H2020 Project: Smart Resilience Indicators for Smart Critical Infrastructure
D3.4 - Monitoring resilience and optimizing the resilience-oriented multi-criteria decision-making (MCDM)

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Monitoring resilience and optimizing the resilience-oriented multi-criteria decision-making (MCDM)
## Release History

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Modern critical infrastructures are becoming increasingly smarter (e.g., smart cities). Making infrastructures smarter usually means making them smarter in the normal operation and use: more adaptive, more intelligent, etc. But will these smart critical infrastructures (SCIs) behave smartly and be smartly resilient when also exposed to extreme threats, such as extreme weather disasters or terrorist attacks? If making existing infrastructure smarter is achieved by making it more complex, would this also make it more vulnerable? Would this affect the resilience of a SCI in terms of its ability to anticipate, prepare for, adapt and withstand, respond to, and recover? What are the resilience indicators (RIs) that need to be looked at?

These are the main questions tackled by SmartResilience project.

The project envisions answering the above questions in several steps: (#1) By identifying existing indicators suitable for assessing resilience of SCIs; (#2) By identifying new smart resilience indicators including those from Big Data; (#3) By developing a new advanced resilience assessment methodology based on smart RIs and the resilience indicators cube, including the resilience matrix; (#4) By developing the interactive SCI Dashboard tool; and (#5) By applying the methodology/tools in 8 case studies, integrated under one virtual, smart-city-like, European case study. The SCIs considered (in 8 European countries) deal with energy, transportation, health, and water.

This approach will allow for benchmarking of best-practice solutions and identifying early warning signs, improving resilience of SCIs against new threats as well as cascading and ripple effects. The benefits/savings to be achieved by the project will be assessed by the reinsurance company participant. The consortium involves seven leading end-users/industries in the area and seven leading research organizations, supported by academia and led by a dedicated European organization. External world leading resilience experts will be included in the Advisory Board.
Executive Summary

The overall goal of the SmartResilience project is to provide an innovative, “holistic” methodology for assessing resilience of critical infrastructures. It is comprised of three main pillars: resilience level assessment in task 3.2, modeling based on functionality assessment of smart critical infrastructures (SCIs) in task 3.3, and monitoring of resilience and optimization based on decision-making models, such as multi-criteria decision-making (MCDM), in task 3.4.

This task proposes the third pillar of decision-making for resilience improvement in SmartResilience methodology. Broadly, this methodology has three stages:

1. Definition of the decision problem
2. Analysis of the optimization criteria used for optimization
3. Optimization of the decision’s outcome

Optimizing resilience based on the MCDM model will complete the "holistic" methodology committed in the project proposal.

The SmartResilience project focuses on answering questions about investment in resilience optimization, e.g. “Which is the best option that garner the most value for money invested in resilience improvement?”

Besides answering such questions, the project proposes a method that provides an opportunity to consider uncertainty. Uncertainty may arise due to factors, such as:

- Use of new and smart technologies
- Rise in unexpected disruptive events

Considering these goals, the proposed methodology can factor in both quantitative and qualitative criteria, transform and normalize them to the same comparable scale and by using a specialized method (fuzzy logic and trapezoidal numbers), capture semantic differences as well as introduce uncertainty. These criteria are used to analyze and score the Optimization Alternatives (OpAs) and identify the best one to improve the resilience of the SCI.

The three primary research outcomes related to the MCDM method are

1. It is fully quantifiable – it is fit to be used even in fuzzy, uncertain scenarios and maintain comparability;
2. It is transparent – requires clearly defined criteria and weights that are easily auditable;
3. Its outcomes are repeatable – in the sense of reliability.

This method can be useful for SCI operators, regulators, and end-users when making decisions surrounding selection of optimal measures to improve the resilience of SCIs.

The report is structured as follows: Chapter 1 provides the introduction to this task. Chapter 2 presents the method selection for the SmartResilience project. Chapter 3 details the structure of the methodology and its components. Chapter 4 showcases the ECHO Case Study from the SmartResilience project, in order to demonstrate the application of the methodology in the SCI dashboard. Finally, Chapter 5 provides conclusions.
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<td>Analytical Hierarchy Process</td>
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<tr>
<td>CI</td>
<td>Critical Infrastructure</td>
</tr>
<tr>
<td>CIRAM</td>
<td>Critical Infrastructure Resilience Assessment Methodology</td>
</tr>
<tr>
<td>CO</td>
<td>Critical Operation</td>
</tr>
<tr>
<td>COA</td>
<td>Center Of Area</td>
</tr>
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<td>FE</td>
<td>Functionality Element</td>
</tr>
<tr>
<td>FI</td>
<td>Functionality Indicator</td>
</tr>
<tr>
<td>FL</td>
<td>Functionality Level</td>
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<tr>
<td>FLI</td>
<td>Functionality Level of the Infrastructure</td>
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<tr>
<td>ICT</td>
<td>Information and Communications Technology</td>
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<td>IoT</td>
<td>Internet of Things</td>
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<td>ISO</td>
<td>International Organization for Standardization</td>
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<td>MCDM</td>
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<td>Optimization Alternative</td>
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<td>RI</td>
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<td>SCI</td>
<td>Smart Critical Infrastructure</td>
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1 Introduction

1.1 Task description

DRS-14 (Call: H2020-DRS-2015, DRS-14-2015) emphasizes the need for “defining measures to achieve better resilience against threats in an integrated manner including natural and human threats/events (e.g. due to human errors or terrorist/criminal attacks).”

Risk is an inescapable part of every decision. For most of the everyday choices people make, the risks are small. But on a scale the size of large infrastructure, the implications (both positive and negative) on the society can be enormous. Even the simply expressed (and rarely encountered) “win-win” situation entails opportunity costs in the form of paths not taken, and in the case of a critical infrastructure, safety, security, resilience, cost, and time could be significant decisive factors [2].

Correspondingly, the overall goal of the SmartResilience project is to provide an innovative, “holistic” methodology for assessing resilience of critical infrastructures. It is comprised of three main pillars: Critical Infrastructure Resilience Assessment Methodology (CIRAM) in task 3.2, modeling based on functionality assessment of smart critical infrastructures (SCIs) in task 3.3, and monitoring of resilience and optimization based on the decision-making models such as multi-criteria decision-making (MCDM) in task 3.4. In this report, the third pillar of the SmartResilience methodology is described. This task proposes a method to make decisions that increase the Resilience Level (RL) of a SCI against threats, including cascading and ripple effects. It is compatible and used in conjunction with the CIRAM methodology. Optimizing resilience, based on the MCDM model, will complete the "holistic" methodology committed in the project proposal.

