Technology forecasting with a probabilistic cross-impact method

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Tiivistelmä

Informaatio mahdollisista tulevaisuudentiloista on tärkeää päätösten vaikuttaessa pitkälle tulevaisuuteen. Uskottavia tulevaisuudentiloja voidaan luoda skenaariomenetelmillä. Tässä työssä käytettiin todennäköisyyspohjaista ristivaikutusmenetelmää luomaan yhteistodennäköisyysjakauma skenaarioille siviili- ja sotilaskäyttöisistä miehittämättömistä lennokeista Suomessa vuonna 2040. Skenaarioiden analysointia varten luotiin Bayes-verkko skenaariotodennäköisyyksien pohjalta.

Ristivaikutusanalyysissä skenaariot ovat tutkittavalle systeemille olennaisten epävarmuustekijöiden tilojen toteumista koostuvia kokonaisuuksia. Skenaariossa jokainen epävarmuustekijä on yhdessä tilassa, jolloin erilaisten skenaarioiden lukumäärä on epävarmuustekijöiden tilojen ainutlaatuisten kombinaatioiden lukumäärä. Skenaarioiden lukumäärä on usein niin suuri, ettei skenaarioiden yhteistodennäköisyysjakauman luomiseksi kannata yrittää arvioida jokaista erillistä skenaariotodennäköisyyttä, vaan ne voidaan laskea todennäköisyyspohjaisella ristivaikutusmenetelmällä. Todennäköisyyspohjaisen ristivaikutusmenetelmän käyttämiseksi asiantuntijapaneeli arvioi tutkittavan systeemin kannalta olennaisten epävarmuustekijöiden tilojen todennäköisyydet ja näiden tilojen väliset ristivaikutuskertoimet. Bayes-verkko rakennettiin skenaariotodennäköisyyksien pohjalta valmiilla ohjelmistolla.

Työssä löydettiin todennäköisimmistä skenaarioista selkeitä yhteisiä piirteitä. Siviilikäyttöiset miehittämättömät lennokit ovat massatuote, joita kuka tahansa voi omistaa. Näiden osalta lainsäädäntö ei muutu merkittävästi nykyisestä. Sotilaskäyttöiset miehittämättömät lennokit ovat vaikeita havaita, mutta toisaalta helppo tuhota kustannustehokkaasti ja ne kykenevät toimimaan ihmisen ohjaamina lähes autonomisesti. Lasketun Bayes-verkon pohjalta tarkasteltiin todennäköisintä osaskenaariota koskien sotilaskäyttöisiä lennokeita, sekä siviilikäyttöisiä lennokeita. Sotilaslennokkien epävarmuustekijöillä havaittiin olevan suurempi vaikutus siviililennokkien epävarmuustekijöihin kuin toisinpäin. Havaittiin myös, että lennokkien kantokyvyn kasvaessa, niiden käyttö keskittyi todennäköisemmin sotilaskäyttöön kuin siviilikäyttöön.

Avainsanat Todennäköisyyspohjainen ristivaikutusanalyysi, skenaarioanalyysi, Bayes-verkko, miehittämätön lennokki

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Abstract of the bachelor's thesis

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Abstract

Information about possible future states is important when the consequences of decisions extend far into the future. Plausible future states can be created using scenario methods.

In cross-impact analysis, scenarios are comprehensive combinations of the states of relevant uncertainties for the system under study. In a scenario, each uncertainty factor is in one state, so that the number of different scenarios being the unique combination of states for the uncertainty factors. The number of scenarios is often so large that attempting to assess each individual scenario probability for creating a joint probability distribution of scenarios is not practical. Instead, probability-based cross-impact analysis can be used. To utilize probability-based cross-impact analysis, an expert panel assesses the probabilities of states for the relevant uncertainty factors from the perspective of the studied system, as well as the cross-impact multipliers between these states. A Bayesian network can be constructed based on scenario probabilities using a pre-existing software.

In this thesis, a probability-based cross-impact method was used to create a joint probability distribution for scenarios of civilian and military unmanned aerial vehicles in Finland in the year 2040. A Bayesian network was constructed for the analysis of scenarios based on scenario probabilities. Clear common characteristics were found among the most probable scenarios. Civilian unmanned aerial vehicles (UAVs) are mass-produced and can be owned by anyone. In terms of legislation, there is no significant change compared to the present. Military UAVs are difficult to detect but, on the other hand, easy to destroy cost-effectively, and they can operate nearly autonomously under human guidance. Using the created Bayesian network, the most probable partial scenarios for military UAVs and civilian UAVs were examined. Military uncertainty factors had greater impact on the civilian uncertainty factor than vice versa and as the carrying capacity of UAVs increased, the use of UAVs was more likely to focus on military use.

