies.

Each Technology Set (TS) is evaluated in terms of the probability that a specific energy density level will be available at least as prototypal ($TRL \geq 7$) by a specific year, *i.e.*, belief and probability parameters, and performance. In the Figure, the technology set TS_4 is interesting because it has high values of belief and plausibility, indicating a high probability that the technology in question will be available in that given year, at least as prototypical. However, the performance level is under the performance constraint. This means that the TS under investigation will be available with a high probability in the given year; however, its performance level is too low to meet the designer's requirements. Conversely, TS_3 is characterized by an acceptable performance level and still maintains high values of belief and plausibility. Instead, TS_2 is very promising in terms of performance, but the plausibility level is very close to the risk constraint. Finally, TS_1 is wonderful in terms of performance, but the belief index is under the risk constraint.

In summary, the map in Figure 2 is a valuable tool that helps the designer identify which particular technology $TS_i \in TS$ is most suitable in terms of performance and adoption risk. Of course, the decision ultimately depends on the designer, who must decide how much risk is acceptable when pursuing a certain level of performance. Additionally, as the map evolves annually, the timeframe in which the new design can be implemented successfully and profitably also changes.

3 INDIGO design as a function of available energy density

One of the most widely used parameters (but not the only one required) to characterize a battery, especially in the aviation field, is the Energy Density (E_d), which indicates how much energy the battery can store per unit of mass. The requirement for the INDIGO preliminary design is $E_d = 400 \text{ Wh/kg}$, which is the minimum goal. It is therefore necessary to assess whether and when it will be possible to exceed this requirement in order to achieve better hybridization, lower environmental impact, and increased performance in hybrid aircraft.

Our investigation, given that the INDIGO aircraft is a project that could materialize not immediately, but in the near future, aims to verify the time frame in which it will be possible to design a configuration with an energy density higher than the minimum level established in the preliminary design phase. Hence, our goal is to predict, with reasonable reliability, when battery technology development will enable us to significantly surpass INDIGO's minimum energy density requirement ($E_d = 400 \text{ Wh/kg}$).

To perform this global prediction using Dempster-Shafer theory, we followed these steps:

1. Expert knowledge elicitation, which is currently mostly conducted through a bibliographic search.

2. Definition of goal and constraints.
3. Dempster-Shafer theory masses definition.
4. Dempster-Shafer theory belief and probability computation (for each mass).

Multi-objective performance-imprecise probability maps will be constructed to rank the performance of various enabling technology sets based on risk and performance. Applying risk and performance constraints will help us identify the most promising technology, considering the energy density value.

Once the energy density level that guarantees an adequate compromise between risk and performance has been identified, the battery technology that ensures the energy level in question and that will be available within a particular year, at least as a prototype ($TRL \geq 7$), is chosen. Just as in the case of the global forecast discussed in the first point, it is also necessary to conduct a bibliographic search, define the hypotheses, identify the masses, and calculate the belief and plausibility parameters for each mass.

3.1 Top-tier battery cell energy density outlook

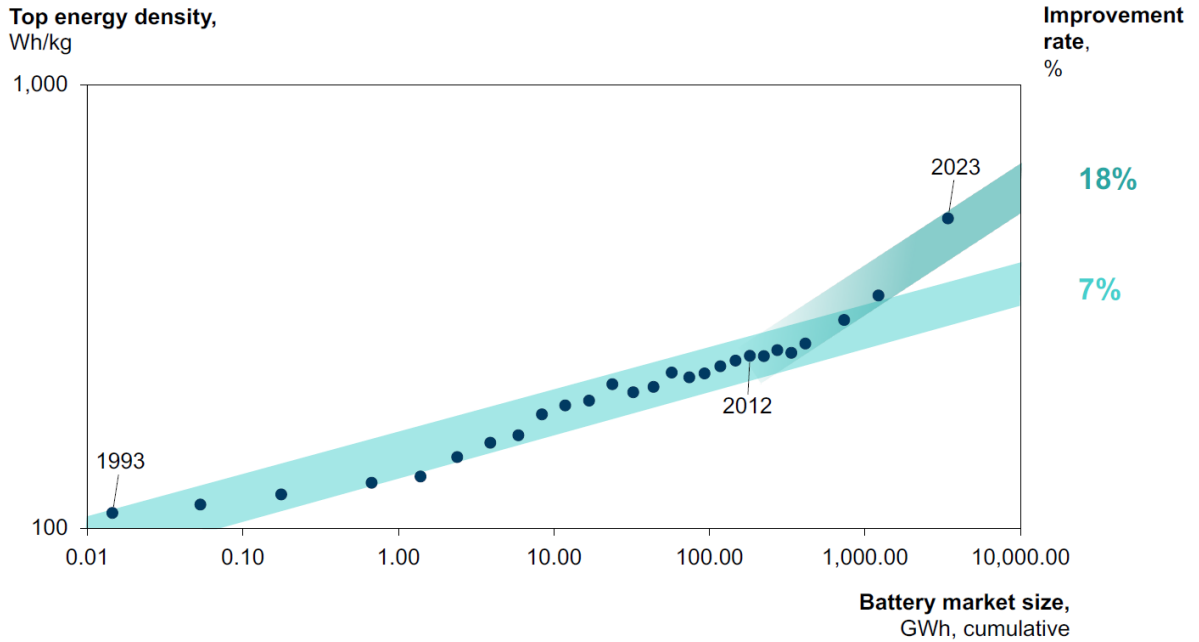


Figure 3: Top-tier battery cell energy density vs. cumulative battery market size.

Figure 3, taken from reference [8], shows that top-tier energy density has increased by 7% for every doubling of battery deployment since 1993, by 18% since 2012. To get a sense of where top-tier energy density may end up by the end of the decade, in reference [8], the 7%-18% improvement rate trend was extended to 2030. We have further extended this improvement rate trend to 2040, as shown in Fig. 4.

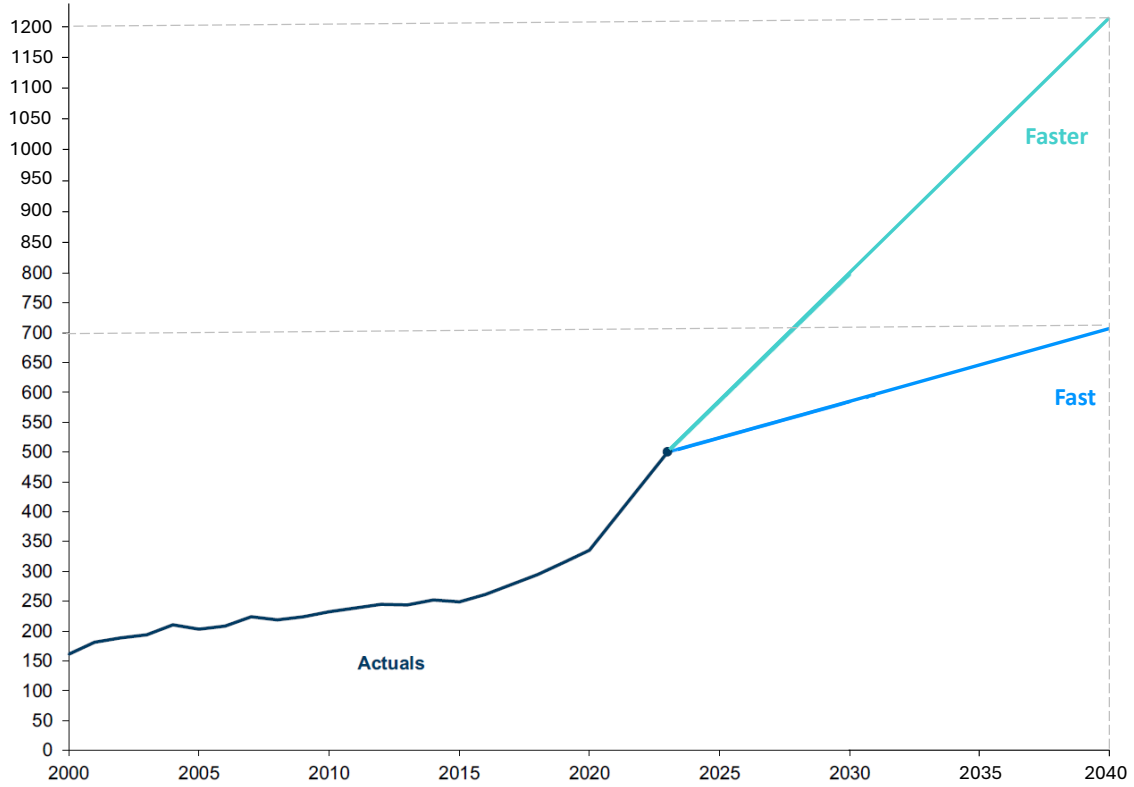


Figure 4: Top-tier battery cell energy density outlook, Wh/kg .

