Multi-criteria decision making techniques for combining different sets of road safety performance indicators into an overall index

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MULTI-CRITERIA DECISION MAKING TECHNIQUES FOR COMBINING DIFFERENT SETS OF ROAD SAFETY PERFORMANCE INDICATORS INTO AN OVERALL INDEX

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Preface

Composite indexes are increasingly recognised as a useful tool in policy analysis and public communication for their remarkable ability to integrate large amounts of information into understandable formats that are often easier to interpret by the general public than finding a common trend in many separate indicators. During the last decade, a large number of composite indexes have been developed in wide ranging fields such as environment, economy, society, sustainable development, globalisation, and innovation. However, the development of a composite index for road safety is relatively new and plenty of research work can be done.

As the topic of my master thesis, I mainly focused on the use of multi-criteria decision making framework for composite index research in the context of road safety. The aim of this thesis is to combine different sets of road safety performance indicators into an overall index by applying one of the well known multi-criteria decision making techniques, i.e., the TOPSIS method. Meanwhile, the subjective kind of uncertainty on data (i.e., linguistic variables given by experts) and the hierarchical structure of the indicators are taken into account. As a result, a hierarchical fuzzy TOPSIS method is realized and proved valuable in creating a composite road safety performance index.

At the final stage of this thesis, which also means the end of my 2-year master programme, it is the place to acknowledge many people for their kind help along the way of my research either directly or indirectly. First and foremost, my deepest gratitude is to my promoter, Prof. Da Ruan, for his invaluable support, gentle encouragement and advice during my master's study. I consider myself fortunate to work under his direction and benefit from his broad international experience. Thank you for giving me this great opportunity to work on this interesting area. My sincere appreciation also goes to my co-promotor, Prof. Elke Hermans, for her constant support, valuable suggestions, and great patience on my master thesis, and long before on my case study. My acknowledgement further goes to Isabel and Nadine, who were always ready to provide administrative assistance when needed. I also want to thank all my classmates for creating an excellent study environment and kindly help during these two years. I wish them all the best in their future careers.

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Summary

With the ever increasing public awareness of the complexity of road safety phenomenon, more detailed aspects of crash and injury causation rather than only crash data (e.g., the number of road fatalities) are extensively investigated in the current road safety research. In this respect, safety performance indicators (SPIs), which are causally related to the number of crashes or to the injury consequences of a crash, are rapidly developed and increasingly used. Furthermore, to measure the multi-dimensional concept of road safety which cannot be captured by a single indicator, the exploration of a comprehensive composite road safety performance index is attractive and desirable. The index can thus present an overall road safety picture by capturing a multitude of risk information in one index score, and offers advantages in terms of communication, benchmarking, and prioritizing road safety actions. In this study, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, as one of the well known classical multi-criteria decision making techniques, is investigated in combining individual SPIs into an overall index for a set of European countries. Moreover, to deal with the subjective kind of uncertainty on data (such as linguistic variables given by experts) which are usually adopted to assess the weights of all criteria (indicators) and the ratings of each alternative (country) with respect to each criterion, the extension of classical TOPSIS method to the fuzzy environment is explored, and two applications (i.e., only weights need to be fuzzified and both weights and indicator values are fuzzified) are successfully conducted based on the fuzzy TOPSIS method. Furthermore, due to the ever increasing number of SPIs used to reflect each road safety risk domain in a more comprehensive way, a hierarchical structure of the indicators is created. Correspondingly, a hierarchical fuzzy TOPSIS model is realized and used to combine the multilayer indicators into one overall road safety performance index. Using the number of road fatalities per million inhabitants as a relevant point of reference, the hierarchical fuzzy TOPSIS method has proven valuable as an alternative way in creating a composite road safety performance index for a given set of European countries. Meanwhile, it effectively handles the problems of linguistic expression instead of crisp values given by experts, and takes the layered hierarchy of the indicators into account which is seldom considered in the current index research.

Keywords: road safety performance indicators, composite index, multi-criteria decision making, TOPSIS, linguistic terms, fuzzy set theory, hierarchical structure

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Chapter 1 Introduction

The economic and structural development of our present society is to a very large extent based on successive improvements in transport. By speeding up communications and the transport of goods and people, the transportation systems have become a crucial component of modernity, and have generated a revolution in contemporary economic and social relations. However, incorporating new technologies have not come about without cost: environmental pollution, urban stress and deteriorating air quality are all directly linked to modern transport systems. Above all, transportation is increasingly associated with the rise in the negative effects on safety, which is important not only because of the lost travel time or cost of property damage, but also because of the loss of human life and serious injuries sustained.

Of all the systems with which people have to deal every day, road traffic systems are the most complex and the most dangerous with the fact that the probability of being involved in road crashes is much greater than that in all other transportation modes (rail, air, maritime, etc.). During the past decades, rapid growth of road traffic volume results in continuously increasing safety problems, such as road crashes, premature deaths, as well as physical and psychological handicaps. These not only lead up to reduced worker productivity and trauma affecting a victim’s private life, but also cause great emotional and financial stress to the millions of families affected. Equally significant are the rising costs in health services and the added burden on public finances representing around 1 to 3% of the Gross Domestic Product (GDP) in most countries [WHO, 2004]. Consequently, road traffic injuries and fatalities have nowadays been recognized as one of the most important public health issues that requires concerted efforts for effective and sustainable prevention.

1.1 The road safety status

A high price in human and economic terms is currently being paid all over the world for motorized road mobility. Current levels and socio-economic costs of fatalities and injuries resulting from road crashes are becoming increasingly socially unacceptable and difficult to justify to citizens. Worldwide, an estimated 1.2 million people are killed in road crashes each year, and as many as 50 million more are injured [WHO, 2004]. This means that every day around the world, more than 3,000 people die from road traffic injury.

Projections indicate that these figures will increase by about 65% over the next 20 years unless there is new commitment to prevention [WHO, 2004].

In higher-income countries, road traffic accidents were already among the top ten leading causes of disease burden in 1998 as measured in DALYs (disability-adjusted life years). In less developed countries, road traffic accidents were the most significant cause of injuries, ranking eleventh among the most important causes of lost years of healthy life. According to a World Health Organization/World Bank report "The Global Burden of Disease" [Murray et al., 1996], deaths from non-communicable diseases are expected to climb from 28.1 million a year in 1990 to 49.7 million by 2020 --- an increase in absolute numbers of 77%. Road traffic accidents are the main cause of this rise. Without appropriate action, by the year 2020, road traffic injuries are predicted to be the third leading contributor to the global burden of disease and injury (see Table 1-1) [Murray et al., 1996].

Table 1-1 Change in rank order of DALYs for the 10 leading causes of the global burden of disease

1990		2020	
Rank	Disease or injury	Rank	Disease or injury
1	Lower respiratory infections	1	Ischaemic heart disease
2	Diarrhoea diseases	2	Unipolar major depression
3	Perinatal conditions	3	**Road traffic injuries**
4	Unipolar major depression	4	Cerebrovascular disease
5	Ischaemic heart disease	5	Chronic obstructive pulmonary disease
6	Cerebrovascular disease	6	Lower respiratory infections
7	Tuberculosis	7	Tuberculosis
8	Measles	8	War
9	**Road traffic injuries**	9	Diarrhoea diseases
10	Congenital abnormalities	10	HIV

DALY: Disability-adjusted life year. A health-gap measure that combines information on the number of years lost from premature death with the loss of health from disability.

In the European Union (EU), road transport accounts for 88% of all passenger transport, but accounts for over 100 times more deaths than all other modes together [FERSI/ECTRI, 2009]. In 2008, about 39,000 persons died as a consequence of road crashes. Fatalities per million inhabitants ranged from about 40 in some countries to over 140 in others, and were about 80 for the EU as a whole [ETSC, 2009]. Moreover, the numbers recorded as seriously injured in the EU amounted to over 240,000 in 2007 [CARE, 2008]. The estimated annual cost of road traffic injury to the EU Member States exceeds €180 billion, or about 2% of the GDP of the EU [WHO, 2004]. In Europe, one in three citizens will need hospital treatment during their lifetime due to road crashes, one in twenty citizens will be killed or impaired by road crashes, and one in eighty citizens will end their life 40 years earlier due to road crashes [ETSC, 1999].

As can be seen in Figure 1-1, the number of road fatalities dropped significantly in Europe at the beginning of the 1990s. However, the trend has been less distinct in the late 1990s.

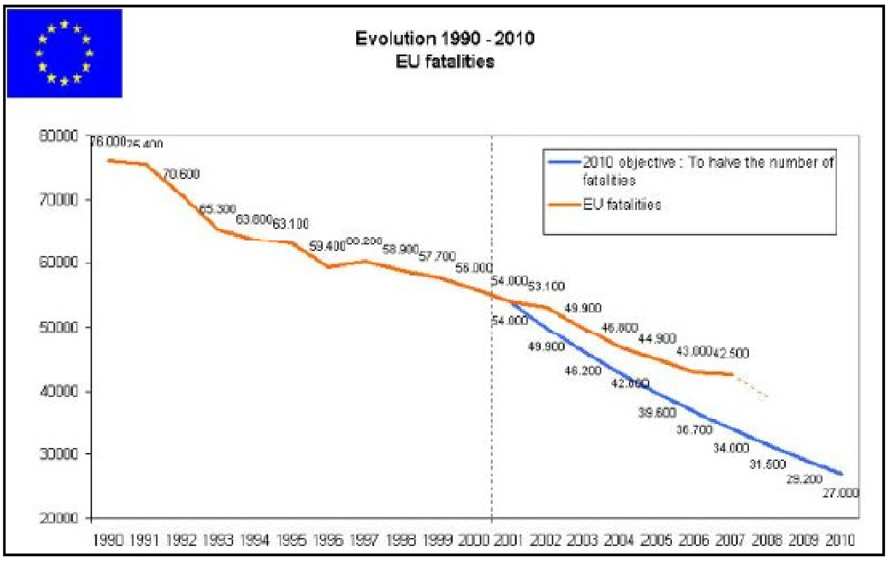

Figure 1-1 Foreseen vs. actual reduction of EU road accidents between 1990-2010

Source: CARE (EU road accidents database) National data

As a result, the EU has set itself a target of halving the yearly number of road deaths between 2001 and 2010 [EC, 2001]. To be on course to reach the EU target in 2010, a reduction of at least 37% between 2001 and 2007 corresponding to an annual average reduction of at least 7.4% is needed. However, road fatalities have been reduced by 20% only during this period, and the EU's yearly reduction in road fatalities is no more than 4.2% on average (also shown in Figure 1-1) [ETSC, 2008]. The European Commission's Mid-term Review of progress towards this target has also shown that Europe is off target and greater efforts are needed, at both the European and national levels [EC, 2006]. The latest European Transport Safety Council (ETSC) PIN study [ETSC, 2009] even indicates that the EU-15, which originally set the target, might halve the number of road fatalities with two years' delay, while the EU-27 as a whole will be able to reduce the yearly number of road fatalities to the 25,000 aim of 2010 only by 2017 (see Figure 1-2), and just three Member States, i.e., Luxembourg, France and Portugal, will be able to achieve the 2010 target at the current rate of advance.

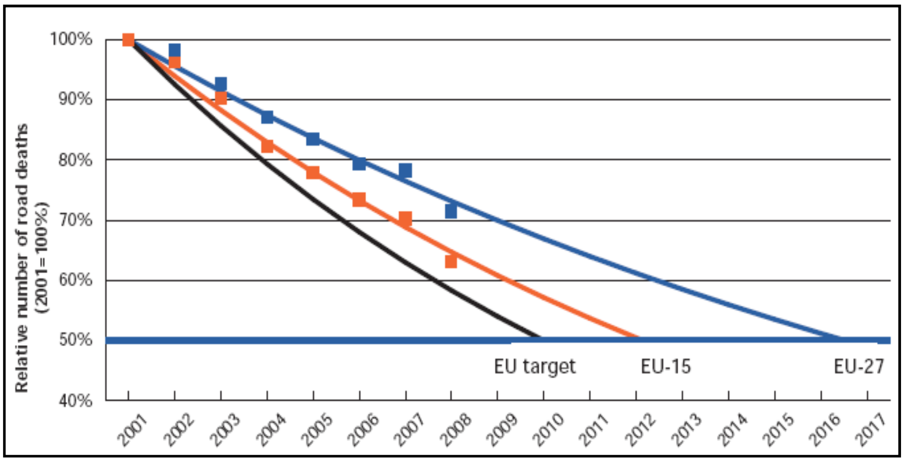

Figure 1-2 Estimated trends in road deaths in the EU, based on developments in 2001-2008

Now, when it arrives at the target year, the momentum of preventing further deaths and disablement is in danger of being lost so that new impetus is needed. To this end, a new European Action Programme for the period of 2010 to 2020 was organized last year, and new targets and measures beyond 2010 have been proposed. Indicatively, the ETSC proposes a shared target of 40% reduction of deaths with a further target to reduce injuries with lasting effects in each Member State by 40% [ETSC, 2010]. However, the overall issue is much more complex, and the need for research and intervention in road safety field are much more pressing both for the EU and its Member States.

1.2 The road safety analysis

Given the high number of road casualties (including fatalities, serious injuries, and slight injuries) and the corresponding suffering and costs as described in Section 1.1, measures are urgently needed in order to reduce this number and make progress in road safety. In this respect, comprehensive data collection and in-depth data analysis are essential in terms of designing effective safety strategies, setting challenging targets, determining intervention priorities and monitoring programme effectiveness.

Traditionally, crash data such as the number of casualties gathered as part of the routine police procedures is widely investigated, and treated as the only criterion in evaluating the level of road safety. For example, the number of fatalities per capita is usually computed for each country and the relative position can then be assessed. However, having recognized the complex character of the traffic safety phenomenon, such a criterion is only considered as the "worst case scenario" in the unsafe operational conditions of traffic system, and is insufficient in explaining more detailed aspects of crash causation and injury prevention. At the same time, road safety policymakers and analysts aiming at a higher level of safety need to take into account as many factors influencing safety as possible or, at least, those factors they are able to affect or control [ETSC, 2001].

To this end, safety performance indicators (SPIs), which are causally related to the number of crashes or to the injury consequences of a crash (e.g., levels of mean traffic speeds, seat belt wearing, drink driving, and vehicle safety ratings), are rapidly developed and increasingly used, especially over the last decade (e.g., [ETSC, 2001; Vis, 2005; OECD/ITF 2008; Wegman et al., 2008; Hermans, 2009]). Knowledge on these indicators is valuable in understanding the processes that lead to crashes, identifying corresponding interventions and monitoring the effectiveness of the safety actions that are taken. Specifically, the indicator values can be compared across countries thereby resulting in the identification of the main problem areas in a particular country, and appropriate measures can then be determined able to deal with the main risk aspects before they lead to crashes and casualties.