![Figure 1: Task 3.4 within the SmartResilience work plan](image-url)
The methodology described in task 3.4 aims to achieve the goals presented in the call text by proposing a step-by-step methodology that allows for:

- Consideration of the decision problem that the CI operator needs to resolve in order to improve their resilience level (RL) (e.g., how to optimize investment in resilience improvement: More money in new sensors? More for training and education or refurbish equipment? What is the “optimal investment portfolio”?)
- Identification of the Optimization Alternatives (OpAs) that users can consider in relation to their context
- Identification of assessment criteria, including their types and importance, to make an informed decision
- Appraisal of the OpAs against the criteria defined by the user and against constraints
- Choice of the best portfolio of measures to improve the resilience level of the SCI
- Consideration of uncertainties regarding unknown, unexpected or emerging threats due to the use of smart and new technologies

1.2 Relation to other parts of the project

T3.4 provides the methodology for decision-making for resilience level improvement and is related to other work packages (WPs) as shown in Figure 2. Since the work in this task has undergone several iterations during the course of the project, the work done in other work packages provided the essential inputs for this task. WP1 provided the basis for development of the methodology by means of defining resilience definition and establishing baseline concepts such as resilience matrix, resilience phases and dimensions, stakeholder analysis, and users’ needs and requirements. WP2 contributed opportunities and challenges identified from use of smart technologies, threats foreseen, and interdependencies analyzed for SCIs. WP4 (specifically T4.1 and T4.2) provided the resilience indicators (RIs), which serve as the criteria for making decisions and identifying the OpAs).

Within WP3, task 3.1 provides information about the contextual factors (regulatory and organizational) that SCI operators may use to define their criteria (constraints/possibilities) for resilience-related decision-making. For example, the Hungarian national protection laws require its police force to maintain a comprehensive training program and conduct regular exercises (see WP5, case study DELTA); these easily translate to mandatory indicators and important criteria for decision-making. T3.2 provides input through identification of weak points where improvements are needed. Subsequently, task 3.4 can provide input to task 3.5 for interactive visualization of the indicator-based decision-making, to task 3.6 on guidelines to use for the method, and to task 3.7 to construct the decision-making tool in the SCI dashboard.
The methodology proposed in this task will be used in WP4 for benchmarking the unsupervised RIs with conventional ones. It will also be applied in the case studies (T5.3–T5.11), and lessons learned (documented in task 5.12) will be used to refine the methodology.

1.3 Report structure
The report is structured as follows: Chapter 2 presents the method selection for the SmartResilience project. Chapter 3 details the structure of the methodology and its components. Chapter 4 showcases the ECHO Case Study from the SmartResilience project, in order to demonstrate the application of the methodology in the SCI dashboard. Finally, Chapter 5 provides conclusions.

1.4 Examples of decision problems to be solved in the SmartResilience project
The SmartResilience project focuses on answering questions about investment in resilience optimization, e.g. “Which is the best option that garner the most value for money invested in resilience improvement?”
Besides answering such questions, the project proposes a method that provides the possibility to consider uncertainty regarding resilience. This uncertainty may arise due to factors such as:

- Use of new and smart technologies
- Rise in unexpected disruptive events
2 MCDM method selection for the SmartResilience project

2.1 Arguments for using MCDM methods for optimization in the SmartResilience project

Generally, decision-making methods may range from a simple pro/con tabletop exercise, through precise mathematical modeling of linear programming, then back to influence diagram analysis and game theory. Each method has its strengths in capturing certain aspects of the decision-making process, but the nature of SCIs and the resilience issues that they evoke tends to mix both quantitative (budgeting, performance indicators, etc.) and qualitative (expectations, procedures, etc.) aspects, as well as (since they are often public) involve a wide range of stakeholders, each with different priorities.

Multi-criteria decision-making (MCDM) methods are preferred over other alternative decision-making frameworks because MCDM methods have “the potential capability of improving the transparency, analytic rigor, auditability and conflict resolution of decision-makers” [13]. MCDM:

- Provides a means to establish accountability and transparency behind decisions, which may otherwise have unclear rationale and motives [1]. This is accomplished by:
  - placing stress on clearly stating and weighting the decision criteria, thereby improving transparency, and by
  - ensuring that decisions taken through this method are explicit, paving way to audit past decisions and thus provide accountability [12].
- Provides the means for conflict resolution. This becomes a crucial issue when multiple perspectives are applied to a single SCI management decision [5] [18]. MCDM methods allow for the visualization of trade-offs among multiple conflicting criteria and the quantification of uncertainties necessary for comparison of available mitigation and corrective alternatives. This process helps decision-makers and stakeholders to systematically consider and apply value judgements to derive the most favorable management alternative [15].
- Provides a path for engagement and participation. Besides aiding decisions related to engineering, scientific studies, and cost analysis, one aspect that is becoming very crucial in decision-making studies is the engagement of multi-stakeholders and participation of communities [11]. The challenge of capturing and organizing this involvement can be addressed through application of the MCDM methods.

There are many MCDM methods that can support decision-making by ranking alternatives. Such examples include simple additive weighting, the value-utility method, analytical hierarchy, etc. MCDM methods permit users to resolve complex problems in a technically valid and practically convenient manner. These methods are applied in several fields, such as adaptive management, resilience-oriented approaches, and infrastructure management. They are mainly used for decisions related to investments, prioritization of human and physical resources, evaluation of policy options, short-term and long-term strategic planning (such as performance and maintenance strategies), identification of important risks, strategies for conflict resolution, etc. [6]. These decisions can frequently have profound and long-term impacts on the stakeholders involved. These decisions also require handling of multiple objectives, for which MCDM is potentially well suited [6].
2.2 MCDM in general

The application of MCDM methods offers a significant improvement in decision-making by allowing use of both quantitative and qualitative decision criteria, regardless of scale, and promotes public acceptance of suggested plans and policies by allowing all stakeholders to participate in the criteria prioritization process. In general, an MCDM problem is considered to have \( m \) alternatives \( (A_1, A_2, ..., A_m) \) and \( n \) decision criteria \( (C_1, C_2, ..., C_n) \). Alternative scores with respect to all criteria are assumed to be known or estimated by the decision maker. Criteria may be categorized into two main groups: costs and benefits. While costs are considered features for minimization, with the smaller the better, benefits are considered features for maximization, so the larger the better. Weights are used to assess the influence of each criterion on the decision so that the weight vector \( w = [w_1, w_2, ..., w_n] \) satisfies:

\[
    w_1 + w_2 + \cdots + w_n = 1
\]

where \( w_j \) represents the weight of the criterion \( C_j \), \( w_j \geq 0 \ (j = 1, 2, ..., n) \). Data normalization is fundamental to ensure dimensionless units from different data measurements can be aggregated for rating and ranking decision alternatives. For benefits, the normalized values can be calculated using the following equation [22]:

\[
    c_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}
\]

and for costs, using the following equation [22]:

\[
    c_{ij} = \frac{x_{ij} - \max_i x_{ij}}{\min_i x_{ij} - \max_i x_{ij}}
\]

where the \( x_{ij} \) is the score of alternative \( i \) with respect to criterion \( j \) before normalization.