Projecting energy density forward with this rate of improvement suggests that by 2040, top-performing battery cells could reach between approximately 700 and 1200 Wh/kg . In this work, we focus not on average energy density but on the energy density of the leading batteries, because the emphasis is on new applications and markets rather than the average across existing ones.

3.2 The Maximum Theoretical Specific Energy (MTSE)

Obviously, we cannot improve the energy density indefinitely. The *Maximum Theoretical Specific Energy* (*MTSE*) has to be taken into account [1].

Considering a simple insertion or formation reaction:



where x is the number of A that reacts per mol of R. If W_t is the sum of the molecular weights of the reactants engaged in the reaction and E is the average voltage of the reaction, the MTSE can be expressed in Wh/kg as:

$$MTSE = 26,805(xE/W_t) \quad (6)$$

Without considering the practicality of building such a battery, we can examine the periodic table and select the lightest elements with multiple oxidation states that form compounds. This thought experiment turns up compounds of hydrogen-scandium. Considering that the maximum value that E can assume is equal to 6V due to the available

electrochemical potentials of the elements, we can obtain from Eq. 6 a theoretical limit (for an ideal battery) around $5 \text{ MJ/kg} \sim 1389 \text{ Wh/kg}$. It is unlikely that a battery exceeding this limit will be built in the future. Therefore, we need to take this limit into account when making the top-tier battery cell energy density outlook. In any case, as shown in Fig. 4, there is no risk of exceeding this limit in our discussion.

3.3 Dempster-Shafer theory masses definition

The top-tier battery cell energy density outlook shown in Fig. 4 is useful to determine the Dempster-Shafer theory masses (see Sec. 2.2). We start collecting raw probability estimations, as shown in Tab. 4, that have to be further processed to obtain suitable DST “masses”.

	Year				
Hypothesis: E_d at $TRL \geq 7$	2026	2028	2030	2035	2040
300	1.00	0.00	0.00	0.00	0.00
400	0.00	0.90	0.10	0.00	0.00
500	0.00	0.50	1.00	0.20	0.00
600	0.00	0.00	0.50	1.00	0.20
700	0.00	0.00	0.20	0.60	1.00
800	0.00	0.00	0.00	0.10	0.70
300 or 400	1.00	0.20	0.02	0.00	0.00
400 or 500	0.00	0.20	1.00	0.30	0.00
500 or 600	0.00	0.10	0.50	0.40	0.10
600 or 700	0.00	0.00	0.01	0.60	0.50
700 or 800	0.00	0.00	0.01	0.40	1.00
300 or 400 or 500	0.10	0.20	1.00	1.00	0.20
400 or 500 or 600	0.00	0.10	0.10	1.00	0.50
500 or 600 or 700	0.00	0.00	0.00	0.20	1.00
600 or 700 or 800	0.00	0.00	0.00	0.05	1.00

Table 4: Probability that a specific event will occur in a specific year.

The values shown in Tab. 4 were established mainly on the basis of the data shown in Fig. 4, but also taking into account the opinions of other experts in the field. The values in the table represent the probability that a specific event will occur in a given year, based on the experts’ opinions. For example, for the experts, a battery technology characterized by $E_d = 300 \text{ Wh/kg}$ will certainly be available in 2026 at least as prototypal ($TRL \geq 7$); indeed, this level of energy density is already available. At the same time, a battery technology characterized by $E_d = 600 \text{ Wh/kg}$ will likely be available in 2035 at least as prototypical, while the probability that this event will occur in 2030 is 50%, 20% in 2040. The probability in 2040 is lower than the one in 2035 because we are *not* looking at the cumulative probability: for the experts, this technology in 2040 will likely

already be available; there is only a 20% probability that it will become available in 2040. The hypothesis $E_d = 300$ or 400 Wh/kg *does not* contradict the other two hypotheses ($E_d = 300$ Wh/kg; $E_d = 400$ Wh/kg), but that introduces uncertainty because that means that the experts do not know which of the two hypotheses will occur.

Therefore, the values shown in Table 4 must be weighted in order to take into account appropriately the uncertainties. Based on a bibliographic search, we can define a multiplier for each hypothesis, as shown in Table 5.

Hypothesis: E_d at $TRL \geq 7$	Multiplier
300	1.00
400	1.00
500	1.00
600	1.00
700	1.00
800	1.00
300 or 400	0.25
400 or 500	0.25
500 or 600	0.25
600 or 700	0.25
700 or 800	0.25
300 or 400 or 500	0.10
400 or 500 or 600	0.10
500 or 600 or 700	0.10
600 or 700 or 800	0.10

Table 5: Multipliers for uncertainty.

Subsequently, normalization is performed for each year in order to obtain the Dempster-Shafer theory masses (Sec. 2.2). The normalized data are shown in Table 6.

	Year				
Hypothesis: E_d at $TRL \geq 7$	2026	2028	2030	2035	2040
300	0.966	0.000	0.000	0.000	0.000
400	0.000	0.513	0.043	0.000	0.000
500	0.000	0.285	0.427	0.078	0.000
600	0.000	0.000	0.214	0.392	0.008
700	0.000	0.000	0.085	0.235	0.389
800	0.000	0.000	0.000	0.039	0.272
300 or 400	0.024	0.142	0.002	0.000	0.000
400 or 500	0.000	0.028	0.107	0.029	0.000
500 or 600	0.000	0.014	0.053	0.039	0.010
600 or 700	0.000	0.000	0.011	0.059	0.049
700 or 800	0.000	0.000	0.011	0.039	0.097
300 or 400 or 500	0.010	0.011	0.043	0.039	0.008
400 or 500 or 600	0.000	0.006	0.004	0.039	0.019
500 or 600 or 700	0.000	0.000	0.000	0.008	0.039
600 or 700 or 800	0.000	0.000	0.000	0.002	0.039

Table 6: Dempster-Shafer theory masses.

The masses reported in Table 6 correspond finally to the Basic Probability Assignment (BPA) of DST. In Fig. 5, the BPA values in Tab. 4 are shown as a function of the year.

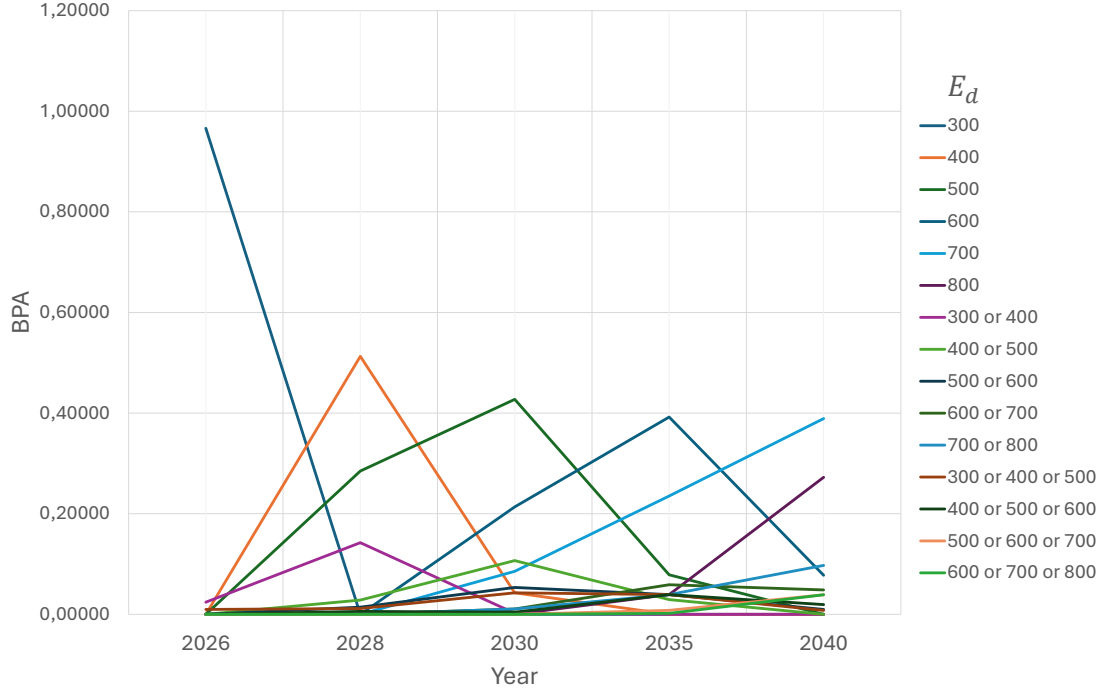


Figure 5: Top-tier battery cell energy density BPAs, Wh/kg .

