

Aircraft design system requirements analysis with Bayesian Networks

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This paper introduces readers with the application of Bayesian Networks in conceptual design tasks. These models can represent in a graph the cause-and-effect logic of requirements and enable the analysis of uncertainty in decision making. A syntax for converting a requirement into a Bayesian network query is also presented. These concepts are applied on a wing design example to demonstrate the flexibility of a Bayesian Network in answering design-related questions. In particular, a feasible design space is identified through inference of the requirements onto the input parameters. This is useful to narrow down configurations for further detailed analysis with an optimization algorithm. The model is capable of estimating the quantities of interest and the effect of the requirement uncertainty on the system variables. Through proper data collection and integration with digital engineering methods, a system-wide Bayesian network would enable reasoning between systems and components, accelerating the industrial development of complex products.

I. Nomenclature

AR	=	Wing Aspect Ratio
C_L	=	Lift Coefficient
$C_{D,cr}$	=	Cruise Drag Coefficient
c	=	Constraint value
F	=	Structural failure variable
$g(x)$	=	QoI function subject to constraints
i	=	design parameter index
k	=	requirement index
λ	=	Wing Taper ratio
M_w	=	Wing Mass
$M_{w,max}$	=	Maximum Wing Mass
P	=	Probability
R	=	Requirement satisfaction statement
R_{wm}	=	Wing mass requirement satisfaction
t_{skin}	=	Skin thickness
t_{spar}	=	Spar thickness
x	=	Input parameter

II. Introduction

The design of complex systems such as aircraft involves the synergy of many disciplines and multidisciplinary thinking from the perspective of the system engineer. The success of the development of these products rests upon the correct understanding of the cause-and-effect links between the variables and systems at play. System modeling approaches such as Model-Based System Engineering (MBSE) have been developed to aid in understanding the links between the components in a system and the interaction between systems [1]. A more explicit representation of the cause-and-effect relationship between controllable design parameters and quantities of interest has been proposed by Rötzer et al. [2] as Attribute Dependency Graph (ADG). ADGs are causal diagrams showcasing the flow of information

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from directly controllable input parameters to uncontrollable quantities of interest. These have been applied in examples of automotive design [3, 4], in particular in the design of a yaw damping system for a car chassis. The ADG provides information on which parameters to focus after sampling the design space for feasible solutions that do not violate the constraint space.

These conceptual maps are useful in providing a general overview of the design problem but do not quantify the influence one variable has on the others. Analysis such as Design Space Exploration and Multi-Disciplinary Optimisation (MDO) problems are used to extract quantitative information from the computational design model. With current computational tools, both approaches can produce large datasets that can be processed with machine learning tools to extract useful information about the underlying design problem. Data-driven surrogate methods have also proven successful in accelerating MDO [5] and identifying the feasible design space [6].

The combination of data-driven methods with causal dependency diagrams would provide new insights into the design space of the problem. Specifically, it would help control the epistemic uncertainty that characterizes the early stages of the design problem [7]. This form of uncertainty is difficult to quantify, unlike the aleatory uncertainty associated with tolerances. Epistemic uncertainty originates from a lack of information about the design space, poor communication between design disciplines, and requirement instability. These cause project delays and cost increments because of unexpected iterative rework to correct design issues [8].

Bayesian Networks (BN), also known as Causal Networks or Causal models, are graphs encoding the dependency between its variables by using probability theory. These models can be learned from data and used for reasoning and decision-making tasks [9]. Because of their inherent probabilistic nature, BNs are a potential tool for modeling the epistemic uncertainty of engineering design problems.

Furthermore, the graph can encode connections between the different levels of the system, as proposed by Kallou et al. [10]. This vertical dependency would begin from the system-of-systems variables, such as the airline transport system, and trickle down to system and component levels (e.g. aircraft and wing). Variables representing a requirement would sit at the system-of-systems level and design variables that can be acted upon are present at the system and component level. Inference can be performed to predict the outcome of design decisions on any system level.

Similarly, different disciplines within the same system level can be represented as horizontal dependencies, highlighting the connections. Figure 1 presents these ideas in a conceptual diagram of a system-level Bayesian Network capturing the relationship between the variables relevant for a wing design problem. This large BN would require large datasets produced from any area of the product development. Generating, managing, and handling data for this scale requires industrial-level protocol of communication between software, disciplines and teams. ISO Standardized communication and frameworks have been proposed to facilitate this task within the context of Digital Engineering [11].

From the perspective of quantitative analysis, BNs allow one to perform any inference on all variables in the graph. This opens many avenues for reasoning with uncertainty, as inference can be performed in any direction of the graph edges. For instance, one could evaluate which input parameters are most likely able to satisfy a requirement and whose constraint value can be a distribution and not fixed. Another possibility is predicting the most likely values of quantities of interest given a range of inputs or a set condition (e.g. a requirement or a technological parameter). The BN inference is flexible and can be used to carry out design space exploration, scenario analysis, requirement propagation, and pseudo-optimization.

This paper aims to introduce the reader to the uses of Causal networks for design space exploration applications and general decision-making support in engineering. It intends to present examples of probabilistic reasoning relevant to aeronautical and engineering design. In addition, it proposes an application of Causal Models for handling requirements uncertainty in design space exploration. The illustrative example showcases a BN representing an aero-structural design problem of a subsonic business jet wing. The ideas presented in this work are exploratory and intended to be further developed as research continues.