However, various underlying risk factors of road safety exist, and each risk factor (e.g., protective system) could be represented by several appropriate SPIs (e.g., seat belt wearing rate in front and rear seats, respectively). Moreover, the indicators belonging to a particular factor might also be linked to one another by a layered hierarchy. Thus, a simple comparison per indicator only shows a small piece of the road safety picture, and it can be misleading since different countries may operate in different circumstances with different focal points. Consequently, to measure the multi-dimensional concept of road safety which cannot be captured by a single indicator, the exploration of a comprehensive composite road safety indicator or index is attractive and desirable. The index thus presents the overall road safety picture by capturing a multitude of risk information in one index score, and offers advantages in terms of communication, benchmarking, and prioritizing road safety actions.

1.3 Composite road safety index

Composite indicators or indices are increasingly recognised as a useful tool in policy analysis and public communication for their remarkable ability to integrate large amounts of information into understandable formats that are often easier to interpret by the general public than finding a common trend in many separate indicators. During the last decade, a large number of composite indicators have been developed in a variety of economic performance and policy areas. Some of them are listed as follows [OECD, 2003]:

- Composite of Leading Indicators – Organisation for Economic Cooperation and Development (OECD);
- OECD International Regulation database – OECD;
- Overall Health Attainment – World Health Organisation (WHO);
- Sustainable Development Index – United Nations (UN);
- Human Development Index – UN;
- Technology Achievement Index – UN;
- Environmental Sustainability Index – World Economic Forum;
- Globalisation Index - World Markets Research Centre;
- Internal Market Index – European Commission (EC);
- Summary Innovation Index – EC;
- Investment in Knowledge-Based Economy – EC.

The proliferation of this kind of indices is a clear symptom of their political importance and operational relevance in decision making [Nardo et al., 2005]. However, composite indicators can send misleading policy messages if they are poorly constructed or misinterpreted, and may invite users (especially policy makers) to draw simplistic analytical or policy conclusions. In the following sections, the main pros and cons of using composite indicators are summarized, the current research on composite road safety index is presented, and the main research questions in this study are indicated.

1.3.1 Pros and Cons of composite indexes

In general terms, an indicator is a quantitative or a qualitative measure derived from a series of observed facts that can reveal relative positions (e.g., of a country) in a given area. When evaluated at regular intervals, an indicator can point out the direction of change across different units and through time. In the context of policy analysis, indicators are useful in identifying trends and drawing attention to particular issues.

Table 1-2 Pros and Cons of Composite indexes

Pros	Cons
Can summarize complex multi-dimensional realities with a view to supporting decision-makers.	May send misleading policy messages if poorly constructed or misinterpreted.
Are easier to interpret than a battery of many separate indicators.	May invite simplistic policy conclusions.
Facilitate communication with general public (i.e. citizens, media, etc.) and promote accountability.	May be misused, e.g. to support a desired policy, if the construction process is not transparent and/or lacks sound statistical or conceptual principles.
Can assess progress of countries over time.	The selection of indicators and weights could be the subject of political dispute.
Make it possible to include more information within the existing size limit.	May disguise serious failings in some dimensions and increase the difficulty of identifying proper remedial action, if the construction process is not transparent.
Place issues of country performance and progress at the centre of the policy arena.	May lead to inappropriate policies if dimensions of performance that are difficult to measure are ignored.
Reduce the visible size of a set of indicators without dropping the underlying information base.	
Help to construct/underpin narratives for lay and literate audiences.	
Enable users to compare complex dimensions effectively.	

They can also be helpful in setting policy priorities and in benchmarking or monitoring performance. A composite index is a mathematical combination, or aggregation, of a set of indicators. More specifically, composite index is based on underlying indicators that have no common meaningful unit of measurement, when there is no obvious way of weighting these underlying indicators [Saisana et al., 2002]. As such, their construction owes more to the craftsmanship of the modeller than to universally accepted scientific rules for encoding. The main pros and cons of using composite indicators are summarized in Table 1-2 [Saisana et al., 2002, Nardo et al., 2005].

In general, "… it is hard to imagine that debate on the use of composite indicators will ever be settled…" [Saisana et al., 2005]. However, based on the comparision between the advantages and the disadvantages, we should say, if the methodological aggregation process is sound and the results clear, the creation of an index over a set of indicators is worthwhile. Moreover, in the road safety context, as the different road safety risk factors jointly affect the frequency and severity of accidents, it is valuable to study the set of indicators simultaneously and combine the information from several risk domains in an overall index. Subsequently, the combined index could help to measure multi-dimensional concepts of road safety which cannot be captured by a single indicator.

1.3.2 Current research on composite road safety index

Compared to other domains, the development of a composite indicator for road safety is relatively new, since the traditional studies mainly consider the final safety outcomes in terms of fatalities per head of population, vehicle fleet or exposure as introduced in Section 1.2. Recently, a number of studies were carried out aiming at the development of a composite road safety index which enabled meaningful national or sub-national (e.g. regional, local etc.) comparisons and monitoring of road safety performance.

Specifically, Al Haji (2005) suggested a road safety development index (RSDI) and used it for a comparison of road safety progress in ten Asian countries plus Sweden. The RSDI development was started with the definition of eight dimensions of the road safety domain (i.e., traffic risk, personal risk, vehicle safety, road situation, road user behaviour, socio-economic background, road safety organization and enforcement). Totally, eleven separate indicators were selected and one composite index was expected. For this purpose, three weighting methods were applied, which were the simple equal average, the use of theoretical weights, and the principal component analysis (PCA). The results of the different methods were consistent and enabled a robust classification of countries into three groups of high, medium or low safety development.

Hermans et al. (2008) studied the issue of assigning weights to individual indicators in order to create a composite road safety index. In the research, the seven safety domains (i.e., alcohol and drugs, speed, protective systems, daytime running lights, vehicle, roads, and trauma management) which were defined by the SafetyNet project [Hakkert et al., 2007a] were considered, one indicator for each domain was suggested, and five weighting approaches were used to combine the separate indicators into one index. They are: factor analysis (FA), analytical hierarchy process (AHP), budget allocation (BA), data envelopment analysis (DEA), and equal weighting (EW). The results were further compared with the countries' ranking according to the personal safety (i.e., the number of road fatalities per million inhabitants). Thereafter, Shen et al. (2008, 2010) further introduced some artificial intelligence techniques to create a composite road safety index based on the same dataset, such as neural networks (NNs), and the hybrid system integrating NNs and rough set theory.

In the SUNflowerNext report [Wegman et al., 2008], a comprehensive composite road safety index based on the recent concepts of road safety target hierarchy [NRSC, 2000; Koornstra et al., 2002] was explored, in which four types of indicators, namely, final outcome indicators (e.g., number of fatalities per million inhabitants), safety performance indicators (e.g., daytime wearing rates of seat belts in the front seats), policy performance indicators (e.g., the availability and ambition of national safety targets), as well as structure and culture indicators (e.g., number of passenger cars per 1,000 inhabitants), were considered simultaneously. Both PCA and FA weighting were examined based on the data collected for 27 European countries. The analysis revealed that the countries' ranking based on the combination of indicators is not necessarily similar to the traditional ranking of countries based only on mortality rates or fatality rates.

1.3.3 Research questions

All the studies mentioned in Section 1.3.2 have clearly demonstrated the possibilities for creating composite road safety indices, and both objective weighting methods (PCA, FA, DEA, and EW) and subjective weighting methods (AHP and BA) are utilized. However, there are still some limitations in practice which need to be paid attention to. Firstly, in the Hermans' and Shen's studies, relatively small number of basic indicators were considered (i.e., one quantitative indicator for each risk domain), which might be insufficient in reflecting the entire situation of the risk domains, while in the other two studies, although one or several indicators were suggested for each domain constituting hierarchical structures, all the indicators were still treated to be in the same layer. In fact, it is valuable information to be considered in index construction since they provide a more detailed insight in the structure of the indicators. Part of the reason why the hierarchical sturtures are commonly ignored is that they are difficult to realize in the traditional weighting methods.

Secondly, of all the weighting methods applied above, those objective ones rely mostly on the quality of information about the indicators. In other words, they are usually used with the precondition that all the indicators are measurable and quantitative. However, in the real situation, some of them may be specified with either ordinal measures or the help of expert subjective judgments, which limits the application of these methods to a great extent. Moreover, concerning those subjective weighting methods which consider experts opinions, It is known that experts prefer to give linguistic valued assessments rather than crisp value judgments, such as 'low', 'relatively low', and 'high', 'extremely high'. This phenomenon results from inability to explicitly state their preferences due to the fuzzy nature of the comparison process. Therefore, how to deal with the concept of linguistic variables should be taken into account.

To settle all the problems indicated above, the multi-criteria decision making (MCDM) technique, and more particularly, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), is adopted in this study with the integration of fuzzy logic, which is one of the fastest growing areas in decision making and operations research during the last two decades [Triantaphyllou, 2000; Pardalos et al., 2008]. From a purely mathematical point of view, the aggregation convention used for composite indicators deals with the classical conflictual situation tackled in multi-criteria evaluation. Thus, the use of a multi-criteria framework for composite indicators is relevant and desirable [Ülengin et al., 2001; Funtowicz et al., 2002; Munda, 1997, 2004, and 2005].

1.4 Multi-criteria decision making techniques

"Decision making is the study of identifying and choosing alternatives based on the values and preferences of the decision maker (DM). Making a decision implies that there are alternative choices to be considered, and in such a case we want not only to identify as many of these alternatives as possible but to choose the one that has the highest probability of success or effectiveness and best fits with our goals, desires, lifestyle, values, and so on." [Robert, 2009] In one word, the process of decision making is the selection of an act or courses of action from among alternative acts or courses of actions such that it will produce "optimal" results under some criteria of "optimization".

Multi-criteria decision making (MCDM) is one of the most well known branches of decision making, which offers the methodology for decision making analysis when dealing with problems that involve multiple objectives under the presence of a number of conflicting decision criteria [Triantaphyllou, 2000]. MCDM can help users understand the results of integrated assessments, including tradeoffs among policy objectives, and can use those results in a systematic, defensible way to develop policy recommendations. A typical MCDM problem is modelled as Eq. (1.1):

$$(MCDM)\begin{cases} Select: A_1, A_2, \cdots, A_m \\ s.t.: C_1, C_2, \cdots, C_n \end{cases} \tag{1.1}$$

where $A=(A_1, A_2, \ldots, A_m)$ denotes m alternatives, $C=(C_1, C_2, \ldots, C_n)$ represents n criteria.

1.4.1 Basic concepts

According to many authors (e.g., [Triantaphyllou, 2000]), MCDM is divided into multi-objective decision making (MODM) and multi-attribute decision making (MADM). MODM problems involve designing the best alternative given a set of conflicting objectives [Hwang et al., 1979]. A typical example is mathematical programming problems with multiple objective functions. In contrast to MODM problems, MADM refers to making preference decisions (e.g., evaluation, prioritization, selection) over the available alternatives that are characterized by multiple, usually conflicting, attributes [Hwang et al., 1981]. Very often the terms MADM and MCDM are used to mean the same class of models (i.e., MCDM).

Although MCDM methods may be widely diverse, many of them share the following common characteristics [Triantaphyllou, 2000]:

Alternatives: Usually alternatives represent the different choices of action available to the decision maker. A finite number of alternatives, ranging from several to thousands, are supposed to be screened, prioritized, selected, and/or ranked. The term ‘alternative’ is synonymous with ‘option’, ‘policy’, ‘action’, or ‘candidate’, among others.

Multiple Attributes: Each MCDM problem is associated with multiple attributes, and they are also referred to as ‘decision criteria’. Attributes represent the different dimensions from which the alternatives can be viewed. The number of attributes depends on the nature of the problem. In case the number of criteria is large, attributes may be arranged in a hierarchical manner. That is, there are some major criteria, and each may be associated with several sub-criteria.

Decision Weights: Almost all MCDM methods require information regarding the relative importance of each criterion to the decision, and it is assumed to be positive. The weights of the criteria are usually determined on subjective basis. They represent the opinion of a single decision maker or synthesize the opinions of a group of experts using a group decision technique, as well.

Decision Matrix: A MCDM problem can be concisely expressed in a matrix format, where columns indicate criteria considered in a given problem and rows list competing alternatives. Thus a typical element x_{ij} of the decision matrix ($D_{m \times n}$) indicates the performance of alternative A_i when it is evaluated in terms of decision criterion C_j (for i=1, 2, ⋯, m, and j=1, 2, ⋯, n). For the sake of simplicity we assume that a higher score value means a better performance since any goal of minimization can be easily transformed into a goal of maximization. It is also assumed that the decision maker has determined the weights of relative performance of the decision criteria which are denoted as w_j (j=1, 2, ⋯, n). The information is summarized in a matrix format in Eq. (1.2):

$$
\mathbf{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \qquad (1.2)
$$

$$
W = [w_1 \quad w_2 \quad \cdots \quad w_n]
$$

where the values of x_{ij} and w_j, $\forall\, i, j$ can be crisp or linguistic variables that are described by any form of fuzzy numbers. For example, in triangular fuzzy numbers, $x_{ij}=(a_{ij}, b_{ij}, c_{ij})$ and $w_j=(w_{j1}, w_{j2}, w_{j3})$.

1.4.2 Multi-criteria decision making process

According to Baker et al., (2002), decision making should start with the identification of the decision makers and stakeholders in the decision, reducing the possible disagreement about problem definition, requirements, goals and criteria. Then, a general decision making process can be divided into the following steps:

Step 1 Define the problem
"This process must, as a minimum, identify root causes, limiting assumptions, system and organizational boundaries and interfaces, and any stakeholder issues. The aim is to express the issue in a clear, one-sentence problem statement that describes both the initial conditions and the desired conditions." Of course, the one-sentence limit is often exceeded in the practice in case of complex decision problems. The problem statement must however be a concise and unambiguous written material agreed by all decision makers and stakeholders. Even if it can be sometimes a long iterative process to come to such an agreement, it is a crucial and necessary point before proceeding to the next step.

The decision problem in this study is to evaluate the road safety performance of a country from the intermediate outcomes' (i.e., safety performance indicators) point of view, which can reflect the current safety conditions of the road traffic system, understand the process that leads to accidents, and illustrate how well the road safety countermeasures are doing in meeting their objectives. In contrast, the traditional approach mainly considers the final outcomes in terms of the number of fatalities, which is insufficient in explaining the detailed aspects of crash causation and injury prevention.