3.4 Dempster-Shafer theory belief and plausibility computation

Once the Dempster-Shafer theory masses are defined, we can determine a likely interval in which the event in question is located by the calculation of the belief and the plausibility, representing the lower and the upper limits of the probability that the event in question will occur (Sec. 2.2). By using Eqs. 1 and 2 allow us to calculate the belief and plausibility for each event. Moreover, it is necessary to obtain belief and plausibility for each year in which the map is to be determined: we use a linear combination to interpolate the BPA and recalculate belief and plausibility, as shown in the example in Fig. 6, where a simple case characterized by three events ($E_d = 315, 350, 315 \text{ or } 350 Wh/kg$) is considered.

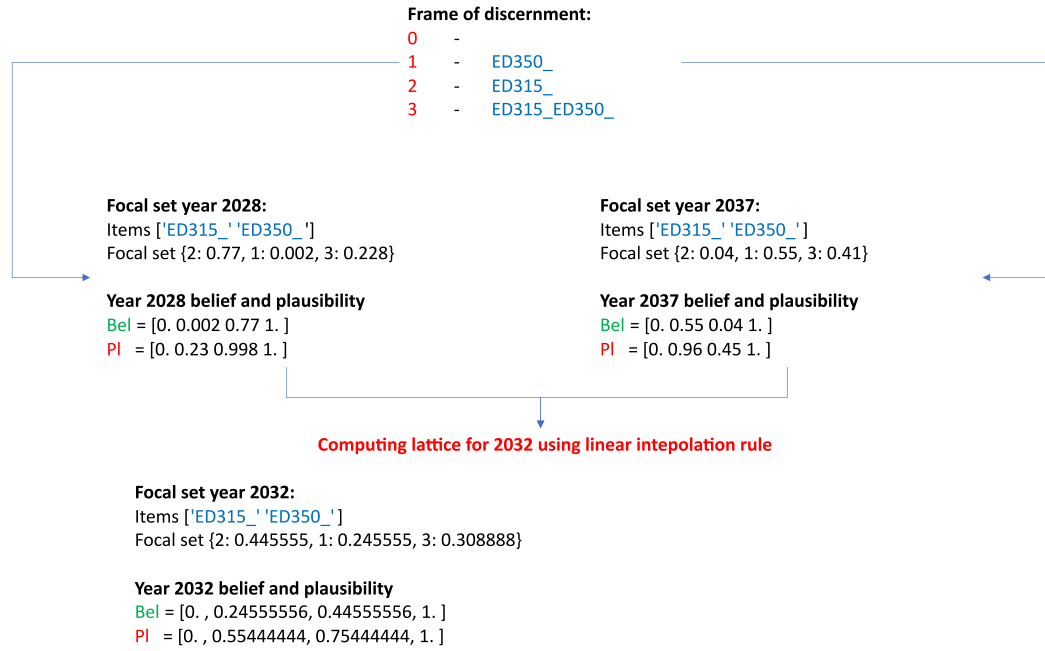


Figure 6: Example of belief and plausibility linear interpolation.

In Fig. 7 the belief and plausibility curves calculated for each considered energy density are shown (Tab. 6).

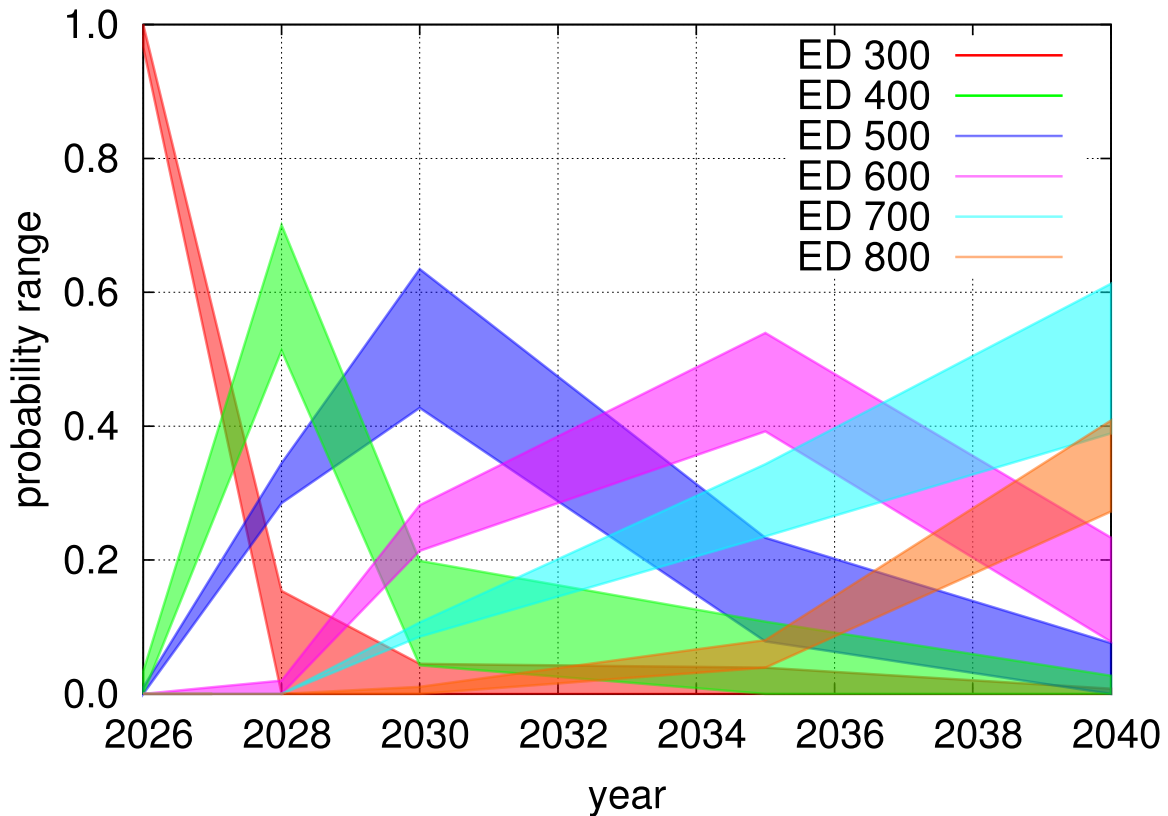


Figure 7: Dempster-Shafer theory belief and plausibility computation results.

Based on these calculations, we can construct the multi-objective map described in Sec. 2.3.

4 Risk assesment results

In Fig. 8 to 22, multi-objective maps of the performance-imprecise probability tradeoff for the data in Tab. 6 are shown from year 2026 to 2040.

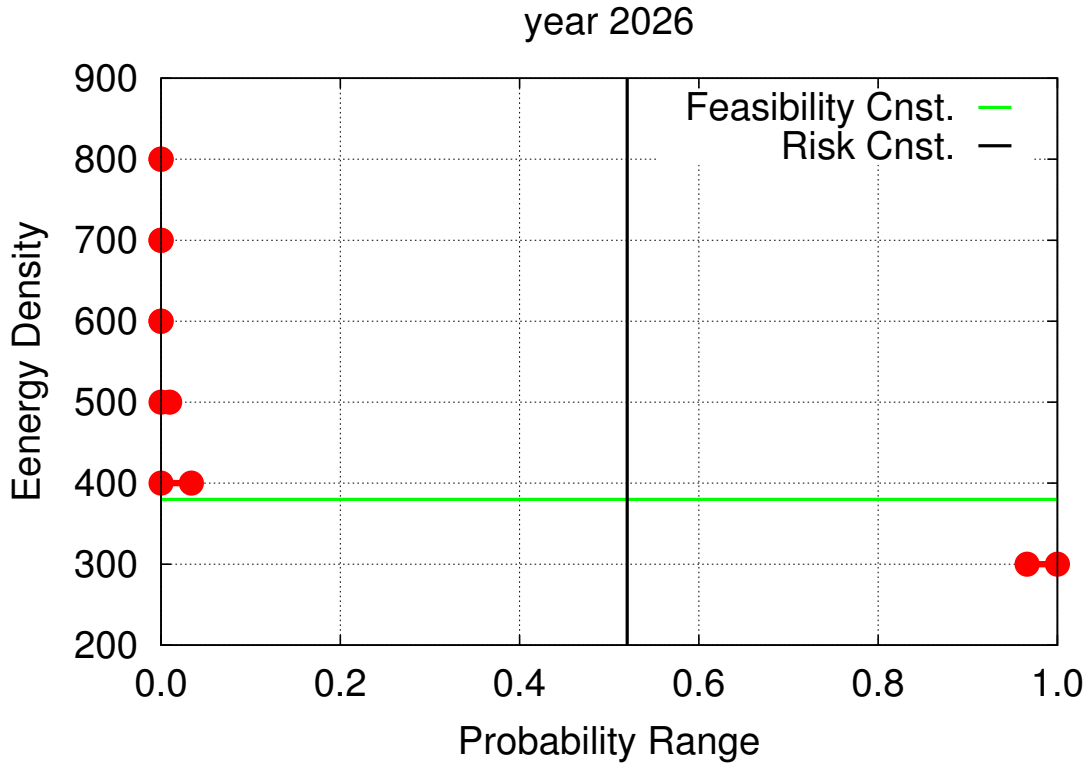


Figure 8: Multi-objective performance imprecise probability map, year 2026.