III. Bayesian Causal Model for engineering requirements

In the design process, requirements are translated from a sentence into mathematical inequalities. These are applied to quantities of interest, such as performance parameters, figures of merit, or generally values that represent the behavior of the system under design. The estimation of these figures comes from a mathematical model that the engineer develops in parallel with the evolution of the concept. Models can span different levels of complexity, ranging from empirical equations to complex computational simulations (e.g. CFD, FEM). In the following discussion, the modeled QOI is referred to as $g_k(x_i)$, which is a function of the design input parameters x_i . A constraint inequality that represents a requirement in g_k can then be represented with Equation 1:

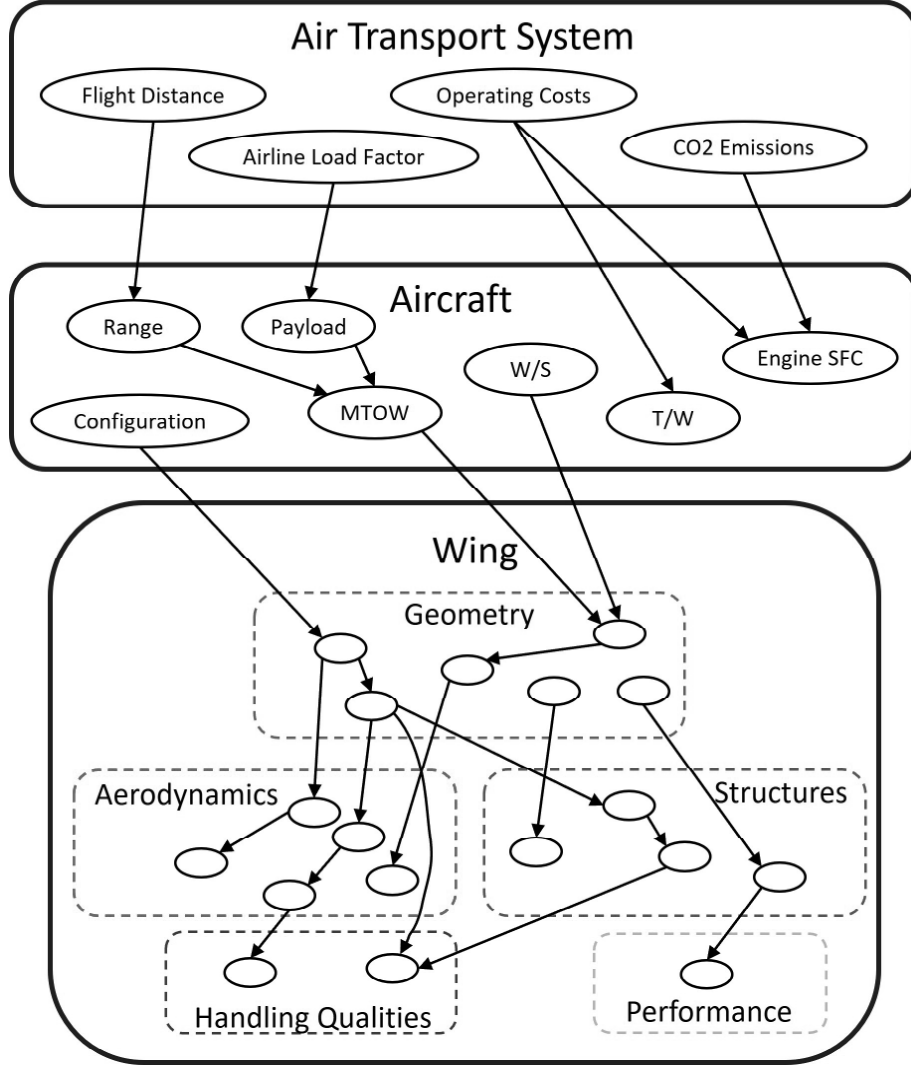


Fig. 1 Conceptual example of a Bayesian Network representing a design problem with its system context.

$$g_k(x_i) \leq c_k \quad (1)$$

where c_k is the constraint value that defines the feasible region. This mathematical statement is True or False depending on the values of x_i and c_k . Intuitively, there is a causal dependency that can be mapped using a directed acyclic graph (DAG). Figure 2 shows a DAG for three input parameters equivalent to the inequality of Eq. 1.

The node labeled "R" is a boolean variable that encodes the state of the constraint being satisfied, i.e. true or false. The graph structure can then be used to build a Bayesian network or Causal model by first assigning the possible states each value can take.

The parameters of the conditional probability tables can be learned directly from the data. The training dataset is produced by sampling the x_i design space and evaluating it with the computational model. The QOIs are then evaluated against the sampled constraint values c_k . The data is binned into discrete levels before training the BN. The model is ready for inference through discretized values.

Continuous-variable Bayesian networks are theoretically possible if the data support the training of conditional probability density functions of a specific family. This restricts the applicability of the model and requires specialized training and inference algorithms [12]. For these reasons, discretization of continuous variables through a suitable policy is preferred as it allows to use of robust discrete BN algorithms.

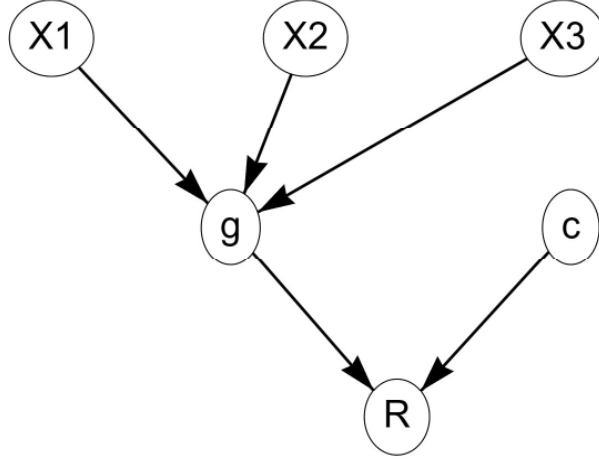


Fig. 2 DAG representation of the inequality in Eq. 1

With the model ready, every variable in the network can be queried by building a *Marginal Probability Distribution*, a distribution on the queried variable taking into account observed events. As an example with the model of Fig. 2, a query of interest would be the probability of satisfying the requirement R given a value of the constraint c_k . The calculated conditional marginal distribution would take into account every possible combination of the inputs x_i , averaging their contribution to the success rate. Adding more information to the query, for example, conditioning on a specific value of x_i would further update the prediction.