Keywords Probabilistic cross-impact analysis, scenario analysis, Bayesian network, unmanned aerial vehicle

Contents

1 Introduction

Energy crisis resulting from Russian invasion of Ukraine has demonstrated the need for structured methodology of futures research. Energy sector and national defence, for example, involve major investments, which have long-lasting effects; thus, requiring well-founded evidence in different stages of decision making process. Numerous methods of scenario analysis have established their place among the most widely employed set of tools for long-term planning (Bunn and Salo, 1993).

Bunn and Salo (1993) defined scenarios as "a route through decision tree, supported by a narrative catalougue of events and opportunities". Scenarios are in the core of cross-impact models which are scenario planning techniques that acknowledge that realizations of events affect other events (Bañuls and Turoff, 2011). These events appear through event probabilities, that is, the conditional probabilities of events are affected once another event has occurred. Monte Carlo simulation methods have been an established way to calculate scenario probabilities (Roponen and Salo, 2022). However, Monte Carlo-based methods demand a large number of simulations to get accurate results, which may be time consuming.

This thesis applies probabilistic cross-impact analysis (PCIA) method developed by (Roponen and Salo, 2022) to scenario analysis. The method utilizes probabilistically interpreted cross-impact statements to produce a joint probability distribution over all possible scenarios by solving a series of optimization models. Furthermore, these probability distributions can be applied to produce Bayesian networks, which open new possibilities to the scenario method. In addition, the probabilistic nature of the method makes it compatible for wide range of risk analysis and decision making applications.

First, in the case study, scenario probability distributions are computed for each scenario on the basis of expert judgments on Unmanned Aerial Vehicles (UAVs). Afterwards, conditional probability distributions and information on conditional independence of the uncertainty factors are then used to construct a Bayesian network using GeNIeModeler software (BayesFusion, 2021). The Bayesian network is then applied to explore relations between the uncertainty factors.

The remainder of this thesis is structured as follows: In Section 2 scientific literature about scenario planning, cross-impact methodologies and Bayesian networks are reviewed. In Section 3 methodology of probabilistic cross-impact analysis and Bayesian networks are presented. In Section 4 PCIA is applied to calculate scenario probabilities for scenarios of Unmanned Aerial Vehicles (UAVs) case study and the results are analyzed using Bayesian network. In Section 5 conclusions and future research suggestions are presented.

2 Background

2.1 Technology forecasting

Technology forecasting plays a vital role in the military by fulfilling two primary objectives: facilitating investment planning for future weapon systems and enabling the anticipation of adversaries' capabilities (Malmi et al., 2011). The former involves modeling various prospective weapon systems and evaluating their potential impact on one's own performance, thereby assisting decision-makers in making informed choices regarding optimal investments. On the other hand, forecasting involves modeling and analyzing potential future weapon systems of adversaries, offering valuable insights for devising preemptive measures to tackle forthcoming challenges.

Cho and Daim (2013) reviewed technology forecasting methods, which can be divided roughly into four categories; Exploratory methods, normative methods, intuitive thinking and the feedback method. Exploratory scenario planning involves exploring a wide range of possible future scenarios without specific preferences or constraints. It aims to uncover various potential futures by considering different factors, trends, and uncertainties. This approach is often used when there is a high level of uncertainty and a need to generate diverse and creative scenarios, which help identifying potential risks, opportunities and challenges. Cross-impact analysis was categorized into discontinuous exploratory technology forecasting tools by Cho and Daim (2013), in their review of origins and historical development of technology forecasting methods. Normative scenario planning, on the other hand, takes a more focused and prescriptive approach. It starts with a desired future outcome or a set of goals and works backward to determine the necessary steps to reach that desired future. Normative scenarios are built based on specific assumptions and preferences, with the intention of guiding decision-making and shaping actions towards a preferred future. This approach is commonly used when organizations have a clear vision or strategic direction and want to align their efforts accordingly. Other two are intuitive thinking and the feedback method. They are employed to improve the scenario development process. Intuitive thinking utilizes individuals' intuition and expertise, encouraging creative brainstorming and subjective judgments to generate scenarios. The feedback method involves obtaining input from stakeholders through interviews, workshops, or surveys, enabling iterative refinement of the scenarios based on their perspectives (Jantsch, 1967).

2.2 Cross-impact analysis

Early forecasting methods were generally based on consensus of expert panels, such as Delphi method (Bañuls and Turoff, 2011). However, these kinds of expert judgement based methods had a weakness in fully recognizing interactions between the forecast elements. The need to consider events having an impact on probabilities of other events occurring led to development of cross-impact analysis by Gordon and Hayward (1968). In further detail, the techniques of CIA uses expert knowledge to produce a set of conditional probabilities for scenario events of how the occurring events impact on probabilities of other related events (Bunn and Salo, 1993). The scenario probabilities achieved by calculating them from the priori probabilities assessed by the experts are assumed to be more accurate than the scenario probabilities the experts could directly assess, because the scenarios often are multidisciplinary in a sense that multiple experts of different disciples must need to be consulted. Furthermore, additional problems may arise, if the experts are not familiar with probabilistic thinking (Bunn and Salo, 1993).