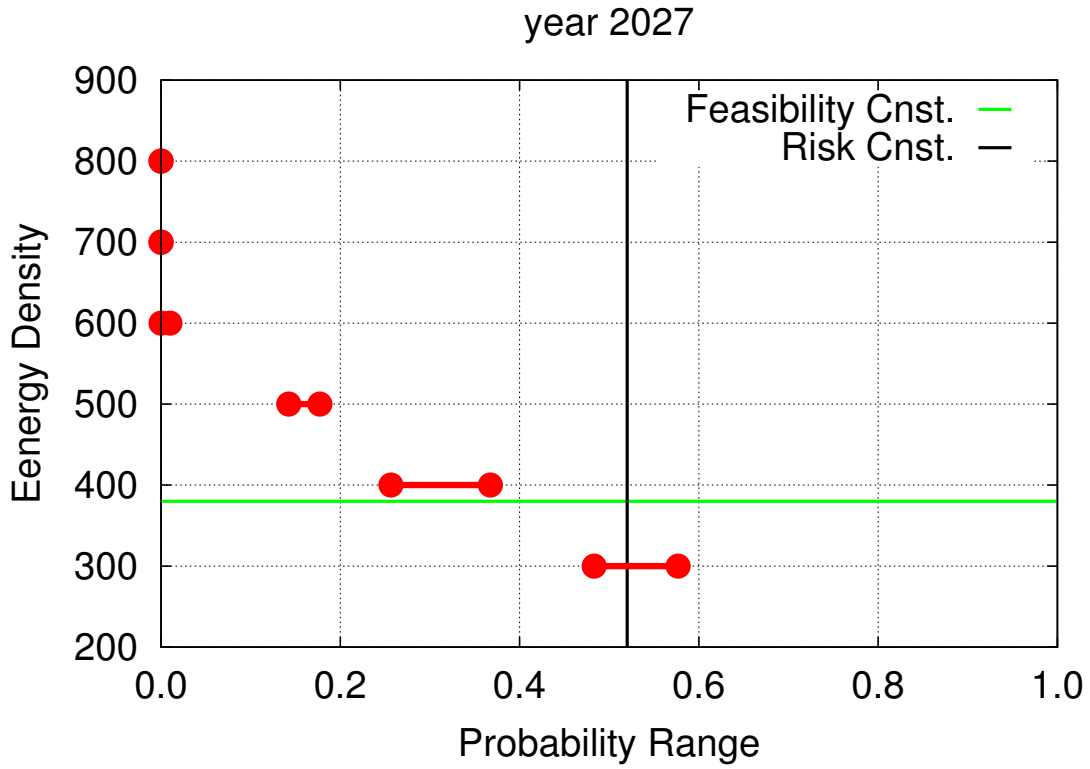


Figure 9: Multi-objective performance imprecise probability map, year 2027.

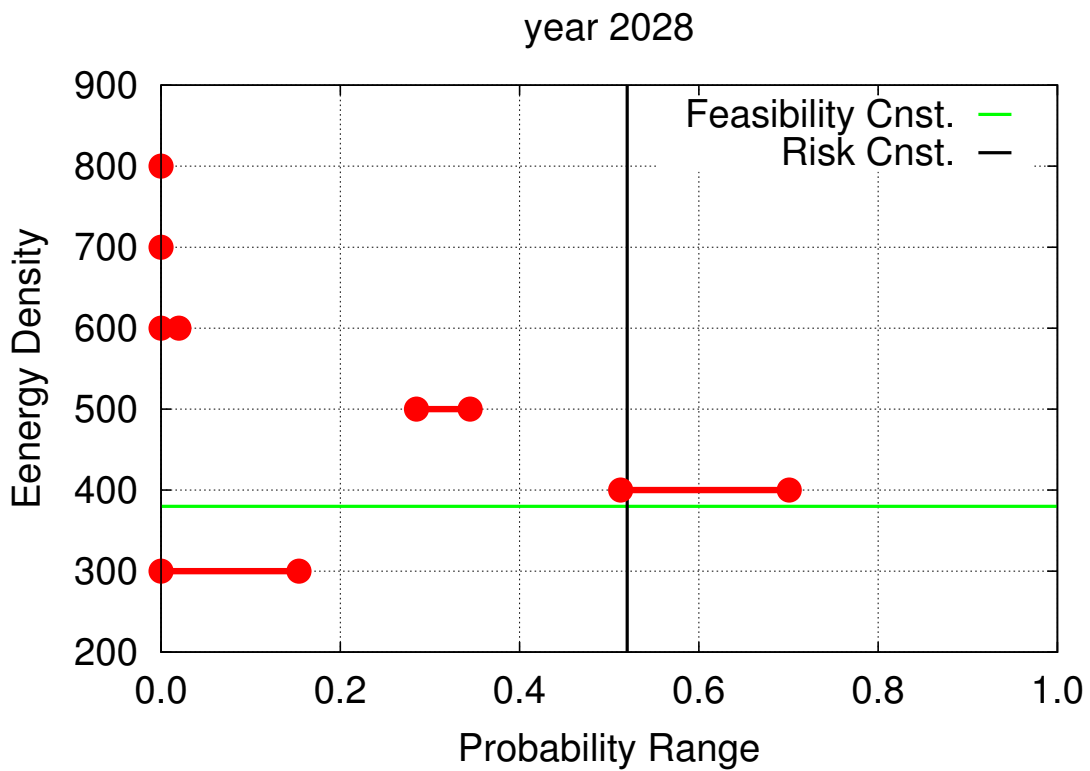


Figure 10: Multi-objective performance imprecise probability map, year 2028.

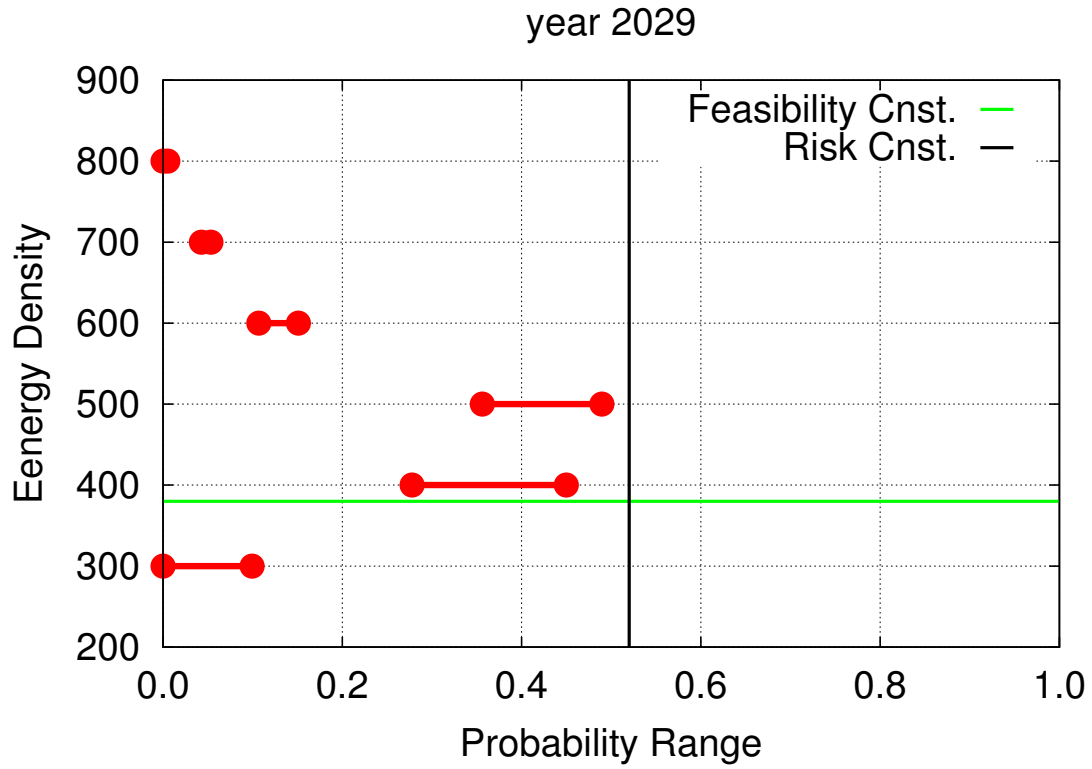


Figure 11: Multi-objective performance imprecise probability map, year 2029.