The probabilistic nature of the model allows one to handle simultaneously the uncertainty in the design space and the constraint value of the requirement. Engineers can query the model and build marginal probability distributions on the design space variables X_i and the quantities of interest g_k , assuming different conditions have been observed (such as a specific constraint value or the requirement must be satisfied). The following sections will elaborate on how to build these queries and which forms of inference are available to the designer once a Causal model of the design problem is available.

IV. Syntax for Probabilistic Reasoning

Inference with Bayesian Networks is performed through probabilistic queries (Eq. 2). These assign a probability to the unobserved variables given some observed evidence, also known as observed variables. The result is a probability distribution on the queried variables, which can be interpreted as a degree of belief that any of the possible values will be actually present.

$$P(\text{unobserved variables} \mid \text{observed variables}) \quad (2)$$

The mathematical statement of Eq. 2 should be read as "What is the probability distribution of the *unobserved variables* given the value of the *observed variables*". Variables can be combined with AND operators; for example, a query on both X_1 and X_2 can be written as:

$$P(X_1, X_2) \quad (3)$$

which would generate a joint probability distribution on the values of X_1 and X_2 . If no conditioning is present, the query returns the join distribution after summing out all the other variables in the Bayesian Network model.

The first step in constructing a query is to identify the variables to investigate. These can be extracted from the sentence that the designer should ask, such as "What value of X_1 is most likely to satisfy R if c is set to 0.5?" (see Fig. 2). The unobserved variables are those which are not assigned a value but are instead the target of the inference. These appear on the left-hand-side of the query. Observed variables or evidence are those quantities that have an assigned value, and appear on the right-hand side of the query. They can be either actually observed values or events that the designer assumes as true (e.g. imposing a requirement to be satisfied). In the example, the unobserved variable is X_1 and the evidence are $R = \text{True}$ and $c = 0.5$; therefore, the query is: $P(X_1 \mid R = \text{True}, c = 0.5)$.

V. Forms of Reasoning with Causal Bayesian Networks

This section is intended to introduce the reader to the basic forms of inference using Bayesian networks and their possible application to engineering problems. A Bayesian Network encodes a full representation of the joint probability distribution over its variables. Conditioning can be done upon any variable subset, supporting any direction of reasoning. If correctly built, the direction of the edges represents the cause-and-effect dependency between the variables. The outcome of the inference is a probability distribution over the queried variable, the marginal probability distribution, indicating the most likely outcomes given the observed evidence.

While the order of the variables in the calculation of a marginal distribution does not matter, it is recommended to build the model following logical cause-and-effect relationship between the variables. This provides intuitive explanation of the node connections and upgrades the BN into a Bayesian Causal network [13]. Figure 3 presents the three atomic inference modes of a BN. In normal practice, inferences mix these three modes, as any variable can be queried on any evidence.

A final point of note is the interpretation of an inference based on evidence observation. In a causal Bayesian Network, the observed variable propagates its information through the graph following the underlying conditional structure. Hence, the calculated probability will reflect the assumed cause-and-effect structure. This may not be correct if the model is used to analyze a counterfactual statement, where a deliberate intervention is present. In this case, the edges may require a modification to reflect the independent action of the node. For instance, consider a BN with three variables (A, B, C) connected the following way: $A \rightarrow B$, $A \rightarrow C$, and $B \rightarrow C$. The variable C is affected by A directly and indirectly through B. Observing B, would propagate the information to A, suggesting that A may have caused the change of state of B. However, if the state of B is changed independently, say through an external action, then the causal link between A and B must be severed for the inference to be correct, as the previous chain of cause-and-effect is no longer valid. This procedure is formalized in Judea Pearl's *do-Calculus* [14, 15]. Do-Calculus is not discussed in this article since there is no example where a potential intervention would sever the dependency connections. Indeed, the nodes where intervention may be required are the input parameters and the constraint values, all nodes without parents. However, more complex design models may have intermediate variables where intervention is necessary for counterfactual ("what if") reasoning.

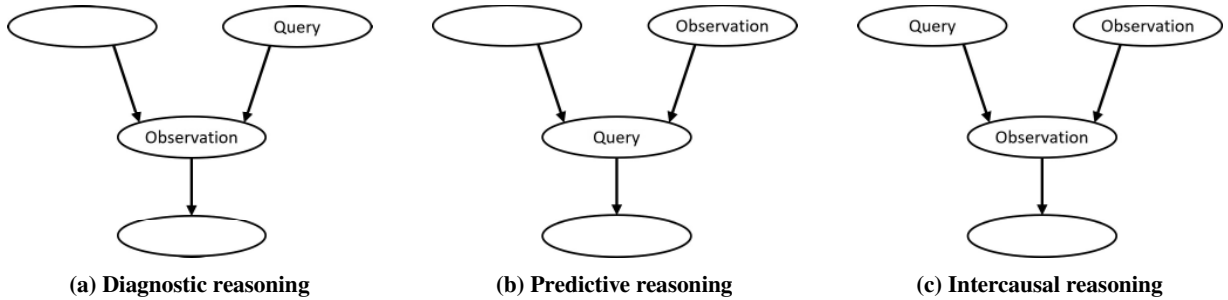


Fig. 3 Three basic forms of Bayesian network inference

A. Diagnostic Reasoning ("Why?")

One of the most common forms of reasoning involves finding the cause of what has been observed. This is called *Diagnostic Reasoning*, as it is common in the medical field, where the practitioner has to infer the underlying illness from the observed symptoms. The question associated with this reasoning mode is "Why" or "What is the cause" associated with an observed event. In a BN model the information would flow from the children nodes towards the parents, in the opposite direction of the edges (Fig. 3a).