Cross-impact methodology has been further expanded into numerous variations in recent decades. Methods that identify plausible scenarios based on non-probabilistic factors used to compute relations among events, can be referred to as structural analysis methods (Roponen and Salo, 2022). The absence of probabilities in these methods make their calculations more straightforward, which result in good applicability for exploratory purposes. Such methods include cross-impact balances method by Weimer-Jehle (2006) and consistency analysis method by Seeve and Vilkkumaa (2022).

Roponen and Salo (2022) develop probabilistic cross-impact method which utilizes a well-justified definition of cross-impact statements and constructs probability estimates that consider all possible scenarios. It is specifically based on estimating the probabilities of all potential scenarios. While many probabilistic cross-impact methods commonly employ Monte Carlo simulation, this technique often necessitates an excessively high number of iterations to achieve accurate results, particularly when dealing with a large number of scenarios. In contrast, the method demonstrates favorable computational scalability when confronted with problems involving numerous uncertainty factors, particularly if the number of probabilistic dependencies between these factors is not too high.

2.3 Bayesian networks

Bayesian networks provide a helpful tool for reasoning scenarios in multiple different disciplines, such as energy policy scenarios (Cinar and Kayakutlu, 2010) and multisectoral flood damages (Harris et al., 2022). Bayesian networks (BNs) are a powerful tool for modeling systems by representing variables as nodes connected by arcs that depict their dependent relationships. Chen and Pollino (2012) examine good ways of BN modeling. These networks explicitly capture cause-effect assumptions and incorporate uncertain information, propagating this uncertainty throughout the model. Conditional probability tables attached to each node define the strength of relationships and express beliefs as probabilities. BNs update the probabilities of other nodes through belief propagation, using Bayes' theorem, by substituting a priori beliefs with observed evidence. This makes BNs suitable for both diagnostic and explanatory purposes, allowing users to understand the reasoning behind model outputs and promoting system learning. Unlike black-box models like neural networks, BNs provide transparency by displaying variable interactions. Another advantage of BNs is their ability to classify and predict states or events even with partial or uncertain data, setting them apart from traditional statistical models that require large empirical datasets (Chen and Pollino, 2012). Roponen and Salo (2022) used Bayesian networks to represent scenarios, so that two nodes of a network that share an edge are not conditionally independent. In this representation, the nodes represent uncertainty factors and edges represent conditional dependencies between the nodes.

3 Methods

3.1 Scenarios

There are many definitions of scenarios. For example, Kahn and Wiener (1967) describe a scenario as a hypothetical sequence of events created to draw attention to causal processes and decision points, while Ducot and Lubben (1980) define a scenario as a collection of potential occurrences connected by various relations within a specific field and time period, allowing for a subset to approximate the entire set based on fundamental hypotheses. For the purpose of probabilistic cross-impact method, a definition by Salo et al. (2022) is used. In their approach, Uncertainty factors are modelled as random variables:

$$X^i, i = 1, ..., n.$$

These uncertainty factors have possible realizations in set:

$$S^i = x^i_1, ..., x^i_{n_i}.$$

A single scenario is a combination of outcomes for all uncertainty factors:

$$s = (x^1, ..., x^n).$$

The set of scenarios can be represented as the Cartesian product, which includes all possible combinations of outcomes:

$$S = \bigtimes_{i=1}^{n} S^i.$$

The number of elements in this set depends on the number of uncertainty factors and their possible outcomes. The total number of elements is

$$|S| = \prod_{i=1}^{n} n_i.$$

For instance, if there are 4 factors with 3 outcomes in each of them, the total number of scenarios is $3^4 = 81$, so the number of scenarios increases exponentially with the number of uncertainty factors.

3.2 Cross-impact multipliers

Cross-impact multipliers are interpreted by Salo et al. (2022) as

$$C_{ab} \coloneqq \frac{P(a|b)}{P(a)}, \tag{1}$$

where C_{ab} is defined to be cross-impact between events a and b. The cross-impact multiplier states how many more times likely is event a to happen when event b has occurred. Furthermore, the cross-impact multipliers are symmetric

$$C_{ab} = \frac{P(a|b)}{P(a)} = \frac{P(a \wedge b)}{P(a)P(b)} = \frac{P(b|a)}{P(b)} = C_{ba}. \tag{2}$$

From Equations 1 and 2 we get

$$p_{k|l}^{i|j} = C_{kl}^{ij} p_k^i \Leftrightarrow p_{kl}^{ij} = C_{kl}^{ij} p_k^i p_l^j, \tag{3}$$

where $p_{kl}^{ij} = P(X^i = k, X^j = l)$ and C_{kl}^{ij} for any $k \in S_i$ and $i \in S_j$.
Figure 1 shows a skeleton of a cross-impact matrix with 4 uncertainty factors. Each rectangle is a submatrix where the cross-impact statements are stored. Only white cells need to be elicited and they can be left empty if the two uncertainty factors are conditionally independent. Cross-impacts in black cells in the diagonal need not be elicited, because they were not defined, because a single uncertainty factor cannot have multiple conflicting outcomes. Grey cells are not elicited because the multipliers are symmetric as shown in Equation 2.