2.3 Methods considered

Considering other projects, various in-depth MCDM approaches such as AIRM, PROMETHEE, and ELECTRE were proposed. However, during the eight case studies included in the SmartResilience project, all of which involve end-user-owners of SCIs, it became clear that the complexity of these methods made understanding them much more difficult and, at the same time, the required processing of the data needed proved to be prohibitively time consuming and expensive. Therefore, a particular method was designed for SmartResilience, aimed to simplify the process of criteria creation and prioritization from the end-user’s perspective while maintaining the strengths of an established method such as Saaty’s Analytic Hierarchy Process (AHP), modified to include fuzzy logic.

The steps taken to develop the method are described below, while the full solution is detailed in chapter 3.

2.3.1 Weighted-Sum Model (WSM)

WSM is possibly the most commonly used approach, especially when single-dimension problems are in consideration [25]. WSM defines the optimal alternative as the one which corresponds to the ‘best’ value (maximum for all benefit criteria and minimum for cost criteria) of the weighted-sum [9]. The model is formulated for problems in which all variables have the same physical dimensions, based on the ‘additive utility’ assumption. Using the WSM, the final score of each alternative is calculated according to the following equation [4]:

Box 1: Available MCDM methods

There are many methods available to support MCDM and over 80 different methodologies were inspected from literature (e.g. Chang and Hwang, 1992), ISO 31010 (Risk Assessment Techniques) and the OECD’s Handbook on Composite Indicators. However, standalone methods could not meet the flexibility required in the context of SmartResilience and its end-users. Therefore, a project specific method was developed in order to support users’ linguistic rules (through fuzzy logic), address their priorities (AHP) and provide simplified results (WSM).
where $S_i$ represents the score for the $i$ alternative, $a_{ij}$ represents the normalized score of the $i$ alternative with respect to the $j$ criterion, and $w_j$ represents the $j$ criteria weight. Afterwards, the final scores of each alternative are ranked, which indicates that the higher the value of $S_i$ the higher is the rank of that alternative. The major weakness of the method is that it requires that all the data are expressed in exactly the same unit otherwise one risks “comparing apples to oranges”, disallowing mixing linguistic and crisp parameters for instance.

2.3.2 Fuzzy Rule-based modeling
Fuzzy reasoning theory aims to provide a model for implementing a knowledge-based system [17]. This knowledge will often be available in rules that link the input variables with the output variables by means of linguistic variables. By far the most frequently used method of representing knowledge is by means of rules. These are usually of the form:

IF a set of conditions is satisfied THEN a set of consequences can be produced WITH a certainty factor $t$.

The Fuzzy rule based approach seems to represent a powerful tool for modeling SCI states because it reflects, quite accurately and through natural language, the decision process that the CI operator has to go through when assigning condition values to the OpA. For example, IF a red light is flashing, THEN a fire sensor is signaling and the operator knows that WITH all likelihood, there is fire in its vicinity and that there is a procedure that should be followed.

Although it is useful for unclear, purely semantic rules but as a standalone system it has a major limitation in that it appears that a large number of fuzzy rules are often required to model a particular phenomenon adequately. The results obtained are clearly sensitive to the number of rules specified, although there are no sufficient conditions to help the user define the optimum number of rules. It requires a considerable investment, if not prohibitive in the case of complex systems, to substantiate the IF-THEN logic; a logic that when broken down piecemeal, is also often counter intuitive to the end-user.

2.3.3 AHP (Analytical Hierarchy Process)
The AHP (Analytical Hierarchy Process) [9] supports a decision maker in solving MCDM problems. Its strength lies in its flexible hierarchal decomposition of alternatives, which is not dependent on the alternatives being on the same scale. Therefore, the method was considered for the MCDM due to the types of decision problems that users are expected to model: these may be completely quantitative, qualitative, or anywhere on the spectrum, yet need to be measured on the same scale. AHP is a powerful tool for ranking alternatives based on a number of criteria. It has been acknowledged that rank reversal is a possibility if the guidelines are not followed and that pairwise comparisons are not always the best method of normalization. Utility functions can also be used for the normalization process, which additionally avoids rank reversal problems.

AHP generally involves four steps:

i. Making pairwise comparisons of the hierarchy elements at all levels, following the rule that at a given level, elements are compared with respect to the elements in higher levels by using Saaty’s importance scale [23], as shown in Table 1.

<table>
<thead>
<tr>
<th>Definition</th>
<th>Numerical value</th>
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<tr>
<td>Equal importance</td>
<td>1</td>
</tr>
<tr>
<td>Moderate importance</td>
<td>3</td>
</tr>
<tr>
<td>Strong importance</td>
<td>5</td>
</tr>
<tr>
<td>Very strong importance</td>
<td>7</td>
</tr>
<tr>
<td>Extreme importance</td>
<td>9</td>
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ii. Obtaining the **judgmental matrix**, which is based on the relative importance between the two criteria. This matrix is also called the **comparison matrix** [23].

iii. Computing local weights and consistency of comparisons. After all the judgements are made, weights or local priorities of the criteria and the alternatives are calculated as suggested by Saaty [23]. This done by summing the values of each column in the comparison matrix and then dividing each element of the matrix by the sum of its column, resulting in normalized relative weight; the sum of each column of the outcome is 1.

iv. Aggregating local weights. This synthesis is performed by multiplying the assigned weights by the values assigned for alternatives.

In the AHP, each element of the hierarchy is considered independent from the rest, which means that the criteria are also considered independent of each other, and furthermore the alternatives are considered independent of the criteria and of each other.

The main strengths of AHP are the following:

- It is applicable when exact and total parameters are collected.
- The decision problem can be fragmented into its smallest elements, providing evidence of each criterion applied [16].
- It is applicable for either single or multiple problems, since it incorporates both qualitative and quantitative criteria [21].
- It calculates a consistency ratio to assure decision makers [24].
- It can be applied in case of uncertainty (due to limited information or imprecision).