In engineering, this form of reasoning can be found in the synthesis process, where the designer is searching the combination of geometry such it would produce the desired outcome. For instance, a beam section has to be designed to carry a given load safely. The flow of causality go from the geometry (and material properties) to its maximum strength, as one influences the other. The flow of information is reversed when the geometry has to be found given that the structure must carry a given load. If the problem would be modeled as a BN, this would be equivalent to conditioning the geometric variables on the observed fact that the maximum strength of the structure is above the load.

B. Predictive Reasoning ("What happens?")

Prediction consists in following the direction of dependence, that is, calculating the probability distribution of the child variables (Fig. 3b). This usage of BN is the most similar to any machine learning application, where the model is used to estimate the outcome of unobserved data. The question associated with this form of reasoning is "What would happen if...", however, it does not correspond completely to a "What if" analysis (also known as counterfactual reasoning). When using a BN for prediction, every form of dependency present in the network that is relevant for the inference are taken into account. Hence, the prediction is only the result of an observation on the parent variables and not an intervention on them. This distinction is important because the intervention breaks the causality connection between variables, modifying local conditional probability distributions.

The corresponding action in engineering is the analysis process. Calculations are carried out to estimate the effect of the design parameters on the figures of merit and system performance.

C. Intercausal Reasoning ("Explaining Away")

This form of inference is used to reason on causes which share a common effect (Fig. 3c). Normally the parent nodes would be independent of each other (no connection between them), but if an observation is made on both the child node and one of the parents, then the other parent node will be conditioned as an explanation of the observed effect. For example, imagine a BN where the statement "The grass is wet" is explained by either "Sprinkler on" or "Rain". If the observed evidence shows that the grass is wet and the sprinkler was on, then the probability that it rained would go down, as the other cause is more likely to have wetted the grass.

In a design setting, this procedure is useful in querying variables that share a common child node. An example include finding the expected values of an input parameter given a desired outcome on the quantity of interest and another input parameter. Similarly, an inference can be made to find the QoI values that can successfully satisfy a requirement for a given constraint value.

VI. Example Application

This example presents a Bayesian Network model of an aerostructural analysis problem encoding the effects of wing geometry and structural thicknesses on weight and performance. The OpenAeroStruct [16] framework was used with a wingbox model [17] to generate the data for training the BN. The aircraft is modeled after the Cessna Model 550 Citation II, a straight-wing business jet. Basic performance data was extracted from Jane's [18] and weight data from Roskam [19]. Two design points are evaluated: a typical drag cruise condition and a maneuvering point to size the structure (Table 1).

Table 1 Analysed flight conditions

C_L	V [KTAS]	Altitude [ft]	Notes
0.15	385	25000	Cruise condition
1.00	170	0	Maneuvering condition with load factor 2.5

The input parameters for the analysis are the aspect ratio and taper ratio of the wings, the thickness of the skin, and the thickness of the spar. The wing area is fixed to the Citation II value (31.83m^2), and the position of the front and rear spar match the original aircraft (30% and 66% of root chord). The thicknesses of the material is constant along the span, to reduce the number of input parameters. The output quantities are the drag coefficient at cruise, the mass of the wing, and if the structure has failed. The failure condition is evaluated through the Von Mises stress of four limit load conditions aggregated with a Kreisselmeier–Steinhauser function, as detailed in [17]. The wing is planar and untwisted. Details about the structural material parameters can be found in Tab. 2.

Figure 4 presents the Bayesian Network of the problem with the causal connections between the variables. Table 3 presents the description of each node and the possible values it can have. The node *Wing Mass Max* represents the budgeted mass of the wing as estimated by a weight engineer in the conceptual design process. It is modeled as a uniform distribution as an example of requirement uncertainty. Both the *Structural Failure* and *Wing Mass Requirement* nodes are boolean values indicating if they are true or false. The other nodes are continuous variables discretized into four ranges, using uniform spacing. The training dataset was generated with Latin Hypercube sampling of the design space of 200 points.

Table 2 Structural Material Specifications (Aluminium Alloy 7075)

Specification	Value	Notes
Material Density	2780 kg/m ³	
Young Modulus	73.1 GPa	
Poisson ratio	1.33	
Yield Strength	420 MPa	Divided by safety factor of 1.5

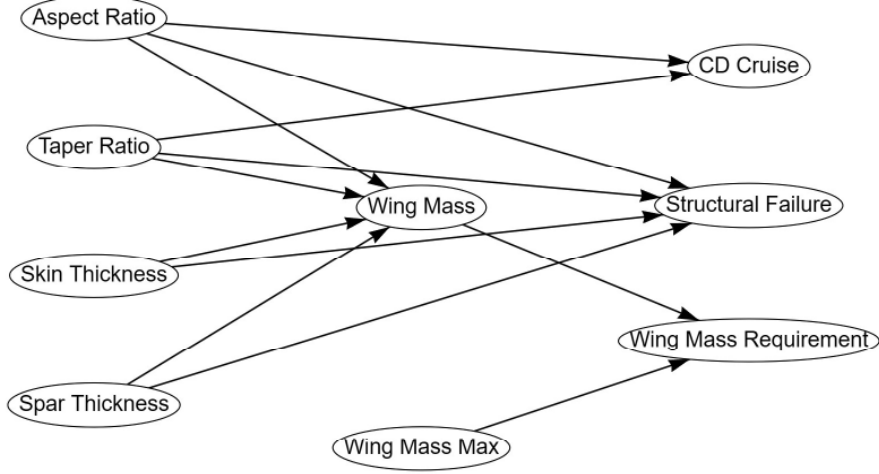


Fig. 4 Bayesian network of the aerostructural problem.