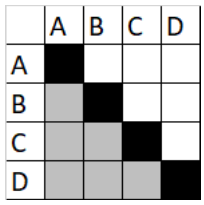


Figure 1: Skeleton of a cross-impact matrix.

3.3 Conditional probability updating

Salo et al. (2022) propose a probabilistic method that involves respondents specifying lower and upper bounds for cross-impact multiplier, converting these bounds into scenario probabilities, and deriving lower and upper bounds for expected disutility to assess the overall risk level and determine its acceptability for the systems. However, the cross-impact statements are presumed to be fully consistent, thus, an optimization problem with quadratic constraints is required to be solved, in order to acquire a probability distribution which fits the best the statements. Roponen and Salo (2022) formulate such an optimization model that incorporates cross-impact statements, including inconsistent ones and various other types of statements that impose constraints on scenario probabilities, and subsequently combines them in a manner that results in a probability distribution over scenarios that maximizes the fitting with the given statements. The derivation of scenario probabilities relies on estimates, including marginal probabilities, $\hat{p}_k^i$ and $\hat{p}_l^j$, for all uncertainty factors and their outcomes, as well as cross-impact multipliers, $\hat{C}_{kl}^{ij}$, for selected pairs of uncertainty factors and their outcomes, allowing for the derivation of a probability distribution over scenarios even when information about certain cross-impact multipliers is lacking.

Scenario probabilities can be calculated by iteratively utilizing the marginal probabilities of the initial uncertainty factor $p(s_1)$, determining the conditional probabilities $p(s_2|s_1)$ that provide the optimal match to the cross-impact multipliers of the outcomes of the first two uncertainty factors. Subsequently, the probabilities for partial scenarios encompassing these two uncertainty factors can be estimated by employing these conditional probabilities. Given the ordering of the uncertainty factors, a relationship is built as follows;

$$\begin{aligned} p(s) &= p(s_N|\boldsymbol{S}_{1:N-1})p(\boldsymbol{S}_{1:N-1}) \\ &= p(s_N|\boldsymbol{S}_{1:N-1})p(s_N-1|\boldsymbol{S}_{1:N-2})p(\boldsymbol{S}_{1:N-2}) \\ &= ... \\ &= p(s_N|\boldsymbol{S}_{1:N-1})p(s_N-1|\boldsymbol{S}_{1:N-2})...p(s_2|s_1)p(s_1). \end{aligned} \tag{4}$$

3.3.1 Optimization model

An optimization model for calculating the conditional probabilities is formulated by Roponen and Salo (2022) as follows:

Objective

$$\min_{q(k|s_{1:i-1})} \quad \sum_{j=1}^{i-1} \sum_{(k,l)\in R_{ij}} [(\sum_{s\in S_{1:i-1|s_j=I}} q(k|\boldsymbol{s})q(\boldsymbol{s})) - \hat{C}^{ij}_{kl}\hat{p}^i_k\hat{p}^j_l]^2 \tag{5}$$

Constraints

$$\sum_{s\in S_{1:i-1}} q(k|\boldsymbol{s})q(\boldsymbol{s}) = \hat{p}^i_k \qquad \forall k \in 1,2,...,n_i \tag{6}$$

$$\sum_{k=1}^{n_i} q(k|\boldsymbol{s}_{1:i-1}) = 1 \qquad \forall \boldsymbol{s}_{1:i-1} \in S_{1:i-1} \tag{7}$$

$$q(k|\boldsymbol{s}_{\boldsymbol{1:i-1}}) \geq 0 \qquad \forall k \in 1,2,...,n_i, \boldsymbol{s}_{i:i-1} \in S_{i:i-1} \tag{8}$$

Where $q(k)$ is set to $\hat{p}^1_k$ at the beginning of the iteration process for any $k \in S_1 = 1,...,n_1$. The third summation in the objective function takes sum over partial scenarios where j-th state of an uncertainty factor is the same as in relation R_{ij}, where R_{ij} is a binary relation $R_{ij} = S_i \bigtimes S_j$, such that $(s_i, s_j) \in R_{ij}$ if and only if the cross-impact multiplier $\hat{C}^{ij}_{kl}$ is available. The probabilities for the next partial scnearios, which are created by adding the states of the i-th uncertainty factor, $k \in S_i$, to the previous partial scenarios, $\boldsymbol{s}_{1:i-1}$, can be defined using formula $q(\boldsymbol{s}_{1:i-1}, k) = q(\boldsymbol{s}_{1:i-1})q(k|\boldsymbol{s}_{1:i-1})$. As a result, constraint (6) ensures that the computed probabilities exactly match the estimated marginal probabilities $\hat{p}^i_k$ for the outcome $s_i = k$. This guarantees a precise alignment between the computed probabilities and the estimated marginal probabilities. Finally, the last two constraints guarantee that the probability distributions are non-negative and they sum up to 1, in other words, are well-defined. MATLAB r2022b is used as a solver.