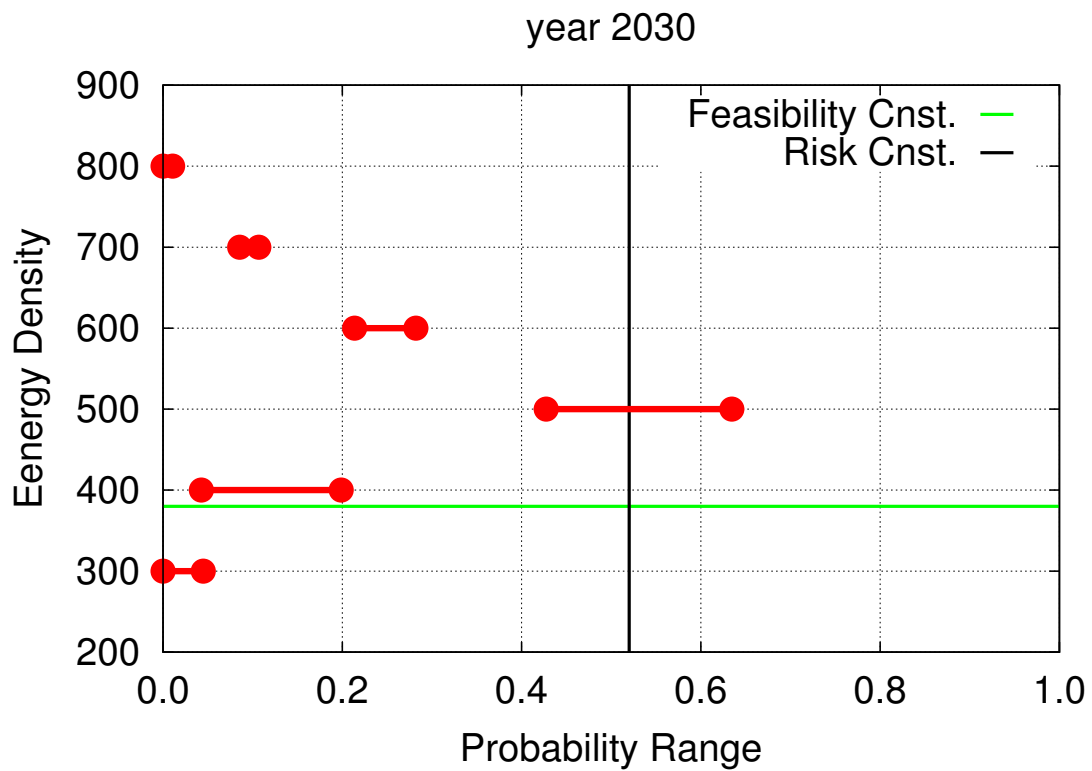


Figure 12: Multi-objective performance imprecise probability map, year 2030.

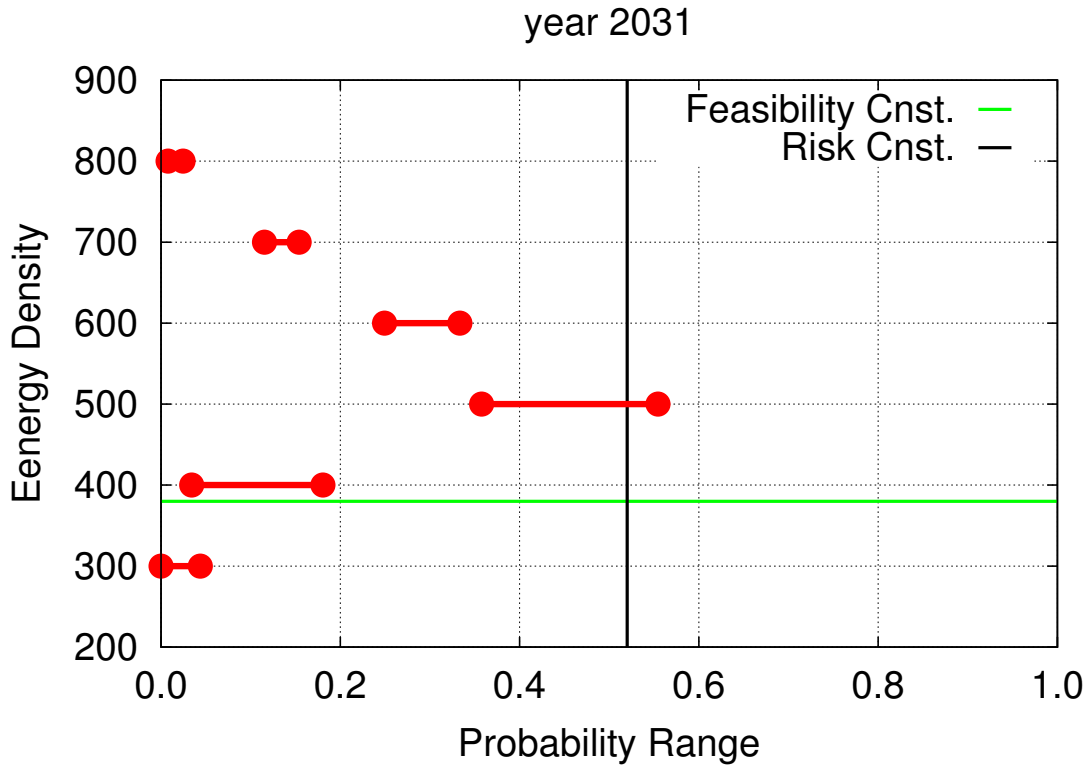


Figure 13: Multi-objective performance imprecise probability map, year 2031.

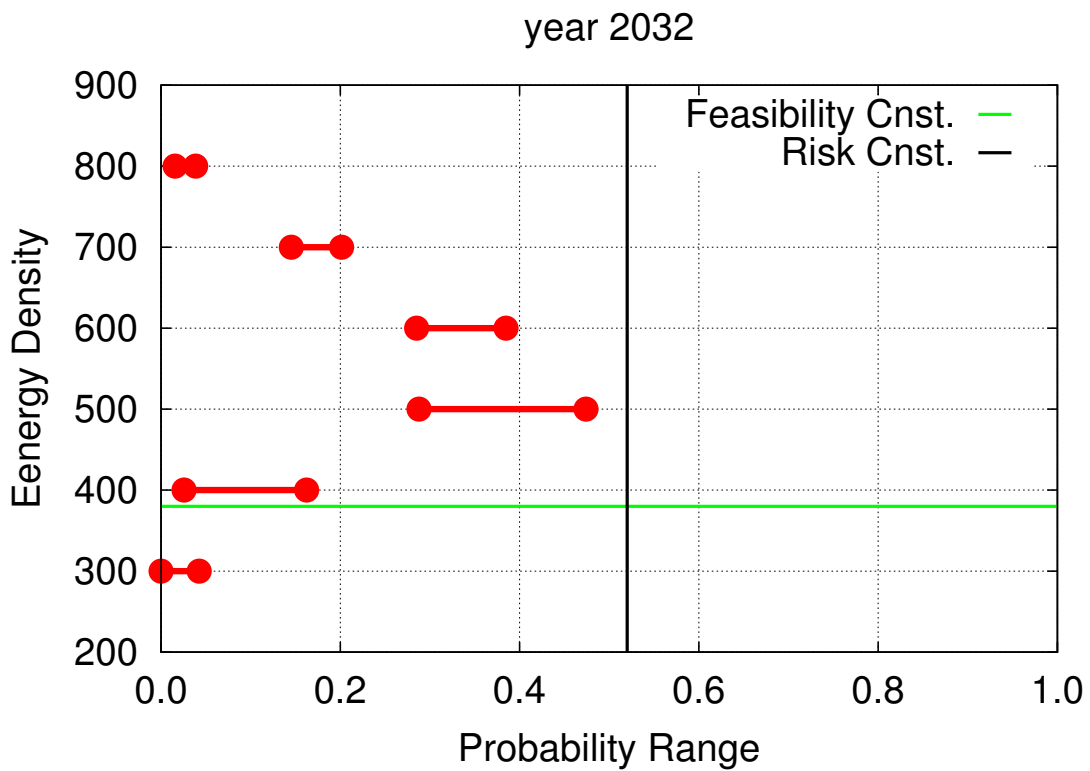


Figure 14: Multi-objective performance imprecise probability map, year 2032.