Table 3 Variables in the Bayesian Network

Name	Symbol	Values (including Range extremities)	Discipline
Aspect Ratio	AR	[6, 7.5, 9, 10.5, 12]	Aircraft Conceptual Design
Taper Ratio	λ	[0.3, 0.47, 0.65, 0.82, 1]	Aircraft Conceptual Design
Skin Thickness [m]	t_{skin}	[0.0015, 0.0086, 0.0157, 0.0228, 0.03]	Structures
Spar Thickness [m]	t_{spar}	[0.002, 0.0089, 0.0159, 0.0228, 0.03]	Structures
Wing Mass [kg]	M_w	[252-2329], 7 levels	Weight Analysis
C_D Cruise [Drag Counts]	$C_{D,cr}$	[9.34-9.77], 7 levels	Aerodynamics
Structural Failure	F	[True, False]	Structures
Wing Mass Max [kg]	$M_{w,max}$	[600,700,800,900,1000]	Aircraft Conceptual Design
Wing Mass Requirement	R_{wm}	[Satisfied, Not Satisfied]	Aircraft Conceptual Design

A. Inference on the Design Space

The design space is queried by imposing the wing structure does not fail under the maximum prescribed load and the maximum wing mass requirement is satisfied. The general mathematical form is:

$$P(AR, \lambda, t_{skin}, t_{spar} \mid F = \text{False}, R_{wm} = \text{True}) \quad (4)$$

This produces a marginal joint probability distribution on the four input parameters. The output from the query is a big probability table with the likelihood of each combination of levels. One could select the most likely ones to further explore with an optimization algorithm.

Figure 5 presents the marginal distributions of aspect ratio and taper ratio, after observing that the wing structure does not fail under its maximum design load and the wing mass requirement is satisfied. The skin and spar thicknesses

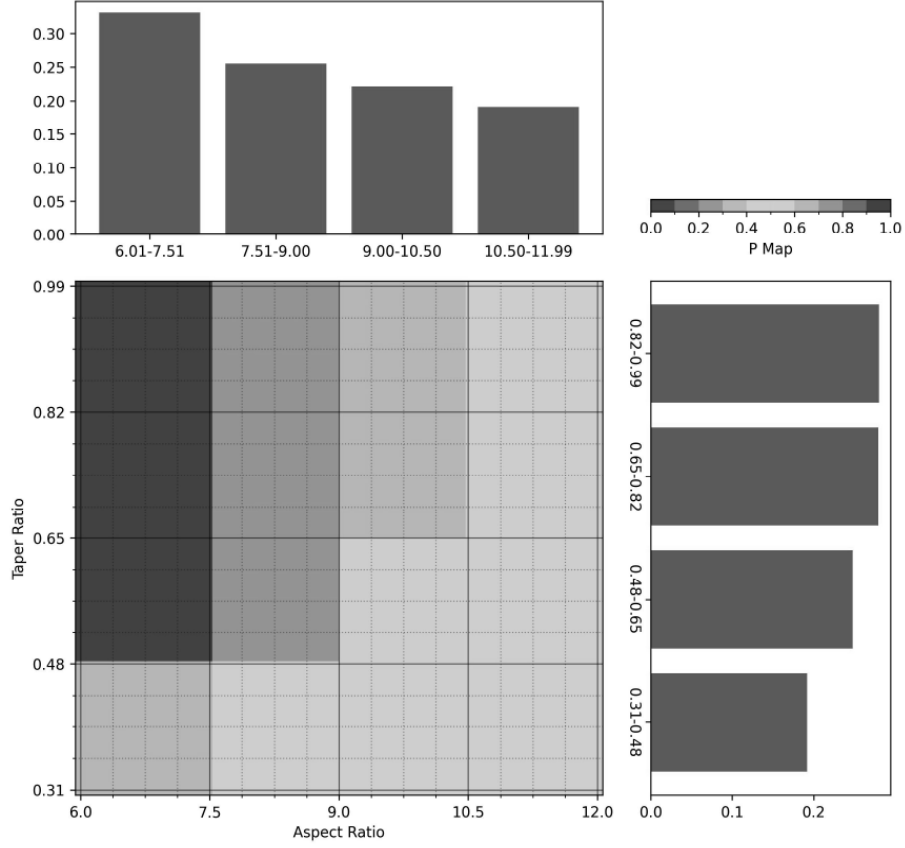


Fig. 5 Marginal probability distributions of Aspect Ratio and Taper Ratio, assuming the structure does not fail and the wing mass is within the budget (Eq. 4).

have been marginalised, averaging their effect out.

The heatmap in the centre is the joint distribution of the two parameters, normalised by the maximum value. The most likely combination, aspect ratio ranging between 6 and 7.5 and taper ratio between 0.82-1, is supported also by the single-parameter marginal distributions. As a consequence, one may approximate the likelihood of the joint distribution by multiplying the single-parameter marginal distributions. The BN indicates a preference for low aspect ratio, where the wing root stresses are smaller due to the lower wingspan. With regards to taper ratio, in the joint distribution the highest preference is in the range 0.48-0.99: higher taper would reduce the airloads at the extremities of the wing, lowering the root bending moment.

Figure 6 presents the full design space query, the darkest regions being the most likely to satisfy the two requirements. In addition of the aspect ratio and taper ratio values, consistent with the previous results, the most likely value of skin thickness ranges between 0.0158 and 0.0229 m. Compared to the previous query (Fig. 5), the two most promising design spaces have the taper ratio range of 0.48-0.65 and 0.65-0.82.