The key issue with AHP however, while it’s designed to capture an expert’s knowledge, it struggles to reflect the human thinking style ([14]) so out of the box, it lends itself mostly to ordinary real variables and leaves the user to create comparable criteria and alternative sets by themselves.

### 2.4 Method selected for SmartResilience

Based on the premise that different users may have different preferences, including preferences or requirements with respect to the level of precision or limitation in the ability to accurately quantify criteria, the method selected is a combination of the above three methods. Specifically, users’ preferences are modeled as fuzzy rule-based statements, which are then converted to (trapezoidal) values to be weighted in an AHP-like decision matrix. The resulting values are ultimately combined into weighted alternatives, which can be used for optimization.

Fuzzy numbers are utilized in order to handle vagueness and imprecision by allowing graduation of the membership function of a particular parameter [26] – the criteria input in SmartResilience. A membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership between 0 and 1). Trapezoidal numbers (Figure 3) receive their name from the shape obtained when their membership function is represented in the Cartesian plane and they represent the area of possible inputs rather than a simple, single value (as opposed to a crisp value) and therefore, are able to capture the aforementioned vagueness and a measure of uncertainty.
2.4.1 Fuzzy-AHP (F-AHP)

The Fuzzy-AHP (F-AHP) method is an extension of the classical AHP method [3] and it’s meant to assist the user in handling intangible criteria. The main difference can be found in the representation of judgments made by the decision maker: In the F-AHP approach, all judgments are modeled by trapezoidal fuzzy numbers, even if they are simple numeric parameters (crisp) in order to ensure that all judgments are normalized on the same scale/unit. As trapezoid numbers actually represent a range, or an interval of possibilities, the user can account for the unknown or the uncertain to a degree, by widening the bounds of the range to include more of the unknown, increasing the chances to catch a black swan. In its adaptation to the project, those judgements are implemented in a AHP like model to develop criteria prioritization from which a weighted value is derived for each alternative.

It is acknowledged that although fuzzy modeling can be a useful approach in situations where the variables are not defined precisely and analytical models are not available for the evaluation of output quantities, it is, however, limited in the complexity of the membership functions, as they must be trapezoidal. Given the project’s explicit goal to simplify the process, this weakness did not raise any particular issues for precision.

Figure 3: A fuzzy trapezoidal number
3 Method structure for the SmartResilience project

As optimization of resilience is continuous, the SmartResilience project proposes to use a MCDM methodology for this process.

Figure 4: Detailed structure of the MCDM methodology in the SmartResilience project
Broadly, the MCDM methodology has the following main stages:

1. Definition of the decision problem, decomposing it into a hierarchy and decision alternatives.
2. Analysis of the decision criteria used for optimization, prioritizing each criterion in every level.
3. Optimization of the decision's outcome (e.g, by optimizing criteria weights).

The following segments (3.2.1) detail the mathematics underlying the method. To keep these concise, brief illustrations are presented only in the following segment 3.2.2.

An elaborated method structure is illustrated in Figure 4 above.

### 3.1 Define the resilience-related decision problem

A decision is a choice between alternatives based on multiple criteria. The different alternatives aim to achieve a particular goal by affecting various parameters; for example, in the case of a fire threat, the goal of improving the local authority's resilience can be achieved by increasing the budget for the fire department's equipment or alternatively, by educating the population in fire avoidance. Either is a possible alternative for different authorities, but the local decision makers may prefer different alternatives depending on their specific case (e.g. budget limitations, preference for alternatives not focused on members of the public, etc.).

### 3.2 Details of the F-AHP methodology as applied in SmartResilience

Each alternative up for consideration is defined by a proposed set of modifications to its attributes, which are measured as a whole against the decision-maker's defined criteria (preferences); in the context of SmartResilience, this is to improve the resilience level (RL) of a SCI.

#### 3.2.1 Formulation of the considered MCDM problem

The general multi-criteria decision-making problem, which we try to solve in this task, can be defined as follows.

Let

\[ A = \{a_i | i = 1, \ldots, m\} \]

be a set of decision alternatives and

\[ C = \{c_j | j = 1, \ldots, n\} \]

a set of criteria against which the desirability \( x_{ij} \) of an alternative \( a_i \) is judged. For each \( j \in \{1, \ldots, n\} \), the elements of the vector \( (x_{1j}, x_{2j}, \ldots, x_{mj})^T \) are called attribute values according to criterion \( j \).

The objective is to determine the optimal alternative \( a^0 \in A \) with the highest degree of desirability with respect to all relevant criteria \( c_j \in C \).

Generally, such a decision problem can be represented by a decision matrix as shown in Figure 5.

<table>
<thead>
<tr>
<th></th>
<th>( c_1 )</th>
<th>( c_2 )</th>
<th>( \ldots )</th>
<th>( c_n )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_1 )</td>
<td>( x_{11} )</td>
<td>( x_{12} )</td>
<td>( \ldots )</td>
<td>( x_{1n} )</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>( x_{21} )</td>
<td>( x_{22} )</td>
<td>( \ldots )</td>
<td>( x_{2n} )</td>
</tr>
<tr>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
</tr>
<tr>
<td>( a_m )</td>
<td>( x_{m1} )</td>
<td>( x_{m2} )</td>
<td>( \ldots )</td>
<td>( x_{mn} )</td>
</tr>
</tbody>
</table>

Figure 5: General decision matrix
Depending on the type of attribute values for each criterion, there are different methods for solving this decision problem; therefore, we first list the different types of possible attribute values.

A criterion \( c_j \), \( j \in \{1, \ldots, n\} \) is called a

- **crisp criterion** if all ratings \( x_{ij}, j \in \{1, \ldots, m\} \) can be represented by real numbers, i.e. \( x_{ij} \in \mathbb{R} \). Used to represent exact and objective information.

- **fuzzy criterion** if all ratings \( x_{ij}, j \in \{1, \ldots, m\} \) can be represented by fuzzy numbers or linguistic terms. Used when representing imprecise, assumed or incomplete information, taking into account a range, or interval, of possibilities.

- **probabilistic criterion** if all ratings \( x_{ij}, j \in \{1, \ldots, m\} \) can be represented by density functions. Used to describe a range of possibilities, weighted to produce the most probable outcome. Requires advanced knowledge regarding their distribution, otherwise assumes it’s normal.

- **intangible criterion** if there are no ratings available. Then, however, the decision maker must be able to judge at least how each pair of alternatives compare against that criterion.