Step 2 Determine requirements
"Requirements are conditions that any acceptable solution to the problem must meet. Requirements spell out what the solution to the problem must do." In mathematical form, these requirements are the constraints describing the set of the feasible (admissible) solutions of the decision problem. It is very important that even if subjective or judgmental evaluations may occur in the following steps, the requirements must be stated in exact quantitative form, i.e., for any possible solution it has to be decided

unambiguously whether it meets the requirements or not. We can prevent the ensuing debates by putting down the requirements and how to check them in a written material.

With respect to this study, the main road safety risk factors (such as protective systems) should be identified, one or several safety performance indictors should be specified per factor, and each of them will contribute to the final evaluation results to a certain extent, which are the requirements for this study.

Step 3 Establish goals

"Goals are broad statements of intent and desirable programmatic values…. Goals go beyond the minimum essential must have's (i.e., requirements) to wants and desires." In mathematical form, the goals are objectives contrary to the requirements that are constraints. The goals may be conflicting but this is a natural concomitant of practical decision situations.

In general, we aim to create a road safety performance index in this study. It is the combination of all individual indicators, and can be used for representing the overall road safety performance of a country and further ranking countries based on their index score. Moreover, a high degree of similarity between the index score/ranking and the final outcome value/ranking are expected.

Step 4 Identify alternatives

"Alternatives offer different approaches for changing the initial condition into the desired condition." Be it an existing one or only constructed in mind, any alternative must meet the requirements. If the number of the possible alternatives is finite, we can check one by one if it meets the requirements. The infeasible ones must be deleted (screened out) from the further consideration, and we obtain the explicit list of the alternatives. If the number of the possible alternatives is infinite, the set of alternatives is considered as the set of the solutions fulfilling the constraints in the mathematical form of the requirements.

Considering this study, the road safety performance of 21 European countries will be ranked and evaluated.

Step 5 Define criteria

“Decision criteria, which will discriminate among alternatives, must be based on the goals. It is necessary to define discriminating criteria as objective measures of the goals to measure how well each alternative achieves the goals.” Since the goals will be represented in the form of criteria, every goal must generate at least one criterion but complex goals may be represented only by several criteria.

It can be helpful to group together criteria into a series of sets that relate to separate and distinguishable components of the overall objective for the decision. This is particularly helpful if the emerging decision structure contains a relatively large number of criteria. Grouping criteria can help the process of checking whether the set of criteria selected is appropriate to the problem, can ease the process of calculating criteria weights in some methods, and can facilitate the emergence of higher level views of the issues. It is a usual way to arrange the groups of criteria, sub-criteria, and sub-subcriteria in a tree-structure.

According to Baker et al., criteria should be

- able to discriminate among the alternatives and to support the comparison of the performance of the alternatives,
- complete to include all goals,
- operational and meaningful,
- non-redundant,
- few in number.

In this study, six main road safety risk factors (i.e., alcohol and drugs, speed, protective systems, vehicle, roads, and trauma management) will be used as the basis for SPIs selection, and one or several appropriate safety performance indictors will be specified for each factor constituting non-hierarchical and hierarchical structures, respectively.

Step 6 Select a decision making tool

There are several tools for solving a decision problem. The selection of an appropriate tool is not an easy task and depends on the concrete decision problem, as well as on the objectives of the decision makers. Sometimes ‘the simpler the method, the better’ but complex decision problems may require complex methods, as well.

Concerning this study, the (fuzzy) TOPSIS method will be applied to combine all the SPIs into an overall road safety performance index.

Step 7 Evaluate alternatives against criteria

Every correct method for decision making needs, as input data, the evaluation of the alternatives against the criteria. Depending on the criterion, the assessment may be objective (factual), with respect to some commonly shared and understood scale of measurement (e.g., money) or can be subjective (judgmental), reflecting the subjective assessment of the evaluator. After the evaluations the selected decision making tool can be applied to rank the alternatives or to choose a subset of the most promising alternatives.

In this study, the indicator values will be collected from a wide range of international databases and recent publications of international working groups.

Step 8 Validate solutions against problem statement

The alternatives selected by the applied decision making tools have always to be validated against the requirements and goals of the decision problem. It may happen that the decision making tool was misapplied. In complex problems the selected alternatives may also call the attention of the decision makers and stakeholders that further goals or requirements should be added to the decision model.

After the calculation of road safety performance index score, the assigned weight for each indicator will be analyzed, and the degree of similarity between the index score/ranking and the final outcome value/ranking (i.e., the number of fatalities per million inhabitants) will be assessed.

1.4.3 Classification of MCDM methods

Among the decision making procedures listed in the above Section, selecting an appropriate decision making method is one of the most important steps, which determines the quality of the final decision making results. Since last 50 or 60 years, operation researchers and practitioners have developed a wide range of methods to find an answer to the question of "How a decision should be selected from a given set of competing alternatives that are evaluated against conflicting objectives". So far, these MCDM methods have been widely used in many research fields, and each method has its own characteristics. According to Løken (2007), the existing MCDM methods can be mainly classified into three broad categories:

(1) Value measurement models
Analytic Hierarchy Process (AHP) developed by Saaty (1980), and Multi-attribute Utility Theory (MAUT) [Winterfeld, 1986] are the best known methods in this group.

(2) Goal, aspiration and reference level models
Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) by Hwang and Yoon (1981) and Goal programming (GP) [Nemhauser et al., 1989] are the most important methods that belong to the group.

(3) Outranking models
Roy (1968)'s ELECTRE (ELimination Et Choix Traduisant la Réalité or Elimination and Choice Translating Reality) and Brans (1985)' PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) are two main families of methods in this group.

Although different categories are classified, the MCDM methods mentioned above own some common properties in providing better understanding of inherent features of decision problem, promoting the role of participants in decision making processes, facilitating compromise and collective decisions, and improving quality of decisions by making them more explicit, rational and efficient. Moreover, negotiating, quantifying and communicating the priorities are also facilitated with the use of these methods.

However, these MCDM methods generally assume that all criteria and their respective weights are expressed in crisp values and thus, the rating and the ranking of the alternatives can be carried out without any problem. Nevertheless, in the real-world decision situation, it has been widely recognized that most decisions taken place in an environment in which the goals and constraints, because of their complexity, are not known precisely. As a result, the application of the classical MCDM methods may face serious practical problems from the criteria to the weights which perhaps contain imprecision or vagueness inherent in the information. To deal with these qualitative, imprecise, or even ill-structured decision problems, Zadeh (1965) suggested employing the fuzzy set theory as a modeling tool for complex systems that can be controlled by humans but are hard to define exactly.

1.4.4 Fuzzy MCDM research

Fuzzy sets were introduced by Zadeh in 1965 to manipulate data and information possessing nonstatistical uncertainties. It was specifically designed to represent mathematical uncertainty and vagueness and to provide formalized tools for dealing with the imprecision intrinsic to many problems. Fuzzy logic provides an inference morphology that enables approximate human reasoning capabilities to be applied to knowledge-based systems. The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning.

As the classical MCDM methods cannot deal with decision makers' ambiguities, uncertainties, and vagueness that cannot be handled by crisp values, and the fuzzy set theory allows us to incorporate unquantifiable information, incomplete information, non-obtainable information, and partially ignorant facts into the decision models. Bellman and Zadeh (1970) introduced the first approach regarding decision making in a fuzzy environment. They cleared the way for a new family of methods to deal with problems that had been inaccessible to and unsolvable with classical MCDM techniques.

Since then fuzzy multi-criteria decision making (FMCDM) has provoked great interest in decision science, systems engineering, management science, and operations research. Many efficient methods for FMCDM problems exist with the decision maker's preference information completely known and completely unknown. The latest research on this topic has continually improved MCDM and solved linguistic and cognitive fuzziness problems. For example, Ling (2006) presents a fuzzy MCDM method in which the criteria weights and decision matrix elements (criteria values) are fuzzy variables. Fuzzy arithmetic operations and the expected value operator of fuzzy variables are used to solve the FMCDM problem. Xu and Chen (2007) develop an interactive method for multi-criteria group decision making in a fuzzy environment. The method can be used in situations where the information about criteria weights is partly known, the weights of decision makers are expressed in exact numerical values or triangular fuzzy numbers, and the criteria values are triangular fuzzy numbers. Wu et al. (2006) develop a new approximate algorithm for solving fuzzy multiple objective linear programming problems involving fuzzy parameters in any form of membership functions in both objective functions and constraints.

1.4.5 Research method for this study --- TOPSIS

TOPSIS method, as one of the well known classical MCDM methods, was first developed by Hwang and Yoon in 1981. It bases upon the concept that the chosen alternative should have the shortest distance from the positive-ideal solution (PIS) and the farthest distance from the negative-ideal solution (NIS), in which the PIS is formed as a composite of the best performance values exhibited (in the decision matrix) by any alternative for each criterion, and the NIS is the composite of the worst performance values. Proximity to each of these performance poles is measured in the Euclidean sense (e.g., square root of the sum of the squared distances along each axis in the 'criterion space'), with optional weighting of each criterion. During the last decades, a large amount of literature existed involving TOPSIS theory and applications. Lai et al. (1994) applied the concept of TOPSIS on MODM problems. Chen (2000) extended the TOPSIS method to fuzzy environments. This extended version used fuzzy linguistic value as a substitute for the directly given crisp value in the rating of each alternative and the weight of each criterion. Then, a vertex method for TOPSIS is proposed to calculate the distance between two triangular fuzzy numbers. Zhang and Lu (2003) presented an integrated fuzzy group decision making method in order to deal with the fuzziness of preferences of the decision makers. Abo-Sinna and Amer (2005) extended the TOPSIS for solving large scale multi-objective nonlinear programming problems, and further considered the situation involving fuzzy parameters [Abo-Sinna, et al., 2006]. Wang and Elhag (2006) presented a nonlinear programming solution procedure using a fuzzy TOPSIS method based on alpha level set. They discussed the relationship between the fuzzy TOPSIS method and the fuzzy weighted average (FWA), and illustrated three examples about bridge risk assessments to compare the proposed fuzzy TOPSIS and other procedure. Jahanshahloo et al. (2006) developed an algorithmic method to extend TOPSIS for decision making problems with interval data. Ates et al. (2006) proposed a new algorithm for fuzzy TOPSIS that took into account the hierarchy in the evaluation model. The obtained results were compared with fuzzy AHP on an application in a faculty performance evaluation problem and some sensitivity analyses were presented. Yang and Hung (2007) explored the use of TOPSIS and fuzzy TOPSIS in solving a plant layout design problem. The merit of fuzzy TOPSIS was to assign the importance of attributes and the performance of alternatives with respect to various attributes by using fuzzy numbers instead of precise numbers.

In this study, the (fuzzy) TOPSIS methods are investigated and applied to create a composite road safety performance index concerning the following four reasons. First of all, the construction process of this method is transparent which makes it easily understood by the general public, and can be used to support a desired policy (see Chapter 3). Secondly, the linguistic valued judgments from experts or decision makers in terms of the indicator scores or weights which are usually expressed by using fuzzy numbers can be easily integrated in the TOPSIS model (see Chapter 4). Moreover, the indicator weights given by the experts or DMs can be directly used in the TOPSIS method without making pairwise comparisons as in the AHP method, thus avoids the inconsistency of each DM's judgments. Last but not least, the realization of a hierarchical TOPSIS model which enables taking the hierarchical structures of criteria into account makes it particularly suitable in combining layered road safety performance indicator into one index (see Chapter 5).

1.5 Structure of the thesis

The main purpose of this paper is to explore the feasibility of using a multi-criteria framework for the construction of a composite index in the road safety context. The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), as one of the well known classical multi-criteria decision making methods, is introduced particularly and applied as an alternative way in creating a composite road safety performance index given a number of individual safety performance indicators representing the main road safety risk domains. The overall index score is obtained for a set of European countries, based on which the countires can be ranked indicating their relative enriched road safety performance. Moreover, to deal with the uncertainty due to imprecision or vagueness involved in the importance weight of each indicator and/or the indicator values of each country which are probably given in linguistic variables instead of crisp data, an extension of the classical TOPSIS method to the fuzzy environment is investigated and two applications are executed. Furthermore, to reflect the characteristics of the main road safety risk domains in a more comprehensive perspective, a hierarchical structure of the indicators is developed. Correspondingly, a hierarchical fuzzy TOPSIS model is created and used to combine multilayer (sub-)indicators into one overall road safety performance index. The structure of this thesis is organized as follows:

Chapter 1 introduces the macroscopic background of this study. Based on the overview of the current road safety status at both worldwide and the European level, as well as the existing problems in the traditional road safety analysis, we demonstrate the advantages of using safety performance indicators and a composite road safety index. Subsequently, by indicating the research problems in current studies with respect to combining individual road safety indicators into an overall index, we introduce the concept of multi-criteria decision making, and select one of the well known classical MCDM methods --- TOPSIS --- as the main research direction of this study. Finally, the structure of the whole paper is presented.

Recognizing the complex character of the road safety phenomenon and intending to explain the more detailed aspects of crash causation and injury prevention in contrast to the traditional way that only considers the final outcomes such as the number of fatalities, Chapter 2 illustrates the use of road safety performance indicators, which serve as the intermediate outcomes between safety countermeasures and casualties in road crashes. Following by a review of the role of SPIs in road safety management system, a number of road safety risk domains are designated, and the relationships between each of them and road traffic casualties are specified. Subsequently, appropriate SPIs with respect to each risk domain are selected, and corresponding data are collected from a wide range of international data sources.

Chapter 3 mainly depicts how the classical TOPSIS method can be applied to create a composite road safety performance index consisting of six SPIs (i.e., one indicator for each risk domain). Firstly, we present the main application procedures of the TOPSIS method, and specify the determination of the weights for each indicator under the single or multiple decision maker circumstances. Subsequently, the application of the TOPSIS method to combine the six indicators into an overall road safety performance index is carried out, and a comparison of several ranking results derived from different approaches as well as the final outcome (i.e., the number of fatalities per million inhabitants) is conducted. In the end, we indicate the possible practical problems existing in the application of the classical TOPSIS method.

The core objective of Chapter 4 is to integrate the fuzzy set theory in the classical TOPSIS method in order to deal with the uncertainty derived from the vagueness of human cognition and expressions. Based on the review of the fuzzy TOPSIS research during the last decades, and the introduction of some basic definitions and notions of the fuzzy set theory, the main adjustments of applying the fuzzy TOPSIS method compared to the classical TOPSIS method are presented. Afterwards, the fuzzy TOPSIS method is applied to create a composite road safety performance index for the selected European countries, and two situations are considered, i.e., only weights need to be fuzzified and both weights and indicator values are fuzzified. Comparisons of the results with the ones from the classical TOPSIS method as well as the road safety final outcome (i.e., fatalities) indicate that the fuzzy TOPSIS method could serve as a promising solution to handle the problems that the weight scores and/or the indicator values are given in linguistic terms instead of crisp values.