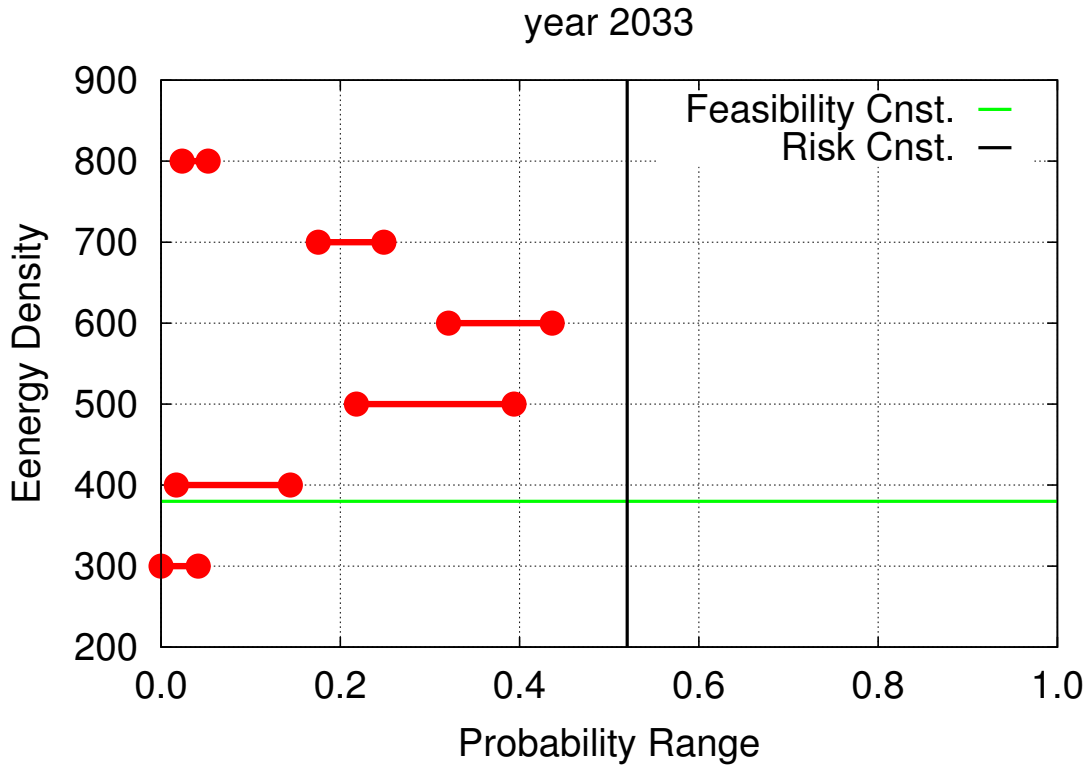


Figure 15: Multi-objective performance imprecise probability map, year 2033.

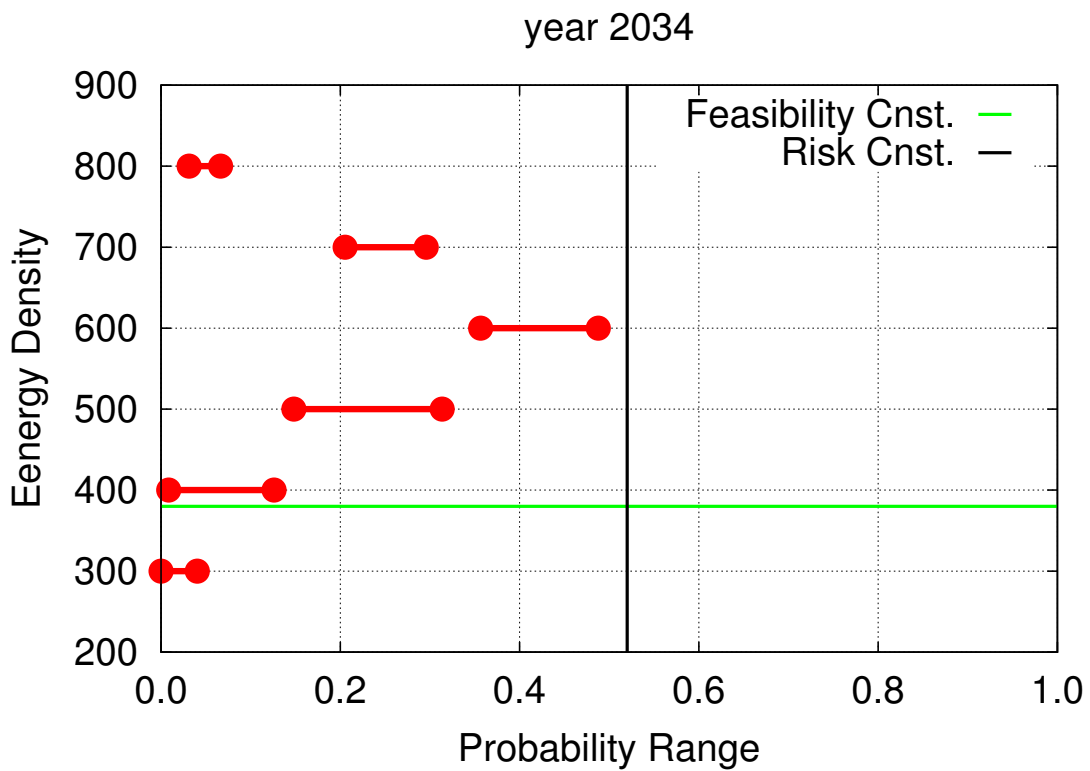


Figure 16: Multi-objective performance imprecise probability map, year 2034.

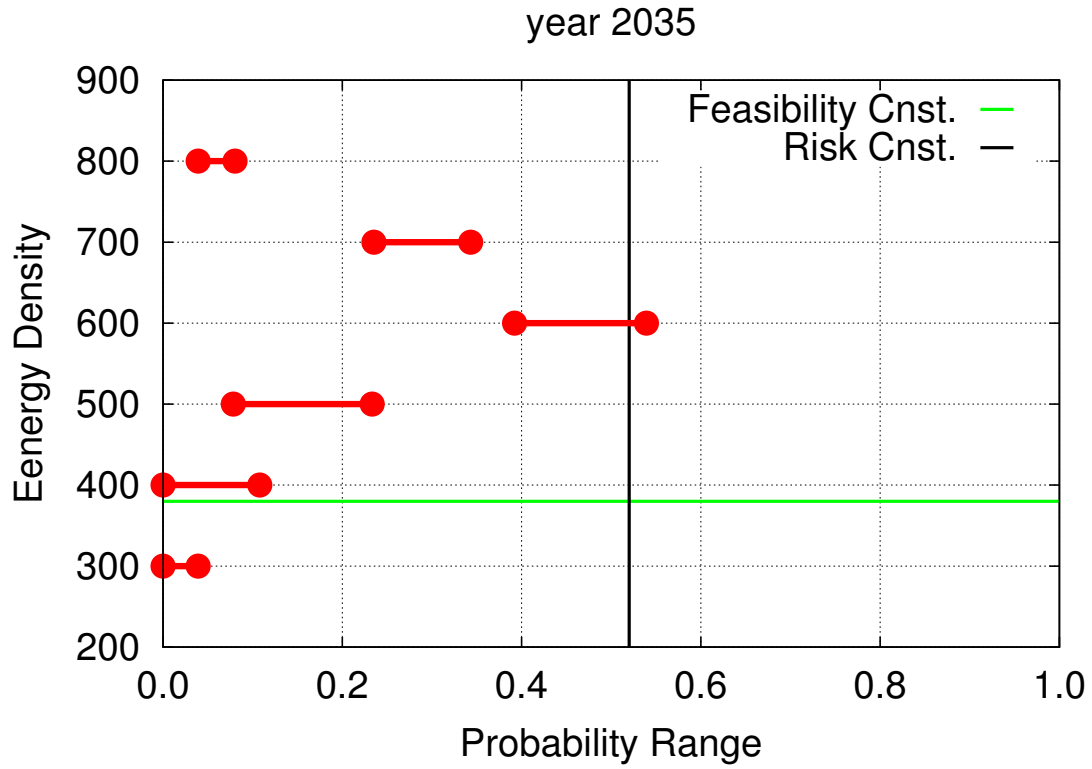


Figure 17: Multi-objective performance imprecise probability map, year 2035.