3.4 Bayesian networks

Bayesian networks are directed acyclic graphs that represent uncertainties and probabilistic dependencies between variables (Stephenson, 2000). Figure 2 is presents a simple example of a Bayesian network, where the two main components are nodes represented by spheres and edges represented by arrows. The nodes represent variables or events, while the edges represent causal relationships between the nodes. The dependencies between the nodes are conditional probability distributions and each node has its own conditional probability table, that quantifies the probabilistic relationship of the node and its parent nodes. Directed edges represent parent-child relationship of the nodes, in other words which variables condition a given variable(Stephenson, 2000). For example, in Figure 2 alphabetical order represents one topological ordering of the graph. Given nodes $\boldsymbol{X} = X_1, X_2, ..., X_n$, the joint probability distribution of a Bayesian network can be calculated by

$$P(\boldsymbol{X}) = \prod_{i=1}^{n} P(X_i|Parents(X_i)), \tag{9}$$

which means that the joint probability of all values can be calculated by taking the product of the probabilities of each variable, given the values of its parent nodes. On the other hand, if there exists no edge between two nodes, then the nodes are conditionally independent given their parents (Stephenson, 2000). In the case study of this thesis, a Bayesian network is employed to compute probability distributions for the states of uncertainty factors, given the specification of probability distributions for certain selected nodes.

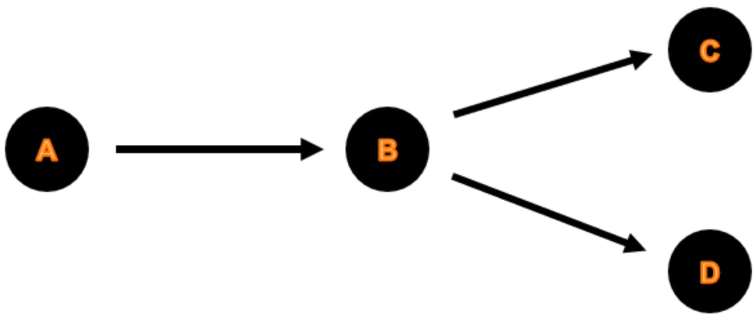


Figure 2: An example of a Bayesian network.

4 Case study

In this section a case study on analysing scenarios concerning unmanned aerial vehicles (UAV) using probabilistic cross-impact method. UAVs have proved to be an interesting topic regarding futures research. For example, in the Russian-Ukrainian war, commercial UAVs have become an irreplaceable tool for reconnaissance and artillery weapons fire adjustment (Chávez, 2023). Commercial drones have been previously used by terrorist groups in conflicts, however, their use to this extent in modern total war by a major power is revolutionary and will likely have great effects to future wars (Chávez, 2023). The rise of new warfare technologies will most likely create a need to counter the enemy's use of the technology. Effectiveness of the future countermeasures is an open question and answer to that will shape the adaptation of any new war technology.

4.1 Expert judgments

Table 1 presents the uncertainty factors, their corresponding outcomes, along with their marginal probabilities. This information, including the cross-impacts, was gathered through expert elicitation. The cross-impact multipliers were assessed values using a seven-point integer scale from -3 to 3. Values were assigned only to pairs of factors where the assigned values contained substantial information about each other. Evaluated pairs of uncertainty factors are indicated as X in Figure 3, while the pairs without X are conditionally independent. The entire cross-impact matrix is presented in Figure 4. Cross-impact multipliers in lower triangle of the cross-impact matrix are not assessed, because the cross-impact multipliers are symmetric, as shown in Equation 2. Another appealing characteristic of PCIA, is that the cross-impact statements do not need to be fully consistent, as pointed out in Subsection 3.3. This reduces the effort required by the elicitation process, because all of the rows of uncertainty factors do not need to sum up to one, as can be seen in Figure 4.

Uncertainty factor	Outcome/Description	Probability
Drone price (Civilian use)	Mass product	0.7
	Rare product	0.25
	Avalaibility collapses	0.05
Legislation for civilian drones	No legislation	0.3
	Some legislation	0.5
	Use banned	0.2
Prevalence in civilian use	Everybody owns a drone	0.6
	Some amateur/professional users	0.35
	Very little	0.05
Carrying capacity	Stays the same as current	0.2
	Doubles	0.4
	Multiples	0.4
Fading properties of military UAVs	Easy to detect	0.2
	Challenging to detect (current)	0.6
	Nearly impossible to detect	0.2
Durability against weapon systems	Easy and cheap to destroy	0.5
	Easy and expensive to destroy	0.35
	Hard to destroy	0.15
Typical autonomy of military UAVs	Remote controlled	0.3
	Self-directed, but under supervision	0.6
	Completely autonomous	0.1

Table 1: Uncertainty factors with descriptions of outcomes and their probabilities.