Since the selection of one indicator for each road safety risk domain (used in the previous two chapters) might be insufficient in reflecting the entire feature of that domain, a hierarchical structure of the indicators is subsequently created. Correspondingly, a hierarchical fuzzy TOPSIS model is realized in Chapter 5 and used to combine multilayer indicators into one overall road safety performance index. In this respect, the adjustments of the algorithm which can take the layered hierarchy of the indicators into account are specified. Then, the application of this model to combine the hierarchical indicators into an overall road safety performance index is carried out, and a comparison of the ranking results with the ones obtained in the previous chapters as well as the final outcome validates the use of this model in road safety performance evaluation.

Finally, the main conclusions of this thesis are given in Chapter 6 and the topics for future research are indicated.

Chapter 2 Road Safety Performance Indicators

In contrast to the traditional approach in evaluating a country's road safety situation which mainly considered the safety outcomes in terms of fatalities per head of population, vehicle fleet or exposure, safety performance indicators (SPIs) as intermediate outcomes between safety countermeasures and casualties in road crashes are nowadays widely investigated with the intention of measuring the factors contributing to road crashes, identifying conditions which are associated with increased accident/injury risks, detailing the structure of traffic injury patterns, and illustrating how well road safety measures and programmes are doing in meeting their objectives or achieving the desired outcomes. Today, recognizing the complex character of the road safety phenomenon, more and more SPIs are developed and increasingly used as a supportive instrument for national or sub-national (e.g. regional, local etc.) comparisons and monitoring of road safety progress, especially over the last decade (e.g., ETSC, 2001; Vis, 2005; Al Haji, 2005; OECD/ITF 2008; ISO, 2008; SRA, 2008; Elvik, 2008; Wegman et al., 2008; Hermans, 2009).

In this chapter, starting with the introduction of the role of SPIs in road safety management (Section 2.1), the definition of SPIs is given in Section 2.2. Next, six main risk domains are indicated and each of them is specified in Section 2.3. Section 2.4 discusses the selection of appropriate SPIs with respect to each risk domain, and Section 2.5 describes the collection of corresponding data from various data sources. Finally, the summary is given in Section 2.6.

2.1 The role of SPIs in road safety management

In 2004, the World Report of Road Traffic Injury Prevention [WHO, 2004] provided a global call to action and blueprint for effective intervention based on past best practice as well as innovative, ambitious 'safe system' approaches. International organizations such as the World Health Organization [WHO, 2004], the International Transport Forum [ECMT, 2004], the United Nation [UN, 2007], the Organization for Economic Co-operation and Development [OECD/ITF, 2008], and the World Bank [Bliss et al., 2008] all acknowledge that the key to achieving better performance in road safety is by more effective safety management, in which the development of safety performance indicators is one of the essential elements and plays an important role.

A model describing the place of SPIs in road safety management system is shown in Figure 2-1 [ETSC, 2001], which allocates the SPIs on the level of intermediate outcomes.

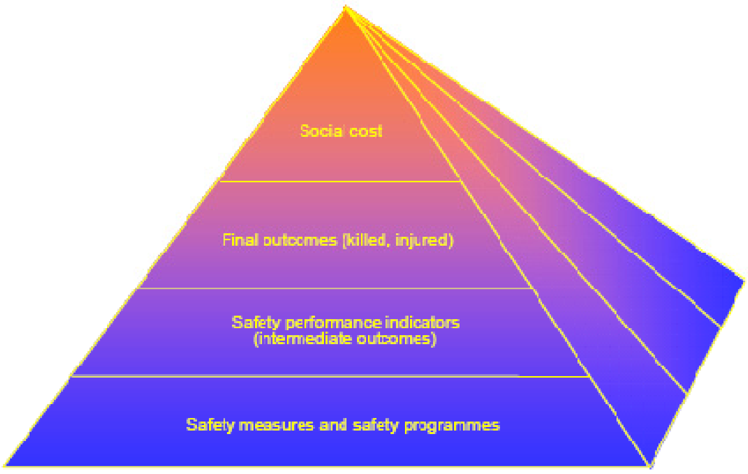

Figure 2-1 Essential elements of safety management system [ETSC, 2001]

Social cost, at the top level of the model, is the monetary outcome resulting from the final outcomes at the next level, i.e. accidents/fatalities/casualties, which are traditionally used to assess a country's road safety situation. However, simply counting crashes and injuries often gives an incomplete indication of the level of road safety, since they are only considered as the "worst case scenario" in the unsafe operational conditions of traffic system, and is insufficient in explaining more detailed aspects of crash causation and injury prevention. Therefore, counts of crashes and injuries need to be supplemented by other road safety indicators. These indicators should give a more complete picture of the level of road safety, and point to the emergence of new problems at an early stage before these problems show up in the form of accidents. At the same time, road safety policymakers and analysts aiming at a higher level of safety need to take into account as many factors influencing safety as possible or, at least, those factors they are able to affect or control [ETSC, 2001].

To this end, safety performance indicators (rather than accidents/casualties) are developed, which are seen as any measurement that is causally related to crashes or injuries and is used in addition to the figures of crashes or injuries, in order to indicate safety performance or understand the process that leads to accidents [ETSC, 2001].

Because of the high information density SPIs allow quicker and more local analyses and monitoring than accidents/casualties do, and they also provide a way of effectively linking safety countermeasures (the lowest level in the model) with final outcomes in terms of fewer casualties [ETSC, 2006]. Moreover, managing road safety with SPIs enables countries to develop process-oriented road safety initiatives which take into account the fact that public policy instruments come in vertical, horizontal and chronological packages, rather than in isolation [Bemelmans-Videc et al., 1998].

2.2 Definition of SPIs

Reflecting the theoretical considerations about the mode of operation of the road safety system, definitions of some key concepts related to SPIs are given as follows [ETSC, 2001; Hakkert et al, 2007a]:

- ***Safety performance***

  Changes over time in the level of transport safety, with a reduction in the number of accidents or the number of killed or injured people defined as an improvement in safety performance.

- ***Safety performance indicator***

  Any measurement (indicator), reflecting those operational conditions of the road traffic system, which influence the system's safety performance.

- ***Importance of a safety performance indicator***

  The strength of the relationship between an indicator and the number of crashes or severity of injuries, expressed in terms of, for example, the risk attributable to changes in the value of the indicator.

The purpose of SPIs is [Hakkert et al, 2007a, b]:

- to reflect the current safety conditions of a road traffic system (i.e. they are considered not necessarily in the context of a specific safety measure, but in the context of specific safety problems or safety gaps);
- to measure the influence of various safety interventions, but not the stage or level of application of particular measures;
- to compare between different road traffic systems (e.g., countries, regions, etc.).

In general terms, SPIs are used to represent certain operational conditions that are related to road traffic safety, often expressed as the proportion of the traffic volume that fulfills the condition. One example could be "the proportion of car occupants using seat belts". The SPI therefore represents a certain safety aspect (seat belt use) as well as a value (proportion of traffic volume) of how this aspect has penetrated to the traffic system. Implicitly, the SPI should have a proven and well-documented relation to the number of casualties, and could be seen as an intermediate measurement of the traffic safety level for that specific aspect. The combination of several SPIs would then also be an intermediate measurement of traffic safety, representing current or future final outcomes in terms of the number of fatally and severely injured [Elvik, 2008; Hermans et al., 2008, 2009]. For the majority of SPIs, there are several countermeasures that could contribute to their improvement. Taking the above example of seat belt use, the improvement could for example follow as a result of seat belt legislation and enforcement, a demerit point system, or intelligent seat belt reminders in isolation or in combination.

2.3 Road safety risk domains for SPIs development

Based on a review of safety policies in the European Union and its member states, the European Transport Safety Council report "Transport Safety Performance Indicators" (2001) [ETSC, 2001] recommended the development of SPIs related to human behavior (i.e., speed, alcohol and seat belts), vehicles, roads and trauma management. On the basis of this report, the SafetyNet project [Hakkert et al., 2007a, b] further provided a methodological basis for the SPIs' development. SPIs that are developed for a certain safety domain should reflect the factors contributing to road accidents/injuries and characterize the scope of the problem identified. The development of SPIs begins with a definition of the problem (i.e. the operational conditions of the road traffic system which are unsafe and result in accidents/fatalities as the 'worst case') and continues with the conversion of this information into measurable variables. Based on the potential of different safety areas for improving road safety as well as on the experiences, a number of road safety risk domains were designated as central to road safety activities in Europe and were selected for the development of SPIs [Hermans, 2009]. They are:

- Alcohol and drugs
- Speed
- Protective systems

- Vehicle
- Roads
- Trauma management

In the work package on SPIs of the SafetyNet project [Hakkert et al., 2007a, b], the usage of daytime running lights is considered as an extra risk domain (in addition to the above six). However, this domain is not considered in this study as, in the literature, the effects of daytime running lights are unclear, road safety experts consider this as the least important risk domain of all, and the availability and quality of the data is very poor compared to the other six domains. In the following sections, the importance of the six risk domains in the road safety context is discussed, respectively.

2.3.1 Alcohol and drugs

Driving while being intoxicated increases the risk of road accidents more than most other traffic law violations. A larger blood alcohol concentration (BAC) implies a higher probability of getting involved in an accident [Elvik et al., 2004]. More specifically, the relative accident risk starts increasing significantly at a BAC level of 0.4 g/l [WHO, 2004]. Al Haji (2005) discusses a study in which a positive correlation between the total number of fatalities in Victoria state (Australia) and alcohol sales was found and an inverse relationship with random BAC breath testing. A study from the United States shows that for single-vehicle accidents, each 0.02% increase in BAC level nearly doubles the risk of getting involved in a fatal accident [WHO, 2004].

The risk of driving under the influence of drugs is less cognized than the risk implied by alcohol, because there is currently insufficient information about the concentration or combinations that may cause driving problems. Moreover, the concentration of drugs is difficult to measure in a reliable way. However, it can be expected that drugs intoxication implies a higher risk. A report from the IMMORTAL project [Assum et al., 2005] shows that the accident risk of a driver who has taken morphine or heroin is 32 times higher than the risk of driver with no drugs or alcohol, alcohol alone above 1.3 g/l gives a risk 87 times higher, and the combination of alcohol above 0.8 g/l and drugs gives a risk which is 179 times higher than that of a driver with no drugs or alcohol.

2.3.2 Speed

Speed is one of the main causes of accident and hence, a major issue for road safety. To some extent, speed is involved in all accidents: no speed, no accidents. More precisely, inappropriate or excessive speed has been identified as a highly important factor influencing both the number of accidents and the severity of injuries [Elvik, 2005; Kweon et al., 2005]. In high-income countries, excessive and inappropriate speed is a main cause in one third of the fatal and serious accidents [WHO, 2004]. The probability of becoming involved in an injury accident increases with a higher (average) speed and/or larger speed differences [Al Haji, 2005; Vis, 2005].

Moreover, the researches indicate that the probability that a crash will result in injury is proportional to the square of the speed; for serious injury proportional to the cube of the speed; and for fatal injury proportional to the fourth power of the speed [WHO, 2004]. In addition, the probability of a pedestrian dying as a result of a car crash increases exponentially as the speed of the car increases. Reducing vehicle speeds appears to have a significant effect on road casualties and pedestrian accidents [Fridstrøm et al., 1995; Balkin et al., 2001].

2.3.3 Protective systems

The use of various protective systems by road users in traffic such as seat belts, helmets and child restrictions has been assessed by numerous European countries since decades and belongs nowadays to a widely accepted road safety risk domain. Protective systems play a role in case an accident has occurred as they determine the severity of the injury. Mandatory seat belt use has been one of the greatest success stories of road injury prevention and has saved many lives. Several empirical studies in Great Britain, Sweden and The Netherlands have shown that seat belt legislation, when followed by law enforcement, significantly reduces the number of fatalities and the severity of injuries [Hakim et al., 1991]. Specifically, the use of seat belts reduces the probability of being killed in an accident by 40 to 50% for drivers and front seat passengers and by 25% for passengers in the rear seats [Elvik et al., 2004]. In case motorized two-wheelers wear a helmet, fatal and serious head injuries are reduced by 20 to 45%, and cyclist helmets diminish the risk on head and brain injuries by 63 to 88% [WHO, 2004].

2.3.4 *Vehicle*

Unlike the risk domains such as speed, passive safety measures do not influence the occurrence of crashes. Thus, the potential of the vehicle to prevent (or indeed cause) injuries in the event of a crash is to determine whether the outcome is a fatality or something less serious.

To assess the passive safety performance, firstly, it can be done by looking at the crashworthiness of a vehicle. The European new car assessment programme, i.e., EuroNCAP, supplies information to consumers about the performance of new cars in crash tests since 1996. A higher EuroNCAP rank implies fewer fatal and severe injuries [ETSC, 2001].

Moreover, improvements in both active and passive safety resulted in a lower frequency and severity of accidents. Active safety features help the driver in avoiding an accident, such as anti-lock braking systems, traction control, driving aid systems and audible warning devices, while passive safety features better protect occupants in the event of an accident, like frontal and side impact protection, airbags, load restraint and crush zones [NRSC, 2000].

In addition, there is a link between vehicle age and risk. Occupants of a car produced before 1984 have approximately a three times higher injury risk compared to occupants of a newer car [WHO, 2004]. As the vehicle fleet is continuously being renewed to higher safety standards the presence of safety features in the overall vehicle fleet can be estimated by means of the age of the fleet.

2.3.5 *Roads*

Infrastructure layout and design also has a strong impact on the safety of the road transport system, since the safety performance of the road transport system is the result of the combination of the functionality, homogeneity and predictability of the network, the road environment and the traffic involved [Vis, 2005]. Four influencing factors are safety awareness in the planning of new road networks, dealing with safety features in the design of new roads, safety ameliorations to existing roads and healing actions on locations with a high accident risk.

Firstly, poor road surface conditions even as defects in road design and maintenance contribute to an increased accident risk [ETSC, 2001; Al Haji, 2005]. Today, the performance tracking of roads in Europe is the focus of EuroRAP [Lynam et al., 2004], which aims at assessing the degree to which roads protect against severe injury in case of an accident.