These forms of inference follow the diagnostic reasoning of section V.A, where information is propagated backwards from the desired effects to the causes. From there, the designer can eliminate the least likely configurations and refine the analysis with the remaining ones. Refinement can be iterative

B. Prediction of Quantities of Interest

After predicting which areas of the design space can satisfy the requirements, the model can be queried to predict which values of $C_{D,cr}$ and Wing mass can be expected. The mathematical query is:

$$P(C_{D,cr}, M_w | AR = a, \lambda = b, t_{skin} = c, t_{spar} = d) \quad (5)$$

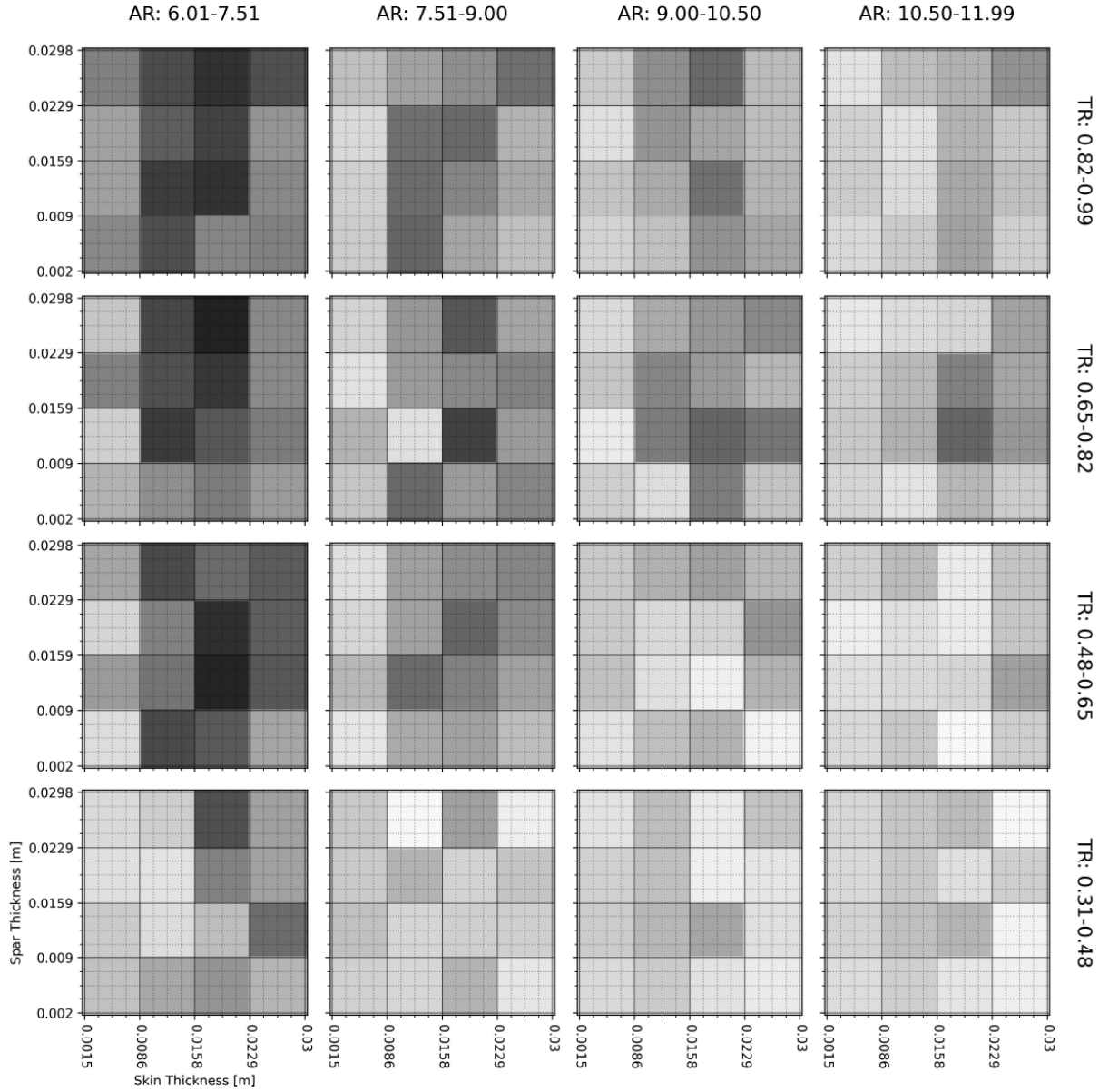


Fig. 6 Marginal probability distributions of all the design parameters, assuming the structure does not fail and the wing mass is within the budget (Eq. 4).

where the values of a , b , c , and d come from the results of the previous query. The information obtained can then be used to estimate the performance of the aircraft. As an example, Fig. 7 presents the query results using the values of the most likely and least likely design spaces of the Fig. 6. Notice that the most probable range of wing masses are within the constraint range (600-1000 kg). In terms of drag counts, both designs present a similar range between 9.53-9.59. This process allows one to check if the selected input space does actually yield the expected results in terms of performance or feasibility.

C. Requirements Uncertainty

In the previous design space exploration, the constraint value node *Wing Mass Max* was not observed. As a consequence, the calculated marginal probability distribution of the input parameters averaged out the effect of the