	1	2	3	4	5	6	7
1. Drone price (Civilian use)		X	X	X			
2. Legislation for civilian drones			X				
3. Prevalence in civilian use				X			
4. Carrying capacity						X	
5. Fadin properties of military UAVs						X	X
6. Durability against weapon systems							
7. Typical autonomy of military UAVs							

Figure 3: Uncertainty factors and independencies. Evaluated cross-impacts are marked with X for each uncertainty factor pair and white cell mark conditional independency of the pairs.

	Drone price (Civilian use)			Legislation for civilian drones			Prevalence in civilian use			Carrying capacity			Fading properties of military UAVs			Durability against weapon systems			Typical autonomy of military UAVs		
Drone price (Civilian use)				2	1	-2	3	0	-3	0	1	1									
				0	0	0	0	1	0	0	0	0									
				-3	0	2	-3	-1	3	2	0	-2									
Legislation for civilian drones							2	-1	-3												
							1	0	-1												
							-3	-1	3												
Prevalence in civilian use										-1	0	2									
										0	0	1									
										0	0	-1									
Carrying capacity																2	0	-2			
																0	0	0			
																-2	1	2			
Fading properties of military UAVs																2	0	-1	2	0	-1
																1	0	-1	0	0	0
																-2	-1	2	-3	1	2
Durability against weapon systems																					
Typical military UAV autonomy																					

Figure 4: Cross-impact matrix of the case study.

4.2 Results

Method developed by Roponen and Salo (2022), presented in Section 3, was used to calculate scenario probability distribution for total number of $3^7 = 2187$ scenarios. Ten most probable scenarios are shown in Table 2. There is clear uniformity among them.

The 10 most probable scenarios

- Drone price → mass product
- Prevalence of civilian use → nearly everyone owns a drone
- Fading properties of military UAVs → challenging to detect
- Legislation for civilian UAVs → some legislation
- Durability against weapon systems → cheap and easy to destroy
- Typical autonomy of military UAVs → self directed, but under supervision

On the other hand, there are no consistent patterns for carrying capacity among these ten most probable scenarios. Indeed, the influence of carrying capacity on uncertainty factors 5-7 was found to be minimal, as evidenced by the data in Table 2. While carrying capacity exhibited significant variation, the remaining uncertainty factors experienced only marginal changes. This observation was further supported by the constructed Bayesian network, wherein no configuration of carrying capacity states demonstrated a substantial impact exceeding a few percentage points on uncertainty factors 5-7.

These results suggest that in 2040, drones are likely to become a mass-produced commodity, resulting in a significant drop in their prices. They have become widely prevalent in civilian use, to the extent that nearly everyone owns a drone. However, the properties of military UAVs have evolved in such a way that they are hard to detect and track effectively.

In terms of legislation, there are some regulations for civilian UAVs. This suggests that authorities have recognized the need to address the increasing prevalence of drones in society. The legislation achieve a balance between risks and concerns of civilian UAVs and reponsible drone use. On the other hand, military UAVs have become relatively easy and cost effective to destroy, because military research centers have started to address the issue of threat potential threats that UAVs pose by advancing counter-UAV technology. Military UAVs are not yet fully autonomous and their operating require human involvement. While military operations cannot solely rely on UAVs, they still offer valuable aid in gathering information, for example.

Scenario	States of uncertainty factors	Probability
1.	1,2,1,2,2,1,2	2.95%
2.	1,2,1,1,2,1,2	1.87%
3.	1,2,1,2,2,2,2	1.75%
4.	1,2,1,3,2,1,2	1.55%
5.	1,2,1,2,2,1,1	1.52%
6.	1,1,1,2,2,1,2	1.47%
7.	1,3,1,3,2,1,2	1.31%
8.	1,2,1,2,3,3,2	1.07%
9.	2,2,2,3,2,1,2	1.00%
10.	1,2,1,2,1,1,1	0.98%

Table 2: Ten most probable scenarios and their states of uncertainty factors.

A Bayesian network was constructed using GeNIeModeler software (BayesFusion, 2021). This required conditional probability distributions and conditional independence information. A network with the elicited state probabilities is in Figure 5. Furthermore, the GeNIeModeler software allowed to change state probabilities and further explore partial scenarios. Two different partial scenarios were generated with the software; most probable civilian UAV and military UAV partial scenarios. In these partial scenarios, uncertainty factors 1-3 describe the state of civilian UAVs and 4-7 describe the state of military UAVs.