Moreover, the road network influences accident risk as it determines how road users perceive the environment and offers instructions by means of signals [WHO, 2004]. Generally, the road network consists of several road types. Despite the high speed allowed, motorways are considered to be the safest type of roads. However, they represent only a few percentages (0 to 2.8%) of the total road network [EURF, 2007]. Besides, rural roads account for a considerable share of all fatalities. The risk of being killed (per kilometer driven) is generally higher on rural roads than on urban roads and is four to six times higher than on motorways [OECD, 2002].

2.3.6 Trauma management

As a post-crash medical treatment, trauma management is considered to be the key component in avoiding preventable death and disability, and reducing the severity and suffering caused by the injury. A review of studies in Europe [ETSC, 1999] concluded that about 50% of road traffic deaths occurred within a few minutes either at the scene of the crash or on the way to a hospital, 15% at the hospital within four hours of the crash and 35% after four hours. It means that many of these deaths could have been prevented if more immediate and better medical care would have been available [WHO, 2004]. Moreover, studies worldwide [Hussain et al, 1994; Mock et al, 1997] have shown that within the time period reaching a hospital, deaths and complications resulting in disability could be prevented in many cases. The European Commission [EC, 2003] has stated that several thousands of lives could be saved in the European Union by improving the response times of the emergency services and other elements of post-impact care in the event of road traffic crashes. A review of 1970-1996 data in several OECD countries suggested that between 5% and 25% of the reductions in road crash deaths may have been due to improvements in medical care and technology [Noland, 2004].

2.4 Selection of SPIs

Having determined the essential road safety risk domains and indicated the relation between each of them and road traffic accidents/casualties (Section 2.3), the focus is now on finding appropriate SPIs for each domain. In this respect, eight selection criteria, i.e., a safety performance indicator should be relevant, measurable, understandable, data available, reliable, comparable, specific and sensitive, were summarized by Hermans (2009) in order to identify the best needed and best available SPIs. As the unavailability of reliable and comparable data limit the use of best needed indicators to some extent, only one–best available–indicator was used to represent each of the six risk domains in her study. They are:

- The percentage of surveyed car drivers disrespecting the alcohol limit (A1);
- The percentage of surveyed car drivers exceeding the speed limit in built-up areas (S1);
- The seat belt wearing rate in front seats (P1);
- The share of relatively new passenger cars (i.e. less than 6 years old) (V1);
- The motorway density (R1);
- The expenditure on health care as share of the gross domestic product (T1).

Since the collection and searching for additional data on the best needed indicators is an ongoing process, currently, some other best available indicators are found and served as the complements of the above six indicators, which are:

- The seat belt wearing rate in rear seats (P2);
- The median age of the passenger car fleet (V2);
- The share of motorcycles in the vehicle fleet (V3);
- The share of heavy goods vehicles (HGV) in the vehicle fleet (V4);
- The share of motorway in total road network (R2).

In other words, two or more SPIs can be formulated to represent some of the six risk domains. Moreover, the indicators belonging to a particular domain may also be linked to one another constituting a hierarchical structure, which is illustrated in Figure 2-2.

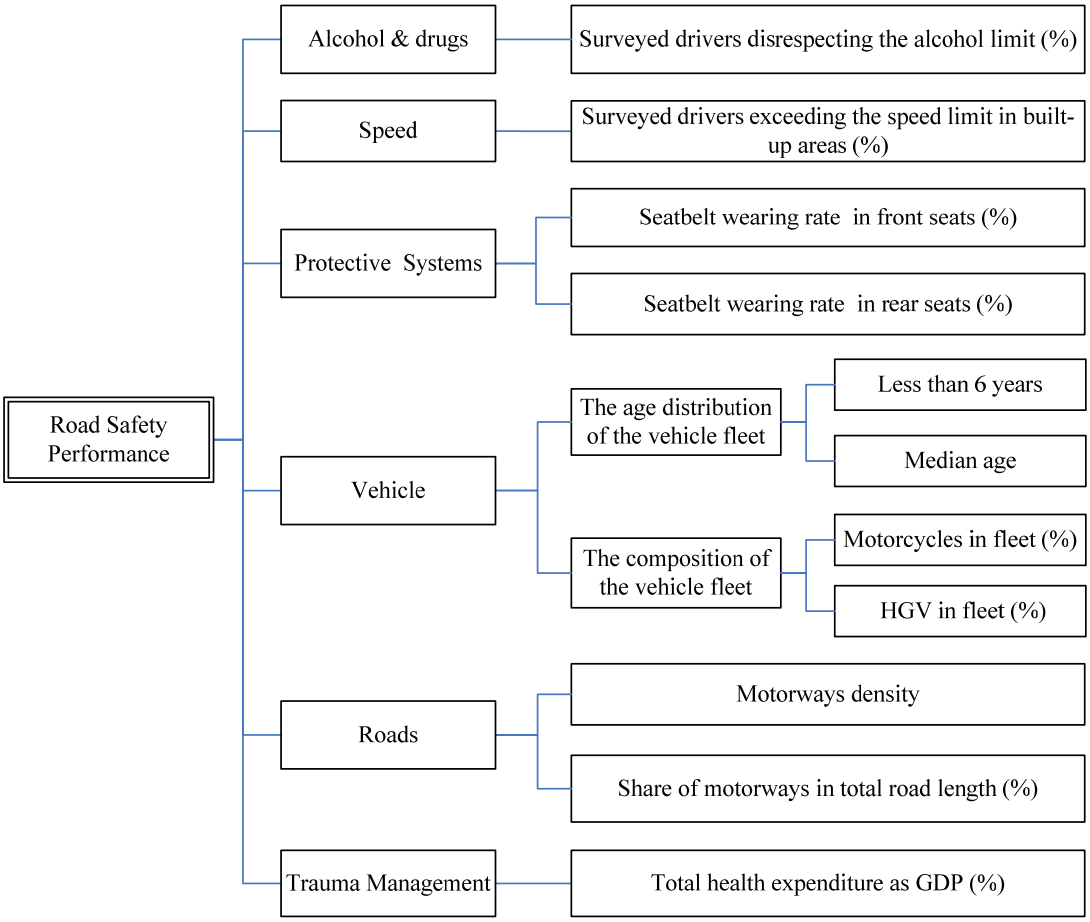

Figure 2-2 The hierarchical structure of the developed SPIs

2.5 Data collection

From a wide range of international databases and recent publications of international working groups, and also based on the research work of Hermans (2009), values related to 2003 were obtained for the developed 11 SPIs for 21 European countries being Austria (AT), Belgium (BE), Cyprus (CY), Czech Republic (CZ), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Hungary (HU), Ireland (IE), Italy (IT), the Netherlands (NL), Poland (PL), Portugal (PT), Slovenia (SL), Spain (ES), Sweden (SE), Switzerland (CH), and United Kingdom (UK). More specifically,

1) as the indicator for the alcohol and drugs domain, i.e., the percentage of car drivers often driving while having a blood alcohol concentration above the legal limit, the data are obtained from the Social Attitudes to Road Traffic Risk in Europe (SARTRE) research [SARTRE Consortium, 2004];

2) For the speed domain, the percentage of drivers exceeding the maximum speed limit in built-up areas is the chosen indicator. These data were also derived from SARTRE;

3) As third domain indicators, we select the percentage of persons wearing a seatbelt in the front seats as well as the percentage in the rear seats, with data from the ETSC [ETSC, 2007] and SafetyNet [Vis et al., 2007], respectively;

4) For the vehicle domain, the first two indicators related to the age distribution of the vehicle fleet, which are the share of relatively new passenger cars (i.e. less than 6 years old) and the median age of the passenger car fleet, and the data are available in the United Nations Economic Commission for Europe (UNECE) [UNECE, 2008]. While for the other two indicators about the composition of the vehicle fleet, i.e., the shares of motorcycles and HGV in the vehicle fleet, respectively, the data are collected from the European Commission [EC, 2009];

5) The infrastructural indicators, the motorway density (defined as the ratio of the total length of the motorway and the area of the country), and the share of motorway in total road network are constructed using data from Eurostat [Eurostat, 2009] and UNECE [UNECE, 2008];

6) Finally, the trauma management domain and specifically the share of the gross domestic product spent on health uses data derived from the World Health Organization [WHO, 2006].

In Table 2-1, the data set with 11 indicators is presented. The last column indicates the 2003 number of road fatalities per million inhabitants in the 21 countries, with the data from the European Commission.

Table 2-1 Data on the 11 hierarchical SPIs and fatalities for the 21 European countries

Country	Alcohol & drugs	Speed	Protective Systems		Vehicle				Roads		Trauma management	Fatality
	% surveyed drivers > BAC limit	% surveyed drivers > speed limit in built-up areas	seat belt wearing rate in front seats	seat belt wearing rate in rear seats	% passenger cars < 6 years	Median age of passenger cars	% Motor-cycles in vehicle fleet	% HGV in vehicle fleet	density of motor-ways	share of motor-ways in total	% total health expenditure as GDP	fatalities per million inhabi-tants
	A1	S1	P1	P2	V1	V2	V3	V4	R1	R2	T1	
Austria	2.6	6	77	49	35.14	7.51	12.4	7.0	2.0	1.56	7.5	115
Belgium	5.8	12	66	40	40.84	6.65	6.0	11.1	5.7	1.16	9.4	117
Cyprus	21.8	12	80	30	17.01	9.30	7.6	21.7	2.9	2.27	6.4	134
Czech Republic	2.0	6	75	41	19.43	11.00	15.1	9.0	0.7	0.44	7.5	142
Denmark	0.3	4	84	63	39.14	7.32	6.7	18.7	2.4	1.42	9.0	80
Estonia	1.6	12	75	68	17.12	12.73	1.9	14.0	0.2	0.18	5.3	121
Finland	0.3	6	89	80	28.79	9.13	10.5	11.6	0.2	0.66	7.4	73
France	5.1	7	97	82	37.18	8.32	6.4	13.7	1.9	1.05	10.1	101
Germany	2.4	7	94	88	37.85	6.00	10.5	5.1	3.4	5.34	11.1	80
Greece	7.9	6	40	25	36.74	8.00	17.2	17.4	0.6	0.30	9.9	146
Hungary	1.3	12	59	34	26.28	8.00	3.7	12.5	0.6	0.34	8.4	131
Ireland	2.5	3	85	46	53.67	5.14	1.6	14.7	0.3	0.26	7.3	84
Italy	7.3	12	71	30	35.26	7.86	20.5	8.7	2.2	0.80	8.4	105
Netherlands	1.9	7	86	64	38.91	6.00	6.5	11.3	6.1	1.76	9.8	63
Poland	0.3	7	71	45	22.29	11.80	4.7	14.4	0.1	0.14	6.5	149
Portugal	4.2	11	88	45	28.69	9.67	9.0	21.3	2.2	1.00	9.6	148
Slovenia	2.7	6	81	49	50.07	4.99	4.8	6.3	2.3	1.48	8.8	121
Spain	7.2	11	86	69	36.11	7.60	14.6	16.7	2.0	6.90	7.7	130
Sweden	0.1	5	92	80	39.43	7.00	9.6	9.2	0.4	1.14	9.4	59
Switzerland	4.2	4	82	53	39.61	7.25	12.5	6.4	3.2	1.89	11.5	74
United Kingdom	0.6	4	93	84	44.42	5.00	3.7	10.7	1.5	0.88	8.0	61

2.6 Summary

The European Transport Safety Council advised the European Union in 2001 to formulate and specify a set of relevant safety performance indicators that can be used on the European and national level as a means to determine trends in the level of road safety and the success of casualty reduction programmes. In this chapter, starting from six main road safety risk domains, i.e., alcohol and drugs, speed, protective systems, vehicle, roads and trauma management, the selection of a set of safety performance indicators suitable for capturing road safety risk in a country, has been conducted. Based on the research work of Hermans (2009), in which one best available indicator was used to represent each of the six risk domains, here, a hierarchical structure of subindicators was introduced, and totally, 11 basic indicators were defined for consideration. Moreover, data related to these 11 hierarchical SPIs were collected for 21 European countries from a wide range of international data sources.

Theoretically, countries can be compared on each risk domain or indicator separately. However, if a large number of performance indicators are available, some summarization is essential for the analysis [Bird et al., 2005]. Therefore, in comparing and monitoring the safety achievements of countries there is a need to reduce the dimensions of the problem and to be able to work with an overall road safety composite indicator or index which can describe all the relevant components in a concise and comprehensive way. In doing so, a composite index value can be computed for each country, thereby presenting the overall road safety picture of the main underlying risk dimensions. As concluded in Nardo et al. (2005), the application of this kind of index is a clear symptom of its political importance and operational relevance in decision making. Consequently, the development of such an index will be the topic of the following chapters.

Chapter 3 TOPSIS Method Analysis

A composite indicator or index joins individual indicators based on an underlying model. An index captures a multidimensional concept that cannot be measured by one indicator. In Chapter 2, the complex road safety phenomenon has been decomposed in several risk domains, which have been further measured by appropriate performance indicators. In this chapter, it is shown how indicators can be aggregated in one road safety performance index using MCDM techniques.

As one of the classical MCDM methods, TOPSIS method was first developed by Hwang and Yoon in 1981 for finding the best option from all of the feasible alternatives. The principle behind the TOPSIS is that the chosen alternative should be as close to the positive-ideal solution as possible and as far from the negative-ideal solution as possible. During the past decades, numerous applications and improvements of the TOPSIS method exist and have verified the feasibility of this method to solve multi-criteria decision making problems [see e.g., Lai et al., 1994; Abo-Sinna and Amer, 2005; Jahanshahloo et al., 2006].

This chapter mainly describes how the TOPSIS method can be applied to create a composite road safety performance index consisting of six SPIs (i.e., one indicator for each risk domain, and the same as in Hermans (2009)). Based on the description of the principle of TOPSIS method, the main application procedures are enumerated in Section 3.1, and Section 3.2 specifies how to determine the weights for each criterion under the single or multiple decision maker circumstances. Subsequently, the application of the TOPSIS method to combine six indicators into an overall index is presented in Section 3.3, and a comparison of several ranking results derived from different approaches as well as the final outcome (i.e., the number of fatalities per million inhabitants) is conducted in Section 3.4. The summary is stated at the end of this chapter.