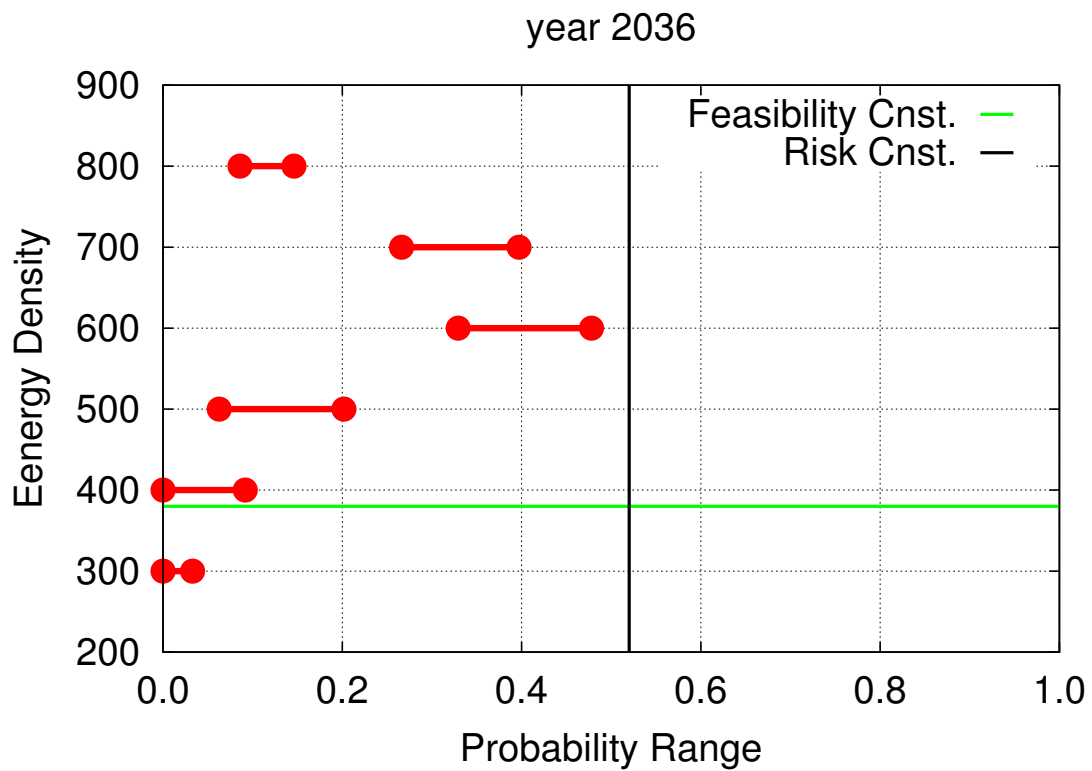


Figure 18: Multi-objective performance imprecise probability map, year 2036.

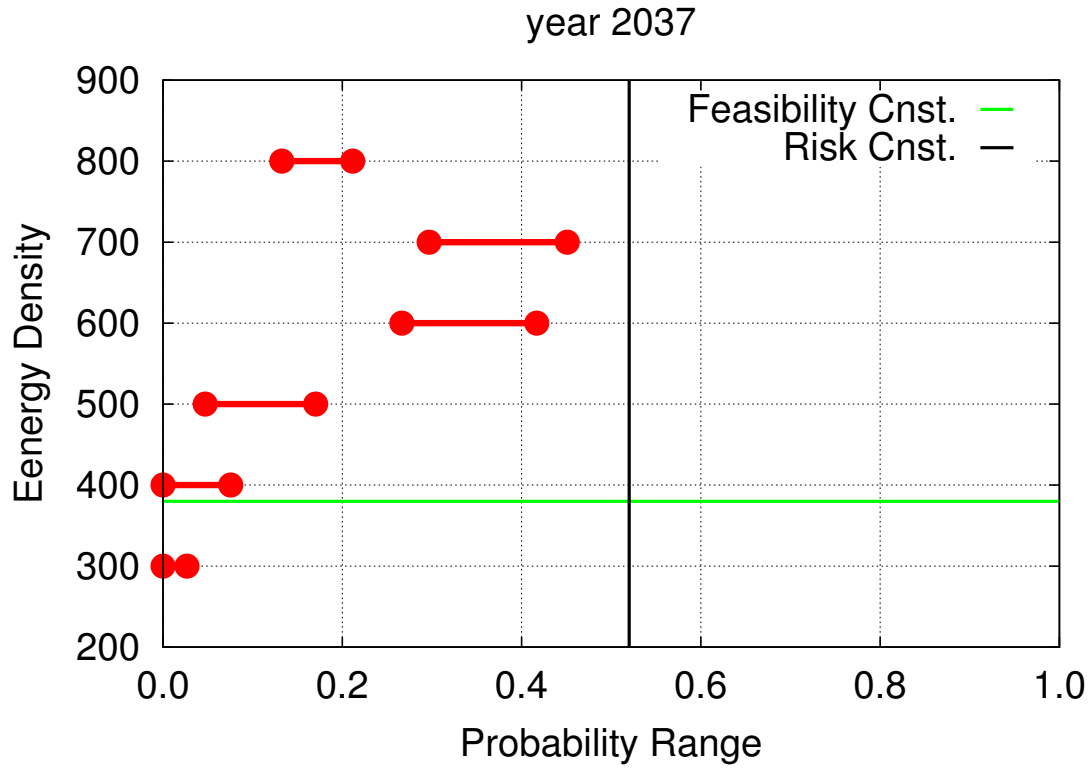


Figure 19: Multi-objective performance imprecise probability map, year 2037.

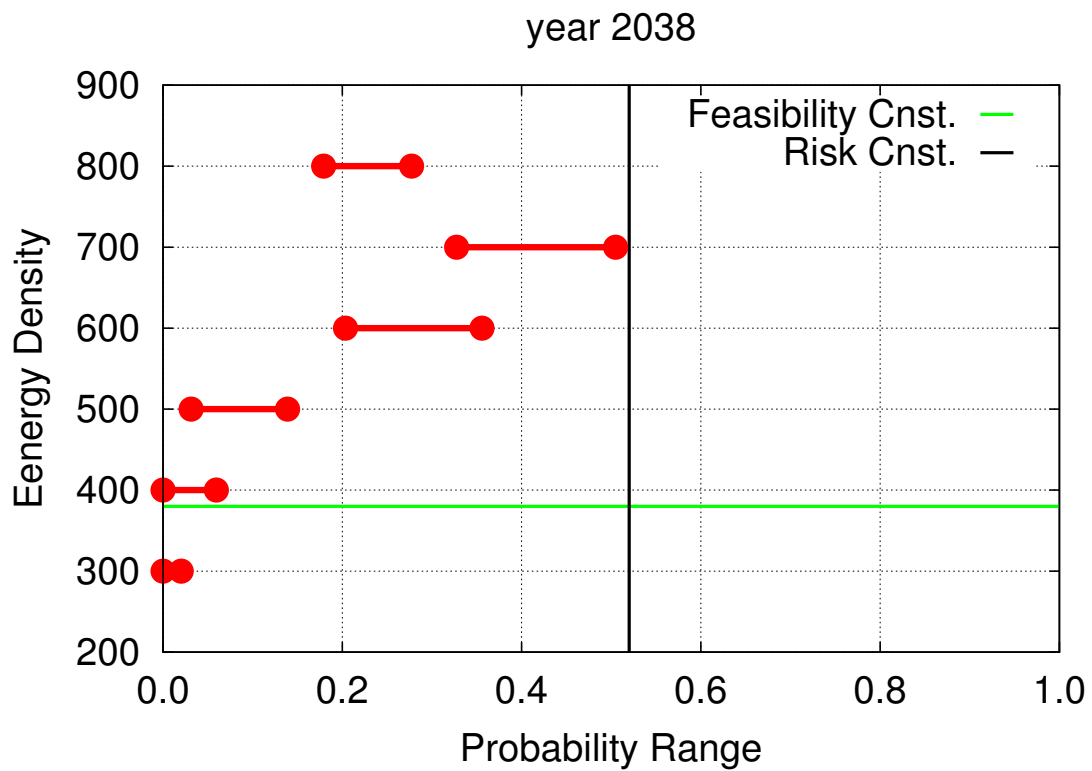


Figure 20: Multi-objective performance imprecise probability map, year 2038.