Figure 6 presents the most probable partial scenario considering civilian UAV factors with a significant probability of 30.9%. Uncertainty factor 1-3 are same as in most of the ten most probable scenarios. Probability distribution of carrying capacity states is uncertain with doubling as its most likely state. This configuration does not have any impact on states 5-7, if it is compared to the most likely scenario.

Figure 7 presents two different military UAV partial scenarios with equal probability of 8.22%. Carrying capacity has significant impact on uncertainty factors 1-3 depending if it is in state 2 or 3. Carrying capacity has a vital role in flight range and applications of UAVs. If carrying capacity doubles, civilian drones are more likely to become a mass product and they are prevalent in civilian use. On the other hand, if carrying capacity multiples, civilian drones are more likely to be rarer and their prevalence in civilian use is also rarer. Furthermore, the use of UAVs tends to have more military applications as the carrying capacity increases. In this case, legislation of UAVs is comparatively more lenient.

It is likely that the limited connecting edges between military and civilian uncertainty factors cause them to act a bit as their own separate worlds that do not interact very much. Moreover, the states of civilian uncertainty factors can be changed only if carrying capacity changes, because only it connects the rest of the military uncertainty factors to the civilian uncertainty factors. In other words, the uncertainty factors 5-7 are conditionally independent with the civilian uncertainty factors. Furthermore, changes in the military uncertainty factors were more likely to change states of the civilian uncertainty factors through carrying capacity than vice versa.

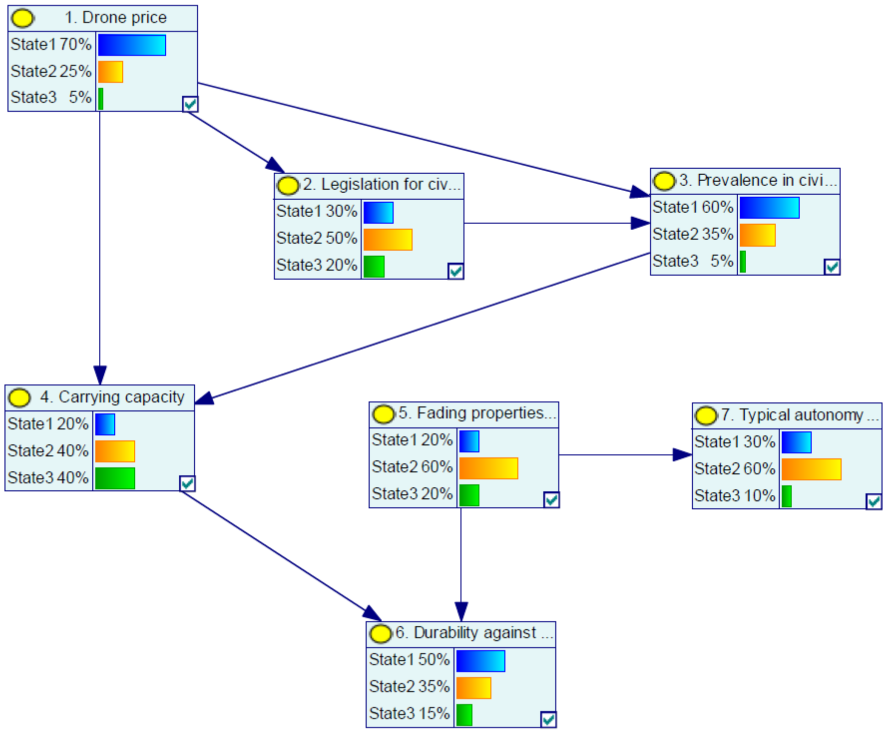


Figure 5: The constructed Bayesian network in GeNIe Modeler software (BayesFusion, 2021).