### 3.2.1.1 Combination of MCDA and fuzzy techniques

The introduction of the fuzzy extension (F-AHP) to the classical AHP method, is done to be able to replace the crisp numbers required by AHP with fuzzy linguistic terms which are allowed in the F-AHP. The objective of this integrated approach is to deal with decision problems in which crisp, fuzzy and intangible criteria are allowed simultaneously; the resulting judgements in the decision matrix are all modeled as fuzzy numbers.

The solution process of the F-AHP approach is represented by the flowchart in Figure 7.

#### 3.2.1.1.1 Fuzzy Analytical Hierarchy Process (F-AHP)

The methodology introduced in this chapter is based on Buckley’s fuzzy AHP version [3] and it supports the decision maker in solving problems of the type mentioned above and is an extension of the classical AHP-method, which is well-documented by sources such as Saaty [23]. Error! Reference source not found. demonstrates how a problem would be formulated for F-AHP.

All fuzzy numbers that are used in this approach are assumed to be fuzzy trapezoidal numbers (see Error! Reference source not found.). They can be represented by a 4-tuple \((a, b, c, d)\). Since every crisp number \( x \in \mathbb{R} \) can be interpreted as a special fuzzy trapezoidal number \((x, x, x, x)\), we will not distinguish between crisp and fuzzy numbers in this chapter.

The F-AHP methodology in detail:

1) First, the methodology rates the importance of the criteria with respect to each other. Fuzzy trapezoidal numbers are used to judge the relative importance of each pair of criteria. This results in fuzzy criteria weights \( \vec{w}_j, j = 1, \ldots, n \) for each criterion (see the following sub-chapter 3.2.1.1.2). Next, all alternatives \( a_i \), \( i \in A \) are rated by fuzzy pairwise comparisons with respect to each single intangible criterion. This results in
fuzzy ratings $\tilde{r}_{ij}$ per alternative $a_i$ and per intangible criterion $c_j$ (see the following sub-chapter 3.2.1.1.2).

2) For each crisp or fuzzy criterion, the methodology normalizes the values given in the respective column of the decision matrix. Similar to what occurs with each single intangible criterion, this results in fuzzy ratings $\tilde{r}_{ij}$ per alternative $a_i$ and per crisp or fuzzy criterion $c_j$ (see sub-chapter 3.2.1.1.3).

3) Next, a fuzzy weight per alternative $W_j^i$, $i = 1, \ldots, m$ is computed for each alternative $a_i$, by adding relative ratings to all criteria, multiplied by their criteria weights $W_j$ (see sub-chapter 3.2.1.1.4).
4) For each fuzzy weight $\tilde{V}_i, i = 1, \ldots, m$, a final crisp (real) number $u_i, i = 1, \ldots, m$ is needed against which it is possible to rank the alternatives. This procedure is called defuzzification. Chen’s method, which will be described in detail in sub-chapter 3.2.1.1.5, is suggested in order to carry out this step.

The next four subsections describe the required mathematical operations for the five steps mentioned above.

![Figure 8: Solution process of F-AHP](image)

3.2.1.1.2 Determination of fuzzy weights from a fuzzy comparison matrix

In steps 1 and 2 of the flowchart given above, it is necessary to have a method of determining a fuzzy weight vector from a fuzzy comparison matrix. We propose a method called the Geometric Mean Method, as proposed by Buckley [3], instead of Saaty’s eigenvector method because it is simpler to extend the Geometric Mean Method to the fuzzy environment.

Given a fuzzy positive reciprocal comparison matrix such as

$$
\tilde{M} = \begin{bmatrix}
\tilde{y}_{11} & \tilde{y}_{12} & \cdots & \tilde{y}_{1n} \\
\tilde{y}_{21} & \tilde{y}_{22} & \cdots & \tilde{y}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{y}_{n1} & \tilde{y}_{n2} & \cdots & \tilde{y}_{nn}
\end{bmatrix}
$$

the elements of which are

$$
\tilde{y}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij}) \forall i, j \in \{1, \ldots, n\}
$$

are trapezoidal fuzzy numbers, fuzzy weights $\tilde{w}_j, j = 1, \ldots, n$ are elicited.

The fuzzy geometric mean for each row is determined as:

$$
\tilde{z}_j = (\tilde{y}_{j1} \otimes \tilde{y}_{j2} \otimes \cdots \otimes \tilde{y}_{jn})^{\frac{1}{n}} j = 1, \ldots, n
$$

where the sign \( \otimes \) represents fuzzy multiplication. The fuzzy weight $\tilde{w}_j$ is given as:

$$
\tilde{w}_j = \tilde{z}_j (\tilde{z}_1 \oplus \tilde{z}_2 \oplus \cdots \oplus \tilde{z}_n) j = 1, \ldots, n
$$

where the signs \((\cdot)\) and \(\oplus\) represent fuzzy division and fuzzy addition, respectively.

3.2.1.1.3 Normalization of fuzzy numbers
Step 3 of the flowchart provided above requires a method to normalize a set of \( n \) trapezoidal fuzzy numbers. Let \( \tilde{x}_j = (x_{i1}, x_{i2}, \ldots, x_{in}) \) be the fuzzy ratings of alternatives \( a_1, a_2, \ldots, a_i, \ldots, a_m \) with respect to a tangible criterion \( c_j \in C \). The normalized vector \( \tilde{r}_j = (\tilde{r}_{i1}, \tilde{r}_{i2}, \ldots, \tilde{r}_{in}) \) is then calculated according to

\[
\tilde{r}_j = \tilde{x}_j (\cdot)(\tilde{x}_{i1} \oplus \tilde{x}_{i2} \oplus \ldots \oplus \tilde{x}_{in})
\]

3.2.1.4 Computation of fuzzy weights

Step 4 of the flowchart necessitates a formula to determine the fuzzy weight for each alternative \( a_i, i = 1, \ldots, m \). The fuzzy weights \( \tilde{V}_i, i = 1, \ldots, m \), for each alternative are obtained based on

\[
\tilde{V}_i = \sum_{j=1}^{n} \tilde{w}_j \cdot \tilde{r}_j, \quad i = 1, \ldots, m
\]

3.2.1.5 Final ranking of fuzzy weights (Defuzzification)

Reiterating that in the effort to evaluate all criteria on equal terms and/or units of measure, all crisp criteria are first transformed into fuzzy numbers so they can be uniformly operated on when applying the criteria to the AHP decision matrix. Alternatives are then analyzed and scored using these criteria but them being fuzzy and represented by trapezoid numbers, the scores are also fuzzy and trapezoidal. In order for them to make sense and usable in MCDM, these need to be transformed into real numbers by means of defuzzification. Within the scope of this project, the **center of area** (COA) method is introduced:

Given a fuzzy set \( \tilde{A} = \{ (x, \mu_{\tilde{A}}(x)) \mid x \in U \} \) the COA of \( \tilde{A} \), which is a real number, is calculated according to

\[
c_{\tilde{A}} = \frac{\int x \cdot \mu_{\tilde{A}}(x) \, dx}{\int \mu_{\tilde{A}}(x) \, dx}
\]

3.2.2 Brief illustrations for the method

3.2.2.1 Optimization Alternatives (OpAs)

As stated above, in the SmartResilience project, Optimization Alternatives (OpAs) are alternatives which can be considered in decisions to improve the resilience of smart critical infrastructure (SCI). As an example, the operator of a particular SCI wants to improve their SCI’s resilience and faces the alternatives presented in Table 2. Each of the alternatives aim in total, to increase resilience by applying a bundle of different measures. These alternatives are scored later in the methodology against the decision maker’s criteria.