3.1 TOPSIS method main procedure

The TOPSIS method views a multi-criteria decision making problem with *m* alternatives as a geometric system with *m* points in the *n*-dimensional space that means *n* criteria. In TOPSIS method, the chosen alternative should have the shortest Euclidean distance from the positive-ideal solution (PIS) whilst simultaneously being furthest away from the negative-ideal solution (NIS). The PIS is a hypothetical solution for which all criterion values correspond to the maximum criterion values in the database comprising the satisfying solutions. The NIS is the hypothetical solution for which all criterion values correspond to the minimum criterion values in the database. TOPSIS thus defines an index called similarity (or relative closeness) to the PIS and the remoteness from the NIS. Then the method chooses an alternative with the maximum similarity to the PIS. Using the vector normalization, the method chooses the alternative with the largest value of C_i^*:

$$C_i^* = \frac{\sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^-\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^*\right)^2} + \sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^-\right)^2}} \tag{3.1}$$

or it chooses the alternative with the least value of C_i^-:

$$C_i^- = \frac{\sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^*\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^*\right)^2} + \sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^-\right)^2}} \tag{3.2}$$

where *i* (*i*=1,…,*m*) and *j* (*j*=1,…,*n*) indicate number of alternatives and criteria respectively; w_j is the weight of the *j*th criterion; x_{ij} is the criterion rating for *i*th alternative's *j*th criterion; v_j^* is the positive-ideal value for *j*th criterion, where it is a maximum for benefit criteria and a minimum for cost criteria; v_j^- is the negative-ideal value for the *j*th criterion, where it is a minimum for benefit criteria and a maximum for cost criteria. The main procedure of the TOPSIS method is described in the following seven steps [Triantaphyllou, 2000]:

Step 1 Identify a decision matrix

In order to obtain the performance of a set of alternatives on a given set of criteria, a decision table or matrix, **D**, of $m \times n$ dimension is constructed consisting of a) alternatives A_i ($i = 1, 2, \dots, m$), b) criteria C_j ($j = 1, 2, \dots, n$), and c) measures of performance x_{ij} ($i = 1, 2, \dots, m$; $j = 1, 2, \dots, n$) of the alternatives with respect to the criteria, which is shown in Eq. (1.2). Given the decision matrix information and a decision-making method, the task of the decision maker is to find the best alternative and/or to rank the entire set of alternatives.

Step 2 Normalize the decision matrix

It should be mentioned that all the elements in the decision matrix must be normalized to the same units, so that all possible criteria in the decision problem can be considered simultaneously. Here, conversion of the decision making matrix to a dimensionless matrix (**D'**) is done by using linear scale transformation as follows:

$$r_{ij} = \begin{cases} x_{ij} / x_j^*, \forall_j, x_j \text{ is a benefit criterion} \\ x_j^- / x_{ij}, \forall_j, x_j \text{ is a cost criterion} \end{cases} \tag{3.3}$$

where the r_{ij} are normalized values. x_j^* and x_j^- are the maximum and minimum values of the columns in the decision matrix, respectively. By applying Eq. (3.3), we can rewrite the decision matrix as:

$$\mathbf{D'} = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & & \vdots & & \vdots \\ r_{i1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & & \vdots & & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \tag{3.4}$$

Step 3 Compute the weighted normalized decision matrix

Now the weighted normalized decision matrix can be obtained by multiplying the normalized decision matrix ***D′*** with the weight vector *W*. Hence, the elements of the weighted normalized matrix V_{ij} are expressed as:

$$v_{ij} = r_{ij} w_j, \forall_j, j \qquad (3.5)$$

In doing so, determination of the weight vector *W*, or the relative importance of each of the criteria is critical and several approaches exist. Normally, the methods can be classified into either subjective approaches or objective approaches. The specific approaches to determine the corresponding weights for each criterion under the single or multiple decision maker circumstances will be further depicted in section 3.2.

Step 4 Identify the positive ideal solution, A^*, and the negative ideal solution, A^-

The PIS and NIS are defined as:

$$A^* = [v_1^*, ..., v_n^*] \qquad (3.6)$$

$$A^- = [v_1^-, ..., v_n^-] \qquad (3.7)$$

where $v_j^* = \max_i v_{ij}$ and $v_j^- = \min_i v_{ij}$.

Step 5 Obtain the separation measures S_i^* and S_i^-

In the classical case, the separation measures are defined as:

$$S_i^* = \sum_{j=1}^{n} D_{ij}^*, \quad i = 1, ..., n \qquad (3.8)$$

$$S_i^- = \sum_{j=1}^{n} D_{ij}^-, \quad i = 1,...,n \tag{3.9}$$

where the difference Euclidean distance D_{ij}^* and D_{ij}^- are given as:

$$D_{ij}^* = \left| v_{ij} - v_j^* \right| \tag{3.10}$$

$$D_{ij}^- = \left| v_{ij} - v_j^- \right| \tag{3.11}$$

Step 6 Compute the relative closeness to ideals

The relative closeness index is used to combine S_i^* and S_i^- indices calculated in Step 4, which is calculated as follows:

$$C_i = S_i^- / (S_i^* + S_i^-) \tag{3.12}$$

Step 7 Prioritize alternatives

According to the composite index value C_i, the set of alternatives can be ranked from the most preferred to the least preferred feasible solutions. C_i may also be called the overall or composite performance score of alternative A_i.

3.2 Determining weight for each criterion

The weight for each criterion reflects the relative importance of criteria to the decision, and is assumed to be positive. The evaluation of the criteria weights may be subjective or objective. The objective approaches often determine weights by making use of the mathematical models based on objective information (i.e. the decision matrix). They include principal component analysis [Nardo et al., 2005], factor analysis [Nardo et al., 2005], entropy method [Hwang et al., 1981], and multiple objective programming model [Choo et al., 1985], etc. The objective approaches provide relative independent results but these weights may be different from one decision matrix to another. In other words, weights which are calculated from two decision matrices with the same criteria but different alternatives will be different. Moreover, these kinds of methods based on mathematical computation, normally need complete dataset, which limit their use to a certain extent.

The subjective approaches select weights based on preference information of criteria given by the decision makers. Although the intuition or the subjectivity of the experts and the lack of quantitative information to provide certainty of support make it difficult to ensure a broad assessment of the reliability of the results, the experts' experience and knowledge allows for providing the most valuable information about the compared criteria. When more than one decision maker is responsible to decide on the problem, it becomes a group decision making application.

Group decision is usually understood as combining different individual preferences on a given set of alternatives to a single collective preference. In a group decision situation, multiple decision makers with different skills, experience and knowledge relating to different criteria of the problem are involved. The aggregation of the different opinions of different decision makers might relieve the subjectivity of the expert grading method to a certain extent and might achieve the assignment of weights to criteria under the incomplete dataset condition.

However, moving from single decision maker to a group decision making situation introduces a great deal of complexity into the analysis since individuals in a group might have different preferences about alternatives, criteria, consequences. To realize the group consensus on which the whole group members agree, rational procedures must be developed to structure the problem, require opinions and making use of information provided. Specifically, we assume that each decision maker considers the same sets of alternatives and criteria. It is also assumed that there is a special decision maker with authority for establishing consensus rules and determining voting powers to the group members on the different criteria. Keeney and Raiffa (1976) call this entity the Supra Decision Maker (SDM). The final decision is derived by aggregating the opinions of the group members according to the rules and priorities defined by the SDM.

There are several approaches for the case of group decision. Some of them are reviewed by Bose et al. (1997). Here a specific algorithm of combining multiple weights for each criterion of alternatives is described as follows:

Consider a decision problem with K decision makers (D_1, D_2, …, D_K), m alternatives (A_1, A_2, …, A_m) and n criteria (C_1, C_2, …, C_n), the individual preferences on the criteria are expressed as weights $w_j^k \geq 0$, which is assigned at criterion C_j by decision maker D_k (j=1, 2, …, n; k=1, 2, …, K).

The different knowledge and priority of the group members are expressed by voting powers both for weighing the criteria. Let $V\left(w\right)_j^k$ denote the voting power assigned to D_k for weighing on criterion C_j (j=1, 2, …, n; k=1, 2, …, K), thus, for each criterion C_j, the individual weights of importance of the criteria will be aggregated into the group weights W_j:

$$W_j = \frac{\sum_{k=1}^{K} V\left(w\right)_j^k w_j^k}{\sum_{k=1}^{K} V\left(w\right)_j^k}, \quad j = 1, \cdots, n. \tag{3.13}$$

In particular, when the decision makers considered to be of similar importance for weighing the criterion, i.e., $V\left(w\right)_j^1 = V\left(w\right)_j^2 = \cdots = V\left(w\right)_j^K$, then the final weights for each criteria convert into the arithmetic mean form, which is denoted as:

$$W_j = \frac{\sum_{k=1}^{K} w_j^k}{K}, \quad j = 1, \cdots, n. \tag{3.14}$$

In addition to the weighted arithmetic mean used in the above aggregations, there are another two methods which are also often used to combine multiple decision makers' opinions into one weight for each criterion. They are trimmean and geometric mean method.

The idea behind trimmean method is to except the extreme points of data before going through the analysis. The number of data being excepted in the evaluation is determined by the executer regarding the total number of data and the designated percentage. The whole weights of all criteria are sorted from highest to smallest at the beginning of computing the Trimmean. Afterwards a percentage of the top and the bottom data points (weights) are excluded and the Trimmean is calculated. At the end of this process it is provided that each criterion has only one weight as the result of a group decision making procedure. This method has been widely used in current competitions such as the Olympic Games.

The geometric mean, in mathematics, indicates the central tendency or typical value of a set of numbers. It is similar to the arithmetic mean, except that instead of adding the set of numbers and then dividing the sum by the count of numbers in the set, the numbers are multiplied and then the *n*th root of the resulting product is taken. This means after listing weight of each criterion the geometric mean is calculated by using the formula below:

$$Geometric\ Mean = \sqrt[n]{\left(w_1 \times w_2 \times \cdots \times w_n\right)} \tag{3.15}$$

where, w_i represents the weight given by different decision makers for each criterion. According to Saaty (1996) taking geometric mean is the proper method to be able to obtain weights in a group.

In summary, no uniformly agreed methodology exists to weight individual indicators and no weighting system is above criticism. However, weights usually have an important impact on the composite index value and on the resulting ranking especially whenever higher weight is assigned to indicators [EC, 2005]. In practice, it should be determined connecting with the actual requirements and constrains. In this study, the geometric mean method is applied to combine different individual weights given by the group decision makers into a single collective weight for each corresponding indicator.

3.3 Creating a composite road safety performance index by applying TOPSIS method

In this section, the application of the TOPSIS method in combining individual SPIs into one composite index is conducted.

Table 3-1 Decision matrix *D* consisting of six SPIs for the 21 European countries

Country	Alcohol & drugs	Speed	Protective Systems	Vehicle	Roads	Trauma management
	% surveyed drivers > BAC limit	% surveyed drivers > speed limit in built-up areas	seat belt wearing rate in front seats	% passenger cars < 6 years	density of motorways	% total health expenditure as GDP
	A1	S1	P1	V1	R1	T1
Austria	2.6	6	77	35.14	2	7.5
Belgium	5.8	12	66	40.84	5.7	9.4
Cyprus	21.8	12	80	17.01	2.9	6.4
Czech Republic	2.0	6	75	19.43	0.7	7.5
Denmark	0.3	4	84	39.14	2.4	9.0
Estonia	1.6	12	75	17.12	0.2	5.3
Finland	0.3	6	89	28.79	0.2	7.4
France	5.1	7	97	37.18	1.9	10.1
Germany	2.4	7	94	37.85	3.4	11.1
Greece	7.9	6	40	36.74	0.6	9.9
Hungary	1.3	12	59	26.28	0.6	8.4
Ireland	2.5	3	85	53.67	0.3	7.3
Italy	7.3	12	71	35.26	2.2	8.4
Netherlands	1.9	7	86	38.91	6.1	9.8
Poland	0.3	7	71	22.29	0.1	6.5
Portugal	4.2	11	88	28.69	2.2	9.6
Slovenia	2.7	6	81	50.07	2.3	8.8
Spain	7.2	11	86	36.11	2.0	7.7
Sweden	0.1	5	92	39.43	0.4	9.4
Switzerland	4.2	4	82	39.61	3.2	11.5
United Kingdom	0.6	4	93	44.42	1.5	8.0

More specifically, the indicators used in the study of Hermans (2009), i.e., only one --- best available --- indicator for each of the six risk domains (see also Section 2.4), are considered, and the data for 21 European countries (alternatives) in 2003 are collected constituting the decision matrix **D** as shown in Table 3-1. Subsequently, the TOPSIS method is utilized to aggregate the individual indicator values into an overall index score. In the end, the ranking order of these 21 countries is obtained in accordance with their closeness coefficient to the ideal solution.

Table 3-2 Normalized decision matrix *D′*

Country	Alcohol & drugs	Speed	Protective Systems	Vehicle	Roads	Trauma management
Austria	0.038	0.500	0.794	0.655	0.328	0.652
Belgium	0.017	0.250	0.680	0.761	0.934	0.817
Cyprus	0.005	0.250	0.825	0.317	0.475	0.557
Czech Republic	0.050	0.500	0.773	0.362	0.115	0.652
Denmark	0.333	0.750	0.866	0.729	0.393	0.783
Estonia	0.063	0.250	0.773	0.319	0.033	0.461
Finland	0.333	0.500	0.918	0.536	0.033	0.643
France	0.020	0.429	1.000	0.693	0.311	0.878
Germany	0.042	0.429	0.969	0.705	0.557	0.965
Greece	0.013	0.500	0.412	0.685	0.098	0.861
Hungary	0.077	0.250	0.608	0.490	0.098	0.730
Ireland	0.040	1.000	0.876	1.000	0.049	0.635
Italy	0.014	0.250	0.732	0.657	0.361	0.730
Netherlands	0.053	0.429	0.887	0.725	1.000	0.852
Poland	0.333	0.429	0.732	0.415	0.016	0.565
Portugal	0.024	0.273	0.907	0.535	0.361	0.835
Slovenia	0.037	0.500	0.835	0.933	0.377	0.765
Spain	0.014	0.273	0.887	0.673	0.328	0.670
Sweden	1.000	0.600	0.948	0.735	0.066	0.817
Switzerland	0.024	0.750	0.845	0.738	0.525	1.000
United Kingdom	0.167	0.750	0.959	0.828	0.246	0.696

To remove scale and measurement unit differences, the values presented in Table 3-1 should be normalized. In doing so, the criteria should firstly be distinguished between benefit and cost ones. In this case, the indicators selected for the first two risk domains (i.e., the percentage of surveyed car drivers disrespecting the alcohol limit (A1) and the percentage of surveyed car drivers exceeding the speed limit in built-up areas (S1)) are the cost criteria with a low value representing a better performance (thus a lower risk). On the contrary, the remaining four indicators (i.e., P1, V1, R1 and T1) belong to benefit criteria, and higher values are aimed at. Therefore, according to Eq. (3.3), the normalized decision matrix **D’** is obtained as in Table 3-2, where all the indicator values are expected to be the higher the better. For instance, in terms of alcohol and drugs domain Sweden performs best and Cyprus worst.