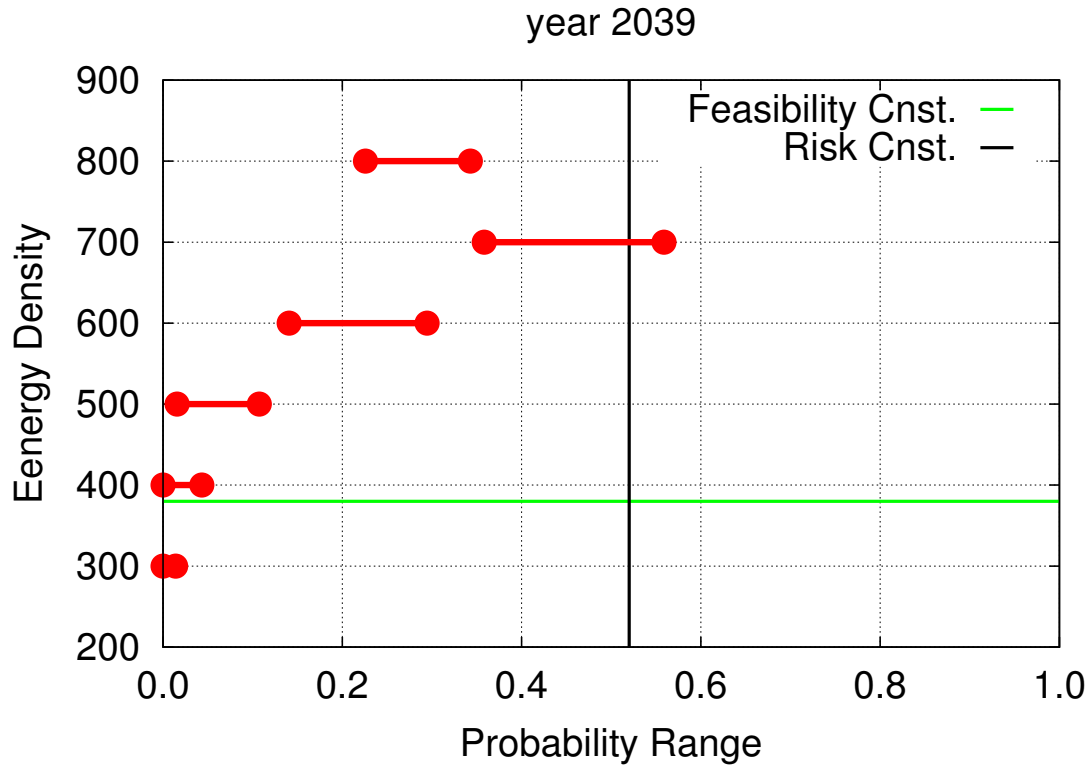


Figure 21: Multi-objective performance imprecise probability map, year 2039.

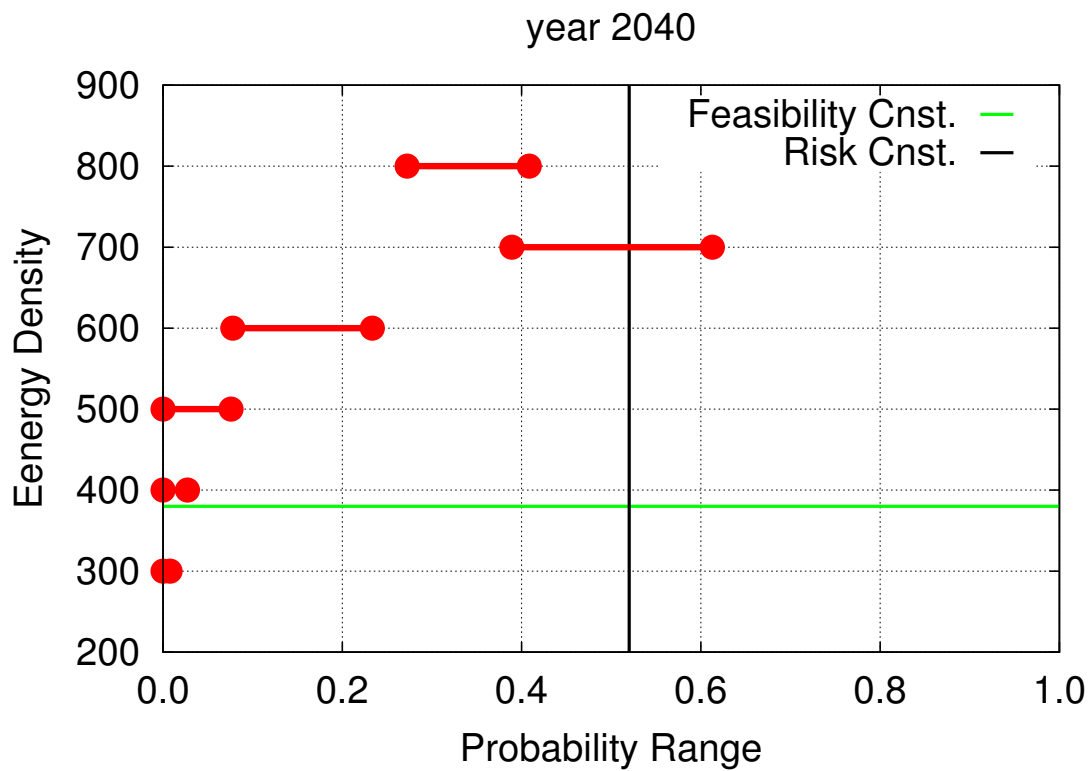


Figure 22: Multi-objective performance imprecise probability map, year 2040.

As shown in Fig. 8, in 2026 the only available energy density level is 300 Wh/kg, but this level falls below the feasibility constraint because the INDIGO energy level requirement is fixed at 400 Wh/kg (Sec. 3). In 2027 (Fig. 9), the energy density level 400 starts to emerge, while 300 is moving backward along the probability range axis. That happens because the probability range shown in Fig. 8 to Fig. 22 is not referred to a cumulative probability but to a BPA. That means that on this graph, we are representing the probability that a specific event will occur in a specific year, *i.e.* energy density level 300 Wh/kg is already available. In 2028 (Fig. 10), we can invest in the technology with the energy level 400 Wh/kg. The plausibility is still below the risk constraint, but only by a small margin. In 2029 (Fig. 11), the energy density level 400 Wh/kg starts to move below the risk constraint, because the energy density level 500 starts to emerge. In 2030 (Fig. 12), we can invest on 500 Wh/kg. In 2031 (Fig. 13), the energy density level 500 Wh/kg starts to move below the risk constraint. In 2032 (Fig. 14), the energy density level 600 Wh/kg starts to emerge. In 2033 (Fig. 15), the energy density level 600 Wh/kg is the most interesting technology. In 2034 (Fig. 16), the energy density level 600 Wh/kg is still the most interesting technology. In 2035 (Fig. 17), investing in the energy density level 600 Wh/kg is still the most viable option. In 2036 (Fig. 18), the energy density level 600 Wh/kg starts to move backward. In 2037 (Fig. 19) and 2038 (Fig. 20), the energy density level 700 Wh/kg is likely the one we can invest in. In 2039 (Fig. 21) and in 2040 (Fig. 22), the energy density level 800 Wh/kg starts to emerge, but we cannot be sure that buy this technology will be characterized by the adequate reliability level.

5 Conclusions

Facts should always support engineering design decisions, but developing new solutions may require technologies whose progress is not always exactly predictable. In this deliverable, we suggested an approach to the decision problem even when there is no precise information about availability times and achievable performances.

Based on the Dempster-Shafer theory, we proposed a multi-objective framework for estimating performance levels versus deployment risks, making it easier to make informed decisions. Then, the framework was used to select the most suitable battery energy density level while maintaining acceptable uncertainty margins for a high-performance hybrid thermal-electric aircraft. To achieve this, we identified, within a specified future time interval, the performance of a technology sufficient to ensure the project's success and reduce risks related to its actual availability.

The results, however, rely on the inherently imprecise opinions of experts. The approach involves risks and demands high precision in gathering expert opinions, along with a dependable method for combining and interpreting conflicting opinions within the Dempster-Shafer framework.

References

- [1] Robert A. Huggins. *Advanced Batteries: Materials Science Aspects*. Springer, New York, NY, 2009.
- [2] Juerg Kohlas. The mathematical theory of evidence — a short introduction. *System Modelling and Optimization, Springer Science+Business Media Dordrecht 1996*, 01 1996.

- [3] Heder Mihaly. From NASA to EU: the evolution of the TRL scale in public sector innovation. *The Innovation Journal*, 22(2):1–23, sep 2017.
- [4] P. Norczyk and R. Cavallaro. Local air quality and noise improvements via optimization of strut-braced wings with distributed electric propulsion. In *AIAA SciTech Forum*, Orlando, FL, USA, 2025.
- [5] Glenn Shafer. *A Mathematical Theory of Evidence*. Princeton University Press, 1976.
- [6] Glenn Shafer. A mathematical theory of evidence turns 40. *International Journal of Approximate Reasoning*, 79:7–25, 2016. 40 years of Research on Dempster-Shafer Theory.
- [7] TEC-SHS. Technology readiness levels handbook for space applications. Technical report, ESA, 2008.
- [8] Daan Walter, Kingsmill Bond, Sam Butler-Sloss, Laurens Speelman, Yuki Numata, and Will Atkinson. X-change: Batteries — the battery domino effect. Technical report, Rocky Mountain Institute, December 2023.
- [9] Wikipedia contributors. Dempster–shafer theory, 2025. Accessed on 2025-06-03.