<table>
<thead>
<tr>
<th>ID</th>
<th>Alternative Name</th>
<th>Alternative Description</th>
</tr>
</thead>
</table>
| 1  | OpA 1            | OpA 1 consists of the following solutions:  
• Increase Big Data Analyst availability (increase indicator value from 2 to 5)  
• Increase the frequency of simulator training for operating personnel (increase indicator value from 1 to 5)  
• Operational agreement with entities (other than emergency responders) for support in the phase of facility functionality restoration (increase indicator value from 2 to 4) |
### Alternative groups

The alternative groups are denoted as Resilience Improvement Portfolios. The Resilience Improvement Portfolios will be analyzed against the selected set of decision criteria.

### Decision criteria

Decision criteria are factors that the decision maker must consider before making a decision. These criteria can be quantitative or qualitative. Examples are presented in Table 3.

#### Table 3: Examples of (multiple) criteria for decision-making for optimizing resilience of SCIs

<table>
<thead>
<tr>
<th>ID</th>
<th>Criterion Name</th>
<th>Criterion Description</th>
<th>Higher Ranking when closer to</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cost</td>
<td>The monetary cost of implementing a particular OpA</td>
<td>Minimum</td>
</tr>
<tr>
<td>2</td>
<td>Time</td>
<td>The time to implement a particular OpA</td>
<td>Minimum</td>
</tr>
<tr>
<td>3</td>
<td>ΔRL</td>
<td>Improvement in Resilience Level</td>
<td>Maximum</td>
</tr>
<tr>
<td>4</td>
<td>PR</td>
<td>The cost to public perception due to implementation</td>
<td>Minimum</td>
</tr>
</tbody>
</table>

### Decision criteria type

While quantitative criteria are based on numerical inputs (e.g. cost), qualitative evaluations are expressed in linguistic terms (e.g. low, medium, high).

#### Crisp

The criteria that are strictly quantitative, i.e. require meaningful numerical inputs (e.g. cost) are considered crisp. Most of the time, these criteria are sufficient alone, but they are also limited in their point of view in terms of what results mean, as they lack human perspective (e.g. is 50 high, just enough, or completely negligible?).

#### Linguistic–crisp

These are similar to crisp but values are grouped into ranges which are then assigned a meaningful linguistic term. For example, linguistic terms for Environmental Impact may be: 0 None or negligible, 1-20 Very low, 21-40 Low, 41-60 Medium, 61-80 High, 81-100 Extreme. These ranges add the user’s assessment to the impact’s numerical values.
3.2.2.7 Linguistic-fuzzy

In the Linguistic-fuzzy criteria type, rules are applied. A rule is written as If situation, Then conclusion, and each fuzzy set corresponds to a linguistic concept, e.g. Very low, Low, Average, High, Very High. During reasoning, the variables are referred to by the defined linguistic terms, and the fuzzy sets determine the corresponding numerical values.

Linguistic-fuzzy is quite a good alternative to linguistic crisp, since the end-user can say something such as "I think it is something between 1 and 2, but it might also extend to 0.5 and 2.5." Normal, classical fuzzy numbers are triangular, but trapezoidal numbers are used in the SmartResilience method since the cases, as described with the sentence above, can be only modeled with trapezoids.

3.2.2.8 Fuzzy

This type of criteria is similar to linguistic fuzzy, but end-users have to manually input the individual values as numbers corresponding to every statement.

3.2.2.9 Decision criteria weights

The criteria can be prioritized by the user by assigning weights to them. The weights can be equivalent weights (default), or the user can assign the weights to the criteria based on individual preferences.

3.2.2.10 Decision criteria groups

The criteria groups are the criterions used to analyze the OpAs.
4 Application example: ECHO Case Study

This chapter presents an example of use case 1 in relation to the ECHO case study in order to demonstrate how to use MCDM for optimization. This use case example demonstrates how application of the proposed decision-making methodology in the SmartResilience project can support end-users in achieving their goals and how users can use the SCI dashboard to optimize the resilience of their SCI.

Table 4 lists use case 1 along with four other use case examples, listed in increasing order of complexity, from ones that address simple problems (e.g. use case 1) to ones involving uncertainty due to the use of new and smart technologies and rise in unexpected disruptive events (e.g. use case 5). While this chapter discusses the application of MCDM only in context to use case 1, MCDM could be applied to achieve the goals of any of these five use cases. A detailed flowchart on how to use the MCDM methodology in the SCI dashboard is presented in Annex 2.

<table>
<thead>
<tr>
<th>Use case</th>
<th>Goal</th>
<th>Beneficiary</th>
<th>Nr. of SCI</th>
<th>Phases/dimensions</th>
<th>Decision maker’s Criteria applied in the use case</th>
<th>Criteria type</th>
<th>Criteria weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Optimize the investment (in resilience)</td>
<td>CI Owner</td>
<td>1</td>
<td>All</td>
<td>Cost, change in resilience level of CI, Time</td>
<td>Crisp</td>
<td>Equal</td>
</tr>
<tr>
<td>2</td>
<td>Optimize the investment in single aspects of resilience management</td>
<td>CI Owners</td>
<td>1</td>
<td>1 Phase, 1 dimension</td>
<td>Per phase &amp; dimension: Cost, Change in resilience level, Time</td>
<td>Crisp, Linguistic-fuzzy</td>
<td>User defined</td>
</tr>
<tr>
<td>3</td>
<td>Overview to select the best/worst CI</td>
<td>Regulators</td>
<td>All</td>
<td>All</td>
<td>Overall: Cost, change in resilience level of all CIs, Time, Environmental impact in CO₂ emissions</td>
<td>Crisp, Linguistic-fuzzy</td>
<td>User defined</td>
</tr>
<tr>
<td>4</td>
<td>Gap analysis</td>
<td>CI Owners</td>
<td>1</td>
<td>5 phases, 5 dimensions</td>
<td>Per phase: Cost, Change in resilience level, Time</td>
<td>Crisp, Linguistic-fuzzy</td>
<td>Equal</td>
</tr>
<tr>
<td>5</td>
<td>Stress-testing</td>
<td>CI Owners, Regulators</td>
<td>1</td>
<td>All</td>
<td>Overall: Cost, change in resilience level of CI, Time</td>
<td>Crisp, Linguistic-fuzzy</td>
<td>Equal</td>
</tr>
</tbody>
</table>
4.1 Case Study ECHO: Use case 1