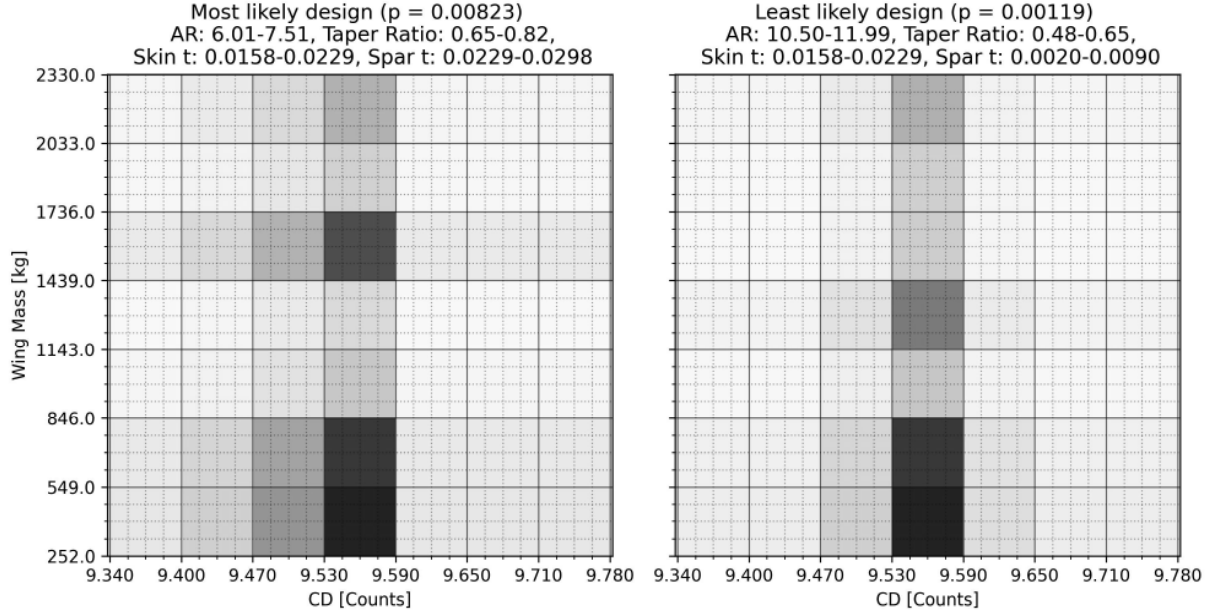


Fig. 7 Prediction of the objective space given the design space inputs (Eq. 5).

requirement. In this section, intercausal reasoning is used to analyze the effect of *Wing Mass Max* on the design space. This query is expressed as:

$$P(AR, \lambda, t_{skin}, t_{spar} | R_{wm} = \text{True}, M_{w,max} = w) \quad (6)$$

where w is a value of the maximum wing mass. Two examples with the lowest and highest ranges of w are shown in Figures 8 and 9. The blue color indicates the highest likelihood, while the red color is the lowest. Notice that with the more relaxed requirement, more of the design space has higher probability of satisfying the constraint. In both cases, the lowest skin thicknesses are preferred to satisfy the weight requirement. These are present because the query did not require to condition on the structural failure requirement. Introducing the non-failure condition, would exclude these portions of the design space like in Fig. 6.

VII. Conclusion

This article presented an application of Bayesian Networks in the context of engineering design. BNs are capable of modeling the cause-and-effect relationship with conditional probability distributions, using data generated from a computational design model. Inference with BNs allows the mapping of requirements to the design space, and the prediction of the effect of parameter selection on the quantities of interest. Additionally, the uncertainty of requirements can be handled and propagated to other variables, either design parameters or quantities of interest.

Several aspects remain open in formalising this method for engineering design. First, quantifying the number of required samples to train the BN and its sensitivity to the sample size. Second, the effects of variable discretisation on the BN inference. An higher discretisation would require more sample points to achieve the same level of accuracy. Finally, the structure of the BN can be learned from data, but the risk of spurious connections limits the full automation of this step.

Further development of this method would require the construction of an interactive software for constructing interactively the reasoning graphs, and managing the variables associated with the nodes. Proper data handling frameworks, such as proposed in [11], would be required for large Bayesian networks to be updated as new analysis is carried out. Finally, further intuitive design integration could be obtained by employing a Large Language Model (LLM) such as ChatGPT for translating common language into a probabilistic query [20, 21].