Next, to derive the relative importance of each indicator, i.e., the corresponding weight, a survey result given by eight independent experts in road safety field from seven European countries is utilized, in which the crisp data ranged from 0 to 10 are assigned with a higher value representing a more importance of a certain risk domain (see Table 3-3). This is a typical group decision problem. Here, the combined weight for each indicator is calculated by applying the geometric mean method ($W_j = \sqrt[8]{\prod_{i=1}^{8} w_i}$, w_i is the weight score given by each expert for each indicator) under the assumption that the opinions from these eight experts are of similar importance. The weights vector *W* resulting from the geometric mean method is shown as follows.

Table 3-3 weight vector *W*

Expert	Alcohol & drugs	Speed	Protective Systems	Vehicle	Roads	Trauma management
E1	10	10	8	7	6	6
E2	8	10	10	10	8	10
E3	8	9	8	7	8	6
E4	10	10	8	8	9	10
E5	10	9	7	8	6	5
E6	8	10	8	6	10	8
E7	9	10	9	9	9	9
E8	10	10	10	9	9	9
Geometric Mean (W_j)	9.077	9.740	8.442	7.905	8.001	7.645

It can be seen that the speed domain is assigned the largest weight score followed by the alcohol and drugs domain. Then the weights for the protective systems, roads, and vehicle domains decrease in turn, and the trauma management domain accounts for the smallest share of all risk domains.

Now, by multiplying the normalized decision matrix **D'** with the weight vector *W*, the weighted normalized matrix **V** is obtained. Then the maximum value in each column of matrix **V** constitutes the positive ideal solution, A^*, and the minimum value in each column turns into the negative ideal solution, A^-. They are shown in Table 3-4.

Table 3-4 The derived PIS (A*) and NIS (A-)

A*	9.077	9.740	8.442	7.905	8.001	7.645
A^-	0.042	2.435	3.481	2.505	0.131	3.523

Based on Eqs. (3.8)--(3.11), the relative Euclidean distance from each country to the ideal solutions can be calculated, and the separation measures S_i^* and S_i^- obtained. The relative closeness index *C* can then be computed for each country by combining the S_i^* and S_i^- indices (see Eq. (3.12)), based on which countries can be ranked. The results are presented in Table 3-5, together with the road safety final outcome (i.e., the number of road fatalities per million inhabitants).

From the ranking order derived from the TOPSIS method, Sweden is the best performing country, while Estonia the worst. Moreover, since the SPIs are causally related to the road crashes or injuries, it is reasonable to compare the composite road safety performance index score of a country with its final outcomes. Here, the number of road fatalities per million inhabitants is considered, and the correlation analysis is conducted which offers a way in measuring the linear dependence relationship between the two matters. As a result, a relatively high Pearson's correlation coefficient is achieved, which equals to -0.802. Furthermore, by comparing the ranking results based on the TOPSIS method with the ones from the final outcome, the significant disagreements can be discovered, which in this case mainly exist in the following three countries, i.e., Estonia, Finland, and Portugal.

Table 3-5 The results and rankings from the TOPSIS and the road safety final outcome

Country	S^*	S^-	C	TOPSIS Ranking	No. of fatalities per mln inhab.	Fatality Ranking
Austria	26.104	12.588	0.325	12	115	11
Belgium	22.734	15.958	0.412	9	117	12
Cyprus	30.807	7.885	0.204	19	134	17
Czech Republic	30.193	8.499	0.220	18	142	18
Denmark	18.273	20.419	0.528	2	80	6.5
Estonia	34.973	3.719	0.096	21	121	13.5
Finland	25.746	12.946	0.335	11	73	4
France	23.333	15.359	0.397	10	101	9
Germany	20.663	18.029	0.466	7	80	6.5
Greece	29.564	9.128	0.236	16	146	19
Hungary	32.300	6.392	0.165	20	131	16
Ireland	20.158	18.534	0.479	6	84	8
Italy	28.408	10.284	0.266	15	105	10
Netherlands	18.426	20.266	0.524	3	63	3
Poland	29.695	8.997	0.233	17	149	21
Portugal	26.785	11.907	0.308	13	148	20
Slovenia	22.313	16.379	0.423	8	121	13.5
Spain	27.482	11.210	0.290	14	130	15
Sweden	15.301	23.391	0.605	1	59	1
Switzerland	18.476	20.216	0.522	4	74	5
United Kingdom	20.070	18.622	0.481	5	61	2

3.4 Comparison and discussion

To further assess the effectiveness of the TOPSIS method in creating a composite road safety index, other five common methods applied in the study of Hermans (2009), i.e., Factor Analysis (FA), Analytic Hierarchy Process (AHP), Budget Allocation (BA), Data Envelopment Analysis (DEA), and Equal Weighting (EW), are taken into account. Based on the same number of indicators for the same countries, the ranking results derived from the above five methods, together with the ones from the TOPSIS method and the number of fatalities per million inhabitants, are shown in Table 3-6. Moreover, the degree of correlation between every two index ranking orders is presented in Table 3-7.

Table 3-6 Countries' ranking results from six index methods and fatalities

Country	FA Ranking	AHP Ranking	BA Ranking	DEA Ranking	EW Ranking	TOPSIS Ranking	Fatality Ranking
Austria	12	10	11	11	11	12	11
Belgium	13	13	15	16	10	9	12
Cyprus	21	21	21	21	21	19	17
Czech Republic	15	12	12	13	15	18	18
Denmark	5	2	2	5	4	2	6.5
Estonia	20	20	20	20	20	21	13.5
Finland	11	11	10	10	13	11	4
France	6	9	9	8	8	10	9
Germany	1	5	5	2	2	7	6.5
Greece	18	17	16	19	17	16	19
Hungary	19	19	18	18	19	20	16
Ireland	9	6	7	6	9	6	8
Italy	16	18	19	17	16	15	10
Netherlands	2	1	4	7	1	3	3
Poland	17	15	13	15	18	17	21
Portugal	10	14	14	12	12	13	20
Slovenia	8	8	8	9	6	8	13.5
Spain	14	16	17	14	14	14	15
Sweden	7	7	6	2	7	1	1
Switzerland	3	4	1	4	3	4	5
United Kingdom	4	3	3	2	2	5	2

In Table 3-6, by computing the average ranking distance between the TOPSIS method and the other five methods, we find that most of the countries (15 out of 21) have an average difference in rank with a maximum of two positions, while the highest disagreement between the TOPSIS method and the other five methods focuses on four countries, which are Belgium, Czech Republic, Germany, and Sweden, with an average difference in rank more than four positions. Moreover, by comparing the index ranking results of these four countries with the ones based on their fatalities per million inhabitants, we find that three of them (i.e., Czech Republic, Germany, and Sweden) result in a more similar ranking position by using the TOPSIS method.

By calculating the Pearson's correlation coefficients, the quantitative analysis will provide a clear insight into the linear dependence relationship among these ranking results. The Pearson's correlation coefficients among the above 7 ranking orders are shown in Table 3-7.

Table 3-7 The Pearson's correlation coefficients among the countries' ranking results

	FA Ranking	AHP Ranking	BA Ranking	DEA Ranking	EW Ranking	TOPSIS Ranking	Fatality Ranking
FA Ranking	1.000	0.943	0.923	0.938	0.979	0.900	0.741
AHP Ranking	0.943	1.000	0.978	0.930	0.955	0.916	0.744
BA Ranking	0.923	0.978	1.000	0.943	0.919	0.890	0.718
DEA Ranking	0.938	0.930	0.943	1.000	0.909	0.891	0.769
EW Ranking	0.979	0.955	0.919	0.909	1.000	0.924	0.745
TOPSIS Ranking	0.900	0.916	0.890	0.891	0.924	1.000	0.804
Fatality Ranking	0.741	0.744	0.718	0.769	0.745	0.804	1.000

It can be seen from Table 3-7 that the ranking results from the five methods used in the Hermans' study and the TOPSIS applied in this study are highly correlated with one another, which implies the feasibility of using this technique as an alternative way in creating a composite road safety performance index. Furthermore, considering the fatality ranking as shown in the last column of Table 3-6, the TOPSIS ranking produces the highest correlation coefficient (0.804), which indicates the best fit of this ranking with the one based on the final road safety outcome.

3.5 Summary

As one of the well known classical MCDM methods, the TOPSIS method is applied in this chapter to create a composite road safety performance index by combining six individual SPIs (one indicator for each risk domain). Based on the weights (the relative importance of each indicator) assigned by the eight road safety experts from seven European countries (each expert is considered to be of similar importance), the geometric mean method is employed to combine different individual weights given by the group decision makers into a single collective weight for each corresponding indictor. Then, the final index score and the ranking result for the 21 European countries are calculated based on the principle of TOPSIS. As a result, Sweden obtains the highest index score and thereby can be treated as the best performing country, while Estonia the worst. Moreover, the road fatalities per million inhabitants is considered as a relevant point of reference, and a relatively high Pearson's correlation coefficient is generated (-0.802). Furthermore, comparing the ranking results based on the TOPSIS method with the ones from the other five widely used methods (i.e., FA, AHP, BA, DEA, and EW), they are highly correlated with one another, and the TOPSIS ranking produces an even higher correlation coefficient when the final outcome ranking is taken into account. Consequently, the TOPSIS can be regarded as an effective and valuable method in creating a composite road safety performance index contributing to choose or compare the given countries.

In this study, all the indicators and their respective weights are expressed in crisp values and thus, the final index scores and the ranking results of a set of countries can be carried out without any problem. However, it has been widely recognized that experts prefer to give linguistic valued advice based on human experience and intuition to avoid possible mistakes connected with qualitative prediction of future events. Moreover, in the decision matrix, probably only part of the indicators can be constructed on the basis of measurable quantitative parameters, and the others need to be specified with either ordinal measures or the help of expert subjective judgments. As a result, the application of the classical TOPSIS method may face serious practical problems from the criteria to the corresponding weights which perhaps contain imprecision or vagueness inherent in the information. To deal with these qualitative and imprecise decision problems, Zadeh (1965) suggested employing the fuzzy set theory as a modeling tool for complex systems that can be controlled by humans but are hard to define exactly. Therefore, extension of the classical TOPSIS to the fuzzy environment is widely investigated and treated as a natural generalization of the classical TOPSIS model. In the next chapter, how to integrate fuzzy logic into TOPSIS will be elaborated and the applications of the new method in creating a composite road safety performance index will be conducted.

Chapter 4 Fuzzy TOPSIS Analysis

The classical TOPSIS method possesses advantages in that it is easy to compute and easily understood, because the method directly produces a definite index score based on the given indicator values and the specific weights. However, under many conditions, crisp data are inadequate or inappropriate to model real-life situations because of the complexity and constraints of the reality. For example, it is known that experts prefer to give linguistic valued judgements rather than crisp values. Thus, to express the weight of a criterion, terms such as 'important,' 'very important' are commonly used, and for an alternative linguistic terms such as 'low' and 'high' are also used. The concept of linguistic variables is useful in reflecting the uncertainty, inaccuracy and fuzziness of decision makers, and they are regarded as natural representations of preferences/judgments. However, precise mathematical approaches are not enough to tackle such uncertain variables and derive a satisfactory solution. As a result, fuzzy set theory [Zadeh, 1965] is introduced to explain the rationality of uncertainty due to imprecision or vagueness. During the last two decades, fuzzy MCDM techniques which integrate fuzzy logic into MCDM are widely investigated and become one of the fastest growing areas in decision making and operations research [Lu et al., 2007; Pardalos et al., 2008]. As one of the most important branches, the classical TOPSIS method is also extended to the fuzzy environment, which is known as fuzzy TOPSIS.

This chapter starts with the overview of the fuzzy TOPSIS research during the last decades (Section 4.1). In Section 4.2, based on the introduction of some basic definitions and notions of fuzzy set theory, the main adjustments of applying fuzzy TOPSIS method compared to the classical TOPSIS method are presented. Two applications (i.e., only weights need to be fuzzified and both weights and indicator values are fuzzified) are then carried out in Section 4.3 to combine the six individual SPIs into an overall index. In Section 4.4, we discuss the ranking results derived from the classical TOPSIS method, the fuzzy TOPSIS method and the road safety final outcome, respectively. Finally, a summary with respect to the methodology and its applications is given in Section 4.5.

4.1 Fuzzy TOPSIS research status

During the last two decades, an extension of the classical TOPSIS to the fuzzy environment was widely investigated and a large number of fuzzy TOPSIS methods were developed in the literature. Chen and Hwang (1992) transformed Hwang and Yoon

(1981)'s method into a fuzzy case. Triantaphyllou and Lin (1996) developed a fuzzy version of the TOPSIS method based on fuzzy arithmetic operations, which led to a fuzzy relative closeness for each alternative. This fuzzy TOPSIS method offered a fuzzy relative closeness for each alternative, and the closeness was badly distorted and over-exaggerated because of the reason of fuzzy arithmetic operations. Chen (2000) described the rating of each alternative and the weight of each criterion by linguistic terms which could be expressed in triangular fuzzy numbers. Then, a vertex method for TOPSIS was proposed to calculate the distance between two triangular fuzzy numbers. Tsaur et al. (2002) applied the fuzzy set theory to evaluate the service quality of airline. By applying AHP in obtaining criteria weight and TOPSIS in ranking, they found the most concerned aspects of service quality. Chu and Lin (2003) proposed a fuzzy TOPSIS approach for robot selection where the ratings of various alternatives under different subjective attributes and the importance weights of all attributes were assessed in linguistic terms represented by fuzzy numbers. Wang and Elhag (2006) presented a nonlinear programming solution procedure using a fuzzy TOPSIS method based on alpha level set. They discussed the relationship between the fuzzy TOPSIS method and the fuzzy weighted average (FWA), and illustrated three examples about bridge risk assessments to compare the proposed fuzzy TOPSIS and other procedure. Zhang and Lu (2003) presented an integrated fuzzy group decision making method in order to deal with the fuzziness of preferences of the decision makers. Abo-Sinna and Amer (2005) extended the TOPSIS for solving large scale multi-objective nonlinear programming problems, and further considered the situation involving fuzzy parameters [Abo-Sinna, et al., 2006]. Jahanshahloo et al. (2006) developed an algorithmic method to extend TOPSIS for decision making problems with interval data. Ates et al. (2006) proposed a new algorithm for fuzzy TOPSIS that took into account the hierarchy in the evaluation model. The obtained results were compared with fuzzy AHP on an application in a faculty performance evaluation problem and some sensitivity analyses were presented. Yang and Hung (2007) explored the use of TOPSIS and fuzzy TOPSIS in solving a plant layout design problem. The difference between TOPSIS and fuzzy TOPSIS chiefly lied in rating approaches. Wang et al. (2009) further proposed a fuzzy hierarchical TOPSIS, which used simplified parameterized metric distance and FAHP to modify Chen (2000)'s fuzzy TOPSIS. Hung and Chen (2009) developed a new fuzzy TOPSIS decision making model using entropy weight for dealing with MCDM problems under intuitionistic fuzzy environment. This model allowed measuring the degrees of satisfiability and non-satisfiability of each alternative evaluated across a set of criteria.