In use case 1, the goal is to optimize the investment in resilience through measures that increase the overall resilience level of a SCI. In this example, the SCI selected for application of use case 1 is the refinery in the city of Pančevo, Serbia, i.e. the ECHO case in the SmartResilience project. (NOTE: The screenshots and instructions provided in this example are taken from an earlier version of the SCI dashboard and may vary slightly from the current version available to users).

Step 1: Define the decision problem

In this case, a user wants to assess which alternative will benefit the SCI better under the three different criteria that they consider to be the most important:

- The total benefit in terms of resilience gained per option,
- The cost to implement each option and
- The time it will take to implement each.

All of these criteria include real numbers that can be modeled as crisp numbers and will be defined as such later in the process.

The user then defines the different alternatives that should be assessed, as operationally as possible, in order to clearly indicate what differs between them and provide a future reviewer with as much information as possible. For example, note the actual effect of a particular improvement on an indicator such as “Increase Big Data Analyst availability (increase indicator value from 2 to 5)” from OpA 1 in Table 2 (i.e. invest in this option so ultimately, its indicator value increases from 2 to 5 and improve total assessed resilience).

Step 2: Data gathering

For each of the defined alternatives, the user has to collect the results for each criterion separately, i.e. calculate a resilience score per individual alternative, the price of an alternative, and so on for all defined criteria; these data will then be input into the MCDM tool.

In the ECHO example, the user assesses each individual alternative’s resilience score as per the examples given in D3.3: “Modeling the impact of an adverse event on the "absorb" and "recover" capacity of a smart critical infrastructure (SCI), based on resilience indicators.” The user also estimates the costs associated with each and the time to implement each.

Step 3: the MCDM tool in the SCI Dashboard

The tool is started from within the SCI Dashboard by choosing ‘Resilience optimization’ on the sidebar and then either choosing an existing analysis or creating a new one.
The ECHO user creates a new analysis for the three alternatives:

**Step 4: Define Optimization Alternatives (OpAs)**

In 'Alternative definition,' the user creates portfolios of the possible solutions, e.g. OpA 1 will focus on improvement in system/physical and organizational/business dimensions, while OpA 2 will increase resilience in information/data/smartness aspects.

This is done by adding new alternatives to the analysis, each detailing how it differs from the rest; see Figure 11 as an example for the ECHO case’s first optimization alternative. The conditions described for this OpA are the ones modeled in the resilience analysis which was done for this particular alternative: All three alternatives are input into the system in a similar manner:

**Figure 10: ECHO case Analysis information**

**Figure 11: ECHO case optimization alternative 1 (OpA1)**
These OpAs are then incorporated into the MCDM tool for further analysis. (Note: In the future, the assessments conducted for each alternative will be automatically connected to the MCDM tool and their relevant optimization analyses).

Furthermore, in cases where a large number of alternatives are defined, the user is given the option to set up the different alternatives into groups to be assessed by some common denominator, e.g. financial or procedural proposed changes, to show resilience improvement by theme. In the ECHO case, the default group setting is used, which contains all alternatives:

**Step 5: Specify the decision criteria**

Given the defined decision problem, the following criteria are used:

- $\Delta RL$ - change (positive) in resilience after the corrective measures were implemented – a crisp number
- Cost of implementation – a crisp number
- Time of implementation – a crisp number
Figure 14: ECHO case first criterion definition in the MCDM tool

In the MCDM tool, the criteria are defined as shown in Figure 14. Information such as name of the criterion; its description; whether it has higher ranking when closer to maximum, minimum, or user-defined values; the criterion type (crisp number or fuzzy linguistic); and the minimum and maximum values are required to define the boundaries.

For instance, the ECHO case first criterion, $\Delta$RL - change (positive) in resilience after the corrective measures were implemented, is the actual numeric difference between the original resilience assessment’s score and that of the alternative. It is defined with higher being better (‘Higher ranking when closer to: maximum’), it is a crisp number, its unit of measure is $\Delta$RL (the change in resilience level), and its values are assessed in a range between 0.01 and 5.0, as shown in Figure 14.

The rest of the criteria are defined in a similar manner to create the entire set:

Figure 15: ECHO case criteria

Box 4: Alternative criteria
When using a fuzzy criterion such as the aforementioned opinion (box 3), it is similarly defined by the user with the addition of defining ordinal values to inputs as well the exact boundaries of the membership function (see 2.4) so it can include more or less uncertainty (these are normalized by default).
Similar to creating groups of alternatives, the user may define groups of common themed criteria to be assessed for resilience improvement.

**Step 6: Set criteria weights (if they are not equivalent)**

Next, assuming there is a difference, the user has to assign weights for the criteria according to their importance. Unless specified, all criteria are considered equal by default, as is the case for ECHO.

![Figure 16: Assigning weights to the criteria](image)

**Step 7: Analyze the alternatives according to the specified criteria**

In order to facilitate different analyses using the same sets of alternatives and criteria, the user defines the particular ‘setup’ for the desired analysis, i.e. defining which group of alternatives is assessed using which group of criteria under which weight group; the default values are to assess all alternatives under all criteria with equal weights.

![Figure 17: Setting up the analysis](image)
Step 8: Input data

The user must now input the data that was gathered in step 2 into the input table which was created according to the criteria definitions; the user should pay attention to the particular Analysis setup to which they are inputting the data to (top left of the table).

Figure 18 shows the data input for the ECHO case:

![Image of data input table]

Figure 18: Appraising the ECHO case alternatives according to the specified criteria

Step 9: Choose the best alternative amongst the options

Finally, the best alternative for optimization can be chosen by clicking on ‘Ranking’ in the left sidebar menu. The values (Mean, Minimum, and Maximum) for each OpA are shown in the tool (see Figure 19). These values are all the same in this example as these result from crisp numbers.