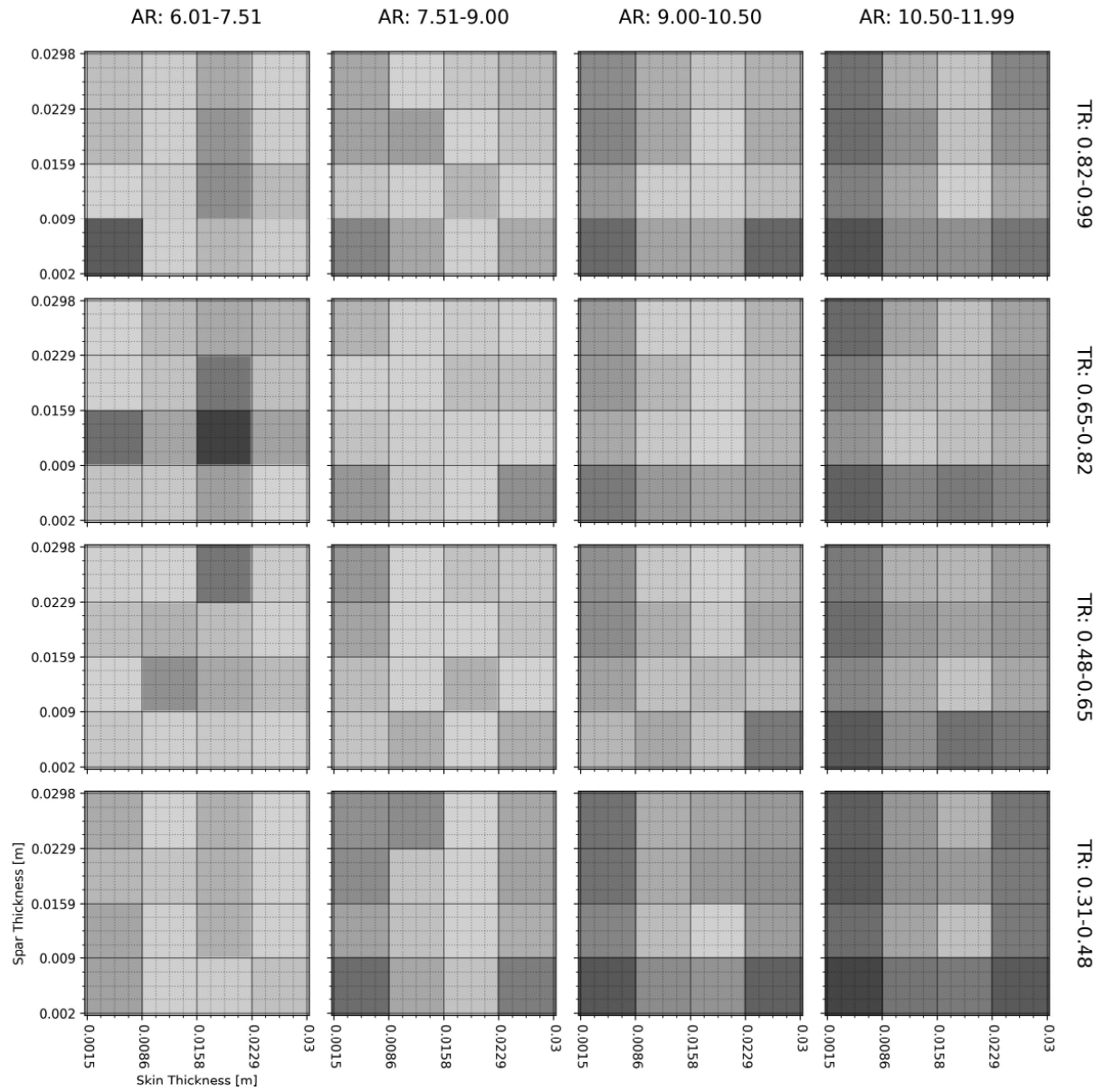


Fig. 8 Design Space query where the maximum wing mass is set to the 600-700 kg range.

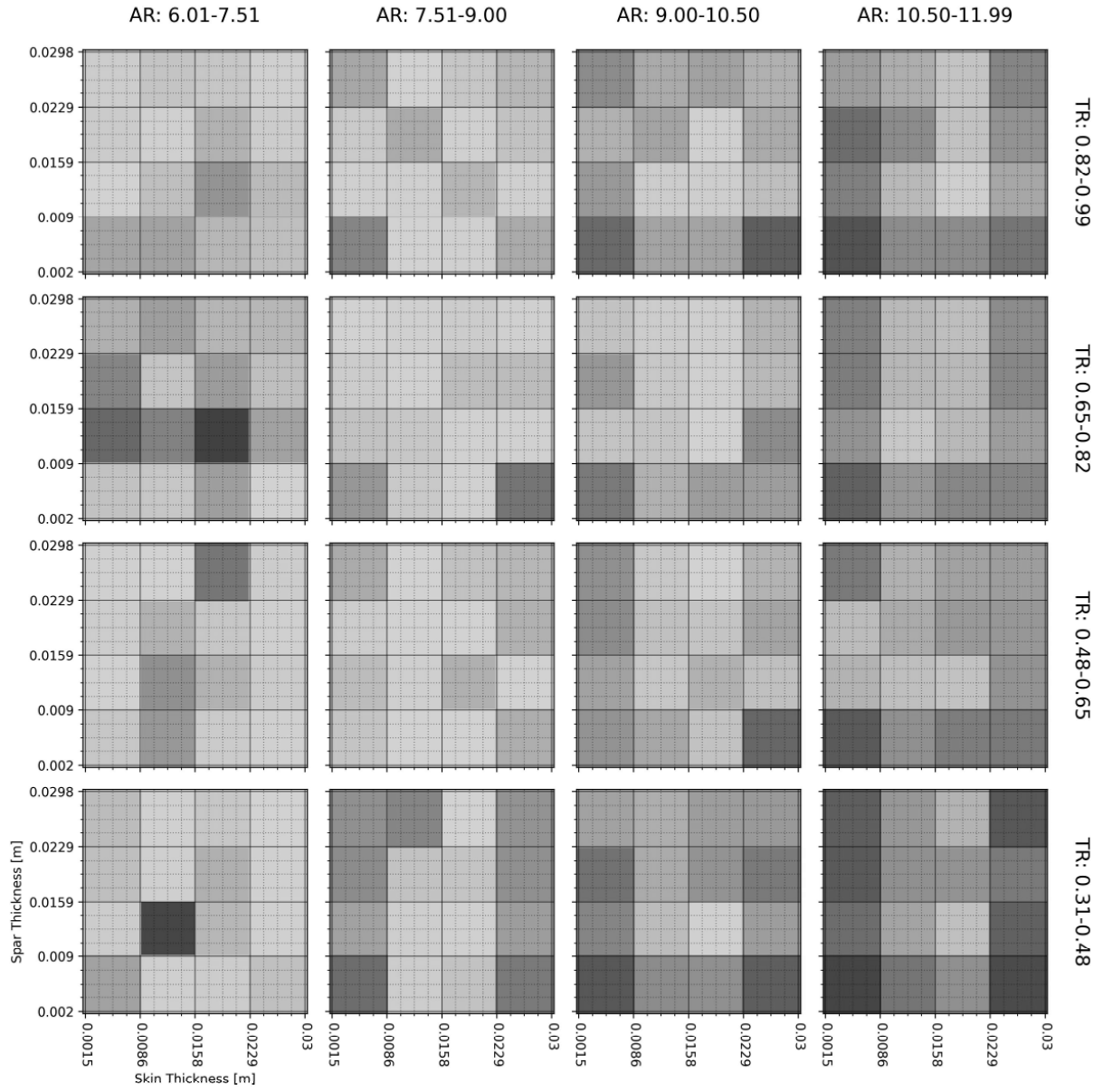


Fig. 9 Design Space query where the maximum wing mass is set to the 900-1000 kg range.

Acknowledgments

This project has received funding from Innovate UK under Grant Agreement No 10003388.

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2025-01-06

American Institute of Aeronautics and Astronautics (AIAA)

<https://doi.org/10.2514/6.2025-2032>

Spinelli A, Kipouros T. (2025) Aircraft design system requirements analysis with Bayesian Networks. In: AIAA SCITECH 2025 Forum, 6-10 January 2025, Orlando, FL, USA. Paper number AIAA 2025-2032