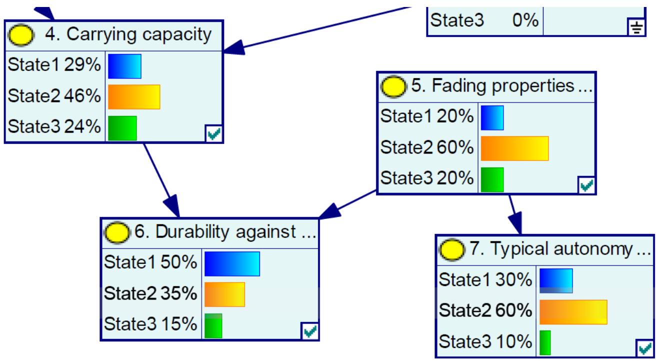
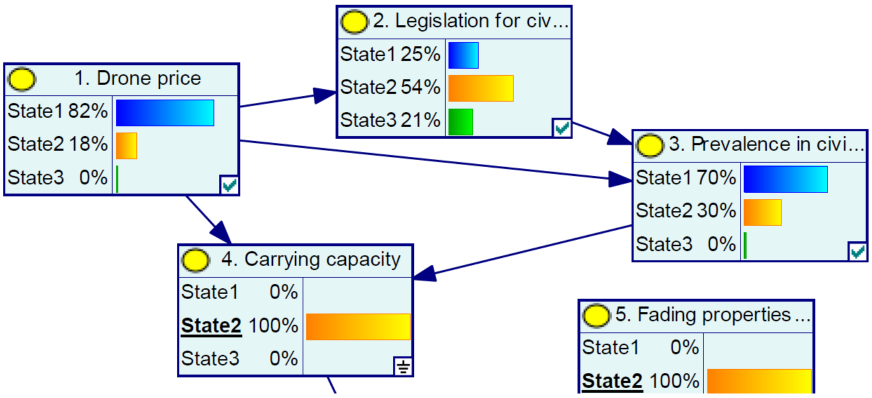
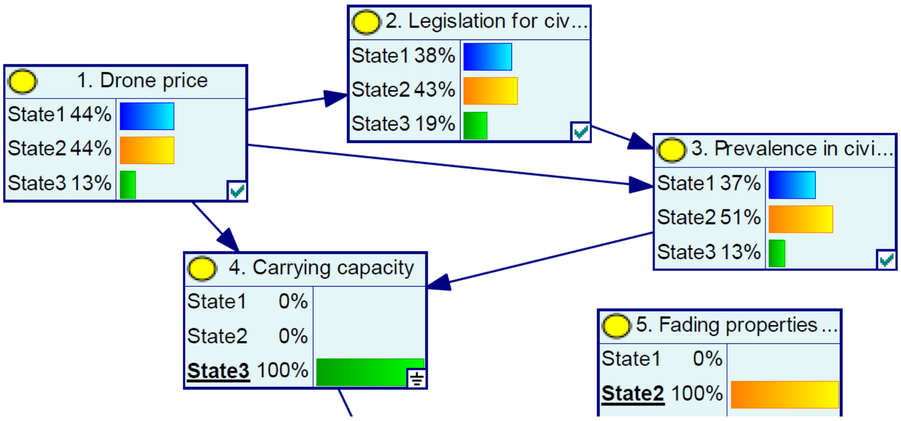


Figure 6: Most probable civilian UAV partial scenario with probability 30.9%. Uncertainty factors 1-3 are in states (1, 2, 1)



(a) Partial scenario with uncertaintyfactors 4-7 in states (2, 2, 1, 2)



(b) Partial scenario with uncertaintyfactors 4-7 in states (3, 2, 1, 2)

Figure 7: Two most probable military partial scenarios with equal probability of 8.22%.

5 Conclusions

In this thesis, we presented methodology of probabilistic cross-impact analysis developed by Roponen and Salo (2022) and applied it to technology forecasting concerning UAVs in Finland year 2040. The method was used to calculate scenario probability distribution for 2187 unique scenarios from the basis of expert judgments. Ten most probable scenarios were analyzed, which exhibited notable level of uniformity. However, when examining carrying capacity in these scenarios, there was a lack of consistency among its states. The most likely scenarios suggest that drones have become an integral part of civilian life in Finland in 2040. Military UAVs, on the other hand, face increased challenges, due to evolution of counter-UAV technologies.

To further investigate relationships between the uncertainty factors, a Bayesian network was constructed from conditional probability and conditional independence information using GeNIe Modeler software (BayesFusion, 2021). First, a Bayesian network with basic marginal probabilities of the uncertainty states was presented in Section 4.2. Afterwards, the network was applied to analyze three partial scenarios: two military UAV scenarios of equal probability of 8.22% and one civilian UAV scenario of probability 30.9%. The conclusion drawn from these is that carrying capacity has a significant impact on uncertainty factors of the civilian UAVs. If carrying capacity doubles, civilian drones are more likely to be mass-produced and more prevalent in civilian use. Conversely, if carrying capacity multiplies, civilian drones becomes rarer and their prevalence in civilian use stays limited. Notably, in the latter case, legislation of UAVs will stay comparatively more lenient.

The limited edges connecting military and civilian UAV uncertainty factors suggest that they function to some extent independently from each other. Regarding the network topology, it would be intriguing to explore whether the network method could incorporate unidentified uncertainty factors that could potentially alter the entire network structure. For instance, it would be valuable to examine the influence of groundbreaking UAV-related technologies on the other uncertainty factors and network edges. However, it is challenging to embed these kinds of black swans into the model, because making expert assessments about unknown unknowns can be arduous (Taleb, 2015).

The obtained results provide primarily information about the uncertainty states and do not offer substantial insights into the broader context. To gain a more comprehensive understanding of the state of the environment of the uncertainty factors, it would be beneficial to employ qualitative scenario methods and develop narratives around the most probable scenarios. This approach would facilitate a clearer and more detailed depiction of the potential future conditions. Currently, both military and civilian UAVs have proved to be significant warfare technologies. However, their countermeasures, especially for the civilian drones, require more research and innovation.

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