![Image of ranking results]

Figure 19: Ranking the alternatives and choosing the best amongst the OpA
In this use case, the best alternative is OpA 1, followed by OpA 3. OpA 2 is the lowest ranked option. The minimum and maximum values relate to the ranges that are inherent to fuzzy criteria (unlike crisp). Depending on the defined ranges for these criteria (even in the case of the normalized default), certain options may yield better scores under certain edge conditions. E.g. OpA 1 could be worse at its hypothetical minimum point compared to the other OpAs. This should then direct the user to investigate the conditions that yielded these results, understand and clarify the underlying uncertainty so the ranges assigned to the fuzzy criteria can be limited and thus eliminate the overlap.
5 Conclusions

The methodology developed here serves as the SmartResilience project third pillar and introduces a decision-making process for resilience improvement into the methodology. Broadly, this methodology has three stages:

1. Definition of the decision problem, setting the goals and criteria by which these can be measured
2. Identification of resilience improvement measures (e.g. investment in physical protection) and assessing their effectiveness, cost, etc.
3. Choosing the best alternative, given the aforementioned criteria and effects

The SmartResilience project focuses on answering questions about investment in resilience optimization, e.g. “Which is the best option that garner the most value for money invested in resilience improvement?”

Based on the well established AHP model, the methodology introduces fuzziness into its criteria so it can factor in both quantitative (crisp) and qualitative (fuzzy) criteria, mixed together in the same decision matrix. This is achieved by transforming all criteria into fuzzy terms and only then normalizing them to the same comparable scale (following AHP). Once scores are derived, these are “de-fuzzified” back into real numbers and applied to the different alternatives

The reason fuzzy logic and trapezoidal numbers are applied is to enable the capturing of semantic arguments as well as to introduce uncertainty, inherent to decision making done without access to complete information.

The three primary research outcomes related to the MCDM method are

1. It is fully quantifiable – it is fit to be used even in fuzzy, uncertain scenarios and maintain comparability;
2. It is transparent – requires clearly defined criteria and weights that are easily auditable;
3. Its outcomes are repeatable – in the sense of reliability.

This method can be useful for SCI operators, regulators, and end-users when making decisions surrounding selection of optimal measures to improve the resilience of SCIs.

Finally, two project partners (in charge of HOTEL and ECHO) applied the methodology in their own operations, outside the scope of the project and indicated that they will adopt the methodology into the operating procedures. More user testimonials may also be found in SmartResilience D9.1\(^1\) and the ResilienceTool homepage\(^2\).


References


ANNEXES

Annex 1  Review table
Annex 2  Procedure for use of MCDM methodology in the SCI dashboard
Annex 1  Review table

The review table will be provided in the Periodic Report submitted to the European Commission.
Annex 2  Procedure for use of MCDM methodology in the SCI dashboard

<table>
<thead>
<tr>
<th>Responsible</th>
<th>Procedure 001</th>
<th>Related document/Description</th>
<th>Due Before</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPP, CSU</td>
<td>Click on ‘Members’ Area and Tools’, then: ‘Dashboard’</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on “open tool” in SCI Dashboard and login</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>From the left panel select: “Optimize”</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on “Add New MCDM Analysis”</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Fill “Analysis Information” (Name, Description)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on Update Data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>From the left panel select: “Alternative definition”</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on “Add New Alternative”</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Fill the information (Name, Descriptions)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on Update Data</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

MCDM: Multi-criteria decision model; RPP: Responsible Project Partner; CSU: Case Study User

Figure 20: Part 1 of the procedure for MCDM methodology implementation in SCI dashboard
**Procedure: Multi-Criteria decision making methodology in SmartResilience**

<table>
<thead>
<tr>
<th>Responsible</th>
<th>Procedure 001</th>
<th>Related document/ Description</th>
<th>Due Before</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPP, CSU</td>
<td>A-1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>From the left panel select: “Alternative group”</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Are “All” the defined alternatives are to be selected for assessment?</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Click on “Add New Alternative group”</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fill the information (Name alternative group, Description, select the Alternatives)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>From the left panel select: “Criteria definition”</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on “Add New Criteria”</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Specify Name, Description, Higher ranking when closer to, Criterion type, Unit of Input, Minimum of Input, Maximum of Input</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on Update Data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>A-3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

MCDM: Multi-criteria decision model; RPP: Responsible Project Partner; CSU: Case Study User

Figure 21: Part 2 of the procedure for MCDM methodology implementation in SCI dashboard
### Procedure: Multi-Criteria decision making methodology in SmartResilience

<table>
<thead>
<tr>
<th>Responsible</th>
<th>Procedure 001</th>
<th>Due Before</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPP, CSU</td>
<td>Are “All” the defined Criteria are to be selected for assessment?</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Click on “Add New Criteria group”</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fill the information (Name, Description, Choose criteria(s))</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>From the left panel select: “Criteria weight”</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Click on Update Data</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Should “Default (equal weight)” be assigned to each criterion?</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Click on “Add New Weight group”</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Specify the Name, Description, Criteria group and Enter weight(s) of each criterion)</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Should “Default (equal weight)” be assigned to each criterion?</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Click on Update Data</td>
<td></td>
</tr>
</tbody>
</table>

**MCDM: Multi-criteria decision model; RPP: Responsible Project Partner; CSU: Case Study User**

Figure 22: Part 3 of the procedure for MCDM methodology implementation in SCI dashboard
Procedure: Multi-Criteria decision making methodology in SmartResilience

<table>
<thead>
<tr>
<th>Responsible</th>
<th>Procedure 001</th>
<th>Due Before</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPP, CSU</td>
<td>A-3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>From the left panel select: “Analysis setup”</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Should “Default analysis setup” be assessed?</td>
<td>No</td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>From the left panel select: “Input data”</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on “Add New Analysis setup”</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Specify the Name, Description, Alternative group, Criteria group and weight group to be assessed</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>From the left panel select: “Analysis setup”</td>
<td>To be assessed</td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Select the “Analysis setup” to be assessed</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Provide values for each criterion against each alternative</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on Update Data</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>From the left panel select: “Ranking”</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Select the “Analysis setup” to be assessed</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>View results about the best ranked Alternative</td>
<td></td>
</tr>
<tr>
<td>RPP, CSU</td>
<td>Click on Close Analysis</td>
<td></td>
</tr>
</tbody>
</table>

MCDM: Multi-criteria decision model; RPP: Responsible Project Partner; CSU: Case Study User

Figure 23: Part 4 of the procedure for MCDM methodology implementation in SCI dashboard