4.2 Fuzzy TOPSIS

In this section, the main procedure of fuzzy TOPSIS for solving multi-person multi-criteria decision-making problems under fuzzy environment is elaborated. Specifically, considering the fuzziness in the decision data and group decision-making process, linguistic variables are used to assess the weights of all criteria and the ratings of each alternative with respect to each criterion. Thus, we can convert the decision matrix into a fuzzy form and construct a weighted normalized fuzzy decision matrix once the DMs' fuzzy ratings have been pooled. According to the concept of classical TOPSIS, we need to define a fuzzy positive ideal solution (FPIS) and a fuzzy negative ideal solution (FNIS), and then calculate the distance of each alternative from FPIS and FNIS, respectively. Finally, a closeness coefficient of each alternative is calculated to determine the ranking order of all alternatives. Similar to the classical TOPSIS method, a higher value of closeness coefficient indicates a better performance of an alternative.

4.2.1 Preliminaries

In the following, some basic definitions and notions of fuzzy sets are introduced (see also [Zadeh, 1965, 1975; Kaufmann et al., 1985; Buckley, 1985; Zimmermann, 1991]):

Definition 1 Let U be a universe set. A fuzzy set $\tilde{A}$ of U is characterized by a membership function $\mu_{\tilde{A}}(x) \in [0,1]$, where $\mu_{\tilde{A}}(x), \ \forall x \in U$ indicates the degree of x in $\tilde{A}$.

Definition 2 A fuzzy set $\tilde{A}$ of the universe set U is convex if and only if for all x, y in U, $\mu_{\tilde{A}}(\lambda x + (1-\lambda) y) \geq Min(\mu_{\tilde{A}}(x), \mu_{\tilde{A}}(y)), \forall x, y \in U$, where $\lambda \in [0,1]$.

Definition 3 A fuzzy set $\tilde{A}$ of the universe set U is called a normal fuzzy set if $\exists x_i \in U, \mu_{\tilde{A}}(x_i) = 1$.

Definition 4 A fuzzy number is a fuzzy subset in the universe set U that is both convex and normal, and the α-cut of fuzzy number $\tilde{n}$ is defined as $\tilde{n}^{\alpha} = \left\{ x \middle| \mu_{\tilde{n}}(x_i) \geq \alpha, x_i \in U \right\}$, $\alpha \in [0,1]$. $\tilde{n}^{\alpha}$ is a non-empty bounded closed interval and it can be denoted by $\tilde{n}^{\alpha} = [n_l^{\alpha}, n_u^{\alpha}]$, n_l^{α} and n_u^{α} are the lower and upper boundaries of the closed interval, respectively. Figure 4-1 shows a fuzzy number $\tilde{n}$ with α-cut, where $\tilde{n}^{\alpha_1} = [n_l^{\alpha_1}, n_u^{\alpha_1}]$, $\tilde{n}^{\alpha_2} = [n_l^{\alpha_2}, n_u^{\alpha_2}]$. From Figure 4-1, we can see that if $\alpha_2 \geq \alpha_1$, then $n_l^{\alpha_2} \geq n_l^{\alpha_1}$ and $n_u^{\alpha_1} \geq n_u^{\alpha_2}$.

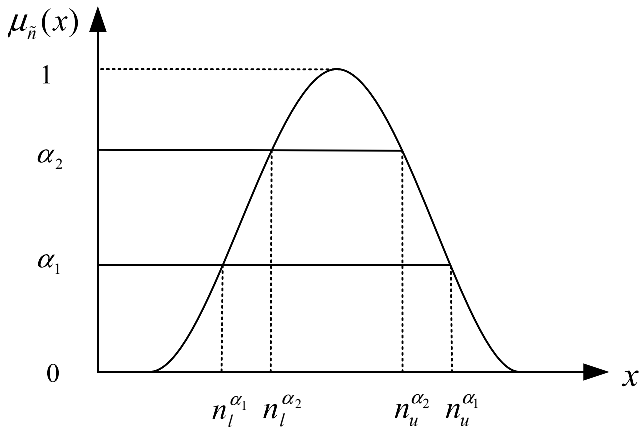

Figure 4-1 Fuzzy number $\tilde{n}$ with α-cuts

Definition 5 A triangular fuzzy number $\tilde{n}$ can be defined by a triplet (n_1, n_2, n_3) shown in Figure 4-2. The membership function $\mu_{\tilde{n}}(x)$ is defined as in Eq. (4.1):

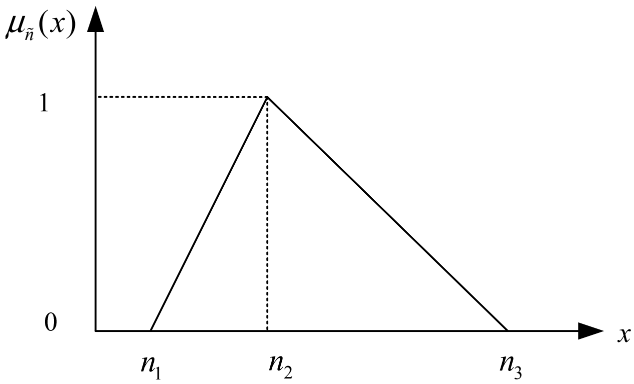

Figure 4-2 A triangular fuzzy number $\tilde{n}$

$$\mu_{\tilde{n}}(x) = \begin{cases} 0, & x < n_1 \\ \dfrac{x - n_1}{n_2 - n_1}, & n_1 \le x \le n_2 \\ \dfrac{x - n_3}{n_2 - n_3}, & n_2 \le x \le n_3 \\ 0, & x > n_3 \end{cases} \tag{4.1}$$

Definition6 If $\tilde{n}$ is a fuzzy number and $n_l^\alpha > 0, \alpha \in [0,1]$, then $\tilde{n}$ is called a positive fuzzy number.

Given any two positive fuzzy numbers $\tilde{m}$, $\tilde{n}$ and a positive real number *r*, the α-cut of two fuzzy numbers are $\tilde{m}^\alpha = [m_l^\alpha, m_u^\alpha]$ and $\tilde{n}^\alpha = [n_l^\alpha, n_u^\alpha]$, respectively. According to the interval of confidence, some main operations of positive fuzzy numbers can be expressed as follows:

$$(\tilde{m}(+)\tilde{n})^\alpha = [m_l^\alpha + n_l^\alpha, m_u^\alpha + n_u^\alpha] \tag{4.2}$$

$$(\tilde{m}(-)\tilde{n})^\alpha = [m_l^\alpha - n_u^\alpha, m_u^\alpha - n_l^\alpha] \tag{4.3}$$

$$(\tilde{m}(\cdot)\tilde{n})^\alpha = [m_l^\alpha \cdot n_l^\alpha, m_u^\alpha \cdot n_u^\alpha] \tag{4.4}$$

$$(\tilde{m}(:)\tilde{n})^\alpha = [\frac{m_l^\alpha}{n_u^\alpha}, \frac{m_u^\alpha}{n_l^\alpha}] \tag{4.5}$$

$$(\tilde{m}^\alpha)^{-1} = [\frac{1}{m_u^\alpha}, \frac{1}{m_l^\alpha}] \tag{4.6}$$

$$(\tilde{m}(\cdot)r)^\alpha = [m_l^\alpha \cdot r, m_u^\alpha \cdot r] \tag{4.7}$$

$$(\tilde{m}(:)r)^\alpha = [\frac{m_l^\alpha}{r}, \frac{m_u^\alpha}{r}] \tag{4.8}$$

Definition 7 Let $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$ be two triangular fuzzy numbers. If $\tilde{m} = \tilde{n}$, then $m_1 = n_1$, $m_2 = n_2$, and $m_3 = n_3$.

Definition 8 If $\tilde{n}$ is a triangular fuzzy number and $n_l^{\alpha} > 0, n_u^{\alpha} \leq 1, \alpha \in [0,1]$, then $\tilde{n}$ is called a normalized positive triangular fuzzy number.

Definition 9 $\tilde{\mathbf{D}}$ is called a fuzzy matrix, if at least an entry in $\tilde{\mathbf{D}}$ is a fuzzy number.

Definition 10 A linguistic variable is a variable whose values are linguistic terms.

The concept of linguistic variable is very useful in dealing with situations which are too complex or too ill-defined to be reasonably described in conventional quantitative expressions. For example, the weight might be a linguistic variable, its values involves 'very low', 'low', 'medium', 'high', 'very high', etc. These linguistic values can also be represented by fuzzy numbers.

Definition 11 Let $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$ be two triangular fuzzy numbers. The distance $d(\tilde{m}, \tilde{n})$ between them can be calculated as:

$$d(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]} \tag{4.9}$$

Definition 12 Let $\tilde{m}$ and $\tilde{n}$ be two triangular fuzzy numbers. The fuzzy number $\tilde{m}$ is close to fuzzy number $\tilde{n}$ as $d(\tilde{m}, \tilde{n})$ approaches zero.

4.2.2 Fuzzy TOPSIS procedure

A systematic approach to extend the TOPSIS to the fuzzy environment is described in this section. Compared to the main procedure of the classical TOPSIS method (see Section 3.1), the main adjustments in applying fuzzy TOPSIS method are presented as follows:

In **Step 1**, since the importance weights of various criteria and/or the values of qualitative criteria are considered as linguistic variables, they can be expressed in positive triangular fuzzy numbers shown in Table 4-1 and Table 4-2, respectively.

Table 4-1 Linguistic terms and related fuzzy numbers for the criteria weights

Linguistic terms	Fuzzy numbers
Absolutely unimportant	$\tilde{\alpha}_1$
Unimportant	$\tilde{\alpha}_2$
Less important	$\tilde{\alpha}_3$
Important	$\tilde{\alpha}_4$
More important	$\tilde{\alpha}_5$
Strongly important	$\tilde{\alpha}_6$
Absolutely important	$\tilde{\alpha}_7$

Table 4-2 Linguistic terms and related fuzzy numbers for criteria values

Linguistic terms	Fuzzy numbers
Very low (VL)	$\tilde{\beta}_1$
Low (L)	$\tilde{\beta}_2$
Medium low (ML)	$\tilde{\beta}_3$
Medium (M)	$\tilde{\beta}_4$
Medium high (MH)	$\tilde{\beta}_5$
High (H)	$\tilde{\beta}_6$
Very high (VH)	$\tilde{\beta}_7$

Assume that a decision group has *K* persons, then the importance of the criteria and the rating of alternatives with respect to each criterion can be calculated based on the geometric mean method expressed as follows:

$$\tilde{x}_{ij} = \sqrt[K]{\tilde{x}_{ij}^1 (\cdot) \tilde{x}_{ij}^2 (\cdot) \cdots (\cdot) \tilde{x}_{ij}^K} \tag{4.10}$$

$$\tilde{w}_{ij} = \sqrt[K]{\tilde{w}_{ij}^1 (\cdot) \tilde{w}_{ij}^2 (\cdot) \cdots (\cdot) \tilde{w}_{ij}^K} \tag{4.11}$$

where $\tilde{x}_{ij}^{K}$ and $\tilde{w}_{ij}^{K}$ are the rating and the weight of the *K*th decision maker.

Thus, a fuzzy multi-criteria decision-making problem can be concisely expressed in matrix format as:

$$\tilde{\mathbf{D}} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \qquad (4.12)$$

$$\tilde{W} = [\tilde{w}_1 \quad \tilde{w}_2 \quad \cdots \quad \tilde{w}_n]$$

where values $\tilde{x}_{ij}$, $\forall i, j$ and weights $\tilde{w}_j$ (j=1, 2, …, n) are linguistic variables that are described by triangular fuzzy numbers, $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}) \in (\tilde{\beta}_1, \tilde{\beta}_2, \ldots, \tilde{\beta}_7)$ and $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}) \in (\tilde{\alpha}_1, \tilde{\alpha}_2, \ldots, \tilde{\alpha}_7)$.

In **Step 2**, the same linear scale transformation is used to convert the various criteria scales into a comparable scale. However, since $\tilde{x}_{ij}$ is fuzzy, its corresponding normalized value $\tilde{r}_{ij}$ must be fuzzy. Eq. (3.3) is then replaced by the following fuzzy operations:

$$\tilde{r}_{ij} = \begin{cases} \tilde{x}_{ij}(:)\tilde{x}_j^* = \left(\dfrac{a_{ij}}{c_j^*}, \dfrac{b_{ij}}{b_j^*}, \dfrac{c_{ij}}{a_j^*} \right), \forall_j, \tilde{x}_j \text{ is a benefit criterion} \\ \tilde{x}_j^-(:)\tilde{x}_{ij} = \left(\dfrac{a_j^-}{c_{ij}}, \dfrac{b_j^-}{b_{ij}}, \dfrac{c_j^-}{a_{ij}} \right), \forall_j, \tilde{x}_j \text{ is a cost criterion} \end{cases} \qquad (4.13)$$

where $\tilde{x}_j^* = (a_j^*, b_j^*, c_j^*)$ and $\tilde{x}_j^- = (a_j^-, b_j^-, c_j^-)$, which present the largest and the lowest values for each criterion, respectively.

In **Step 3**, considering the different importance weight of each criterion, we can construct the weighted normalized fuzzy decision matrix as:

$$\tilde{v}_{ij} = \tilde{r}_{ij}(\cdot)\tilde{w}_j, \forall_j, j \tag{4.14}$$

Moreover, since either $\tilde{r}_{ij}$ or $\tilde{w}_j$ or both of them are fuzzy numbers, Eq. (4.14) will be calculated by the following fuzzy operations:

$$\tilde{v}_{ij} = \tilde{r}_{ij}(\cdot)\tilde{w}_j = \begin{cases} \left(\dfrac{a_{ij}}{c_j^*} w_{j1}, \dfrac{b_{ij}}{b_j^*} w_{j2}, \dfrac{c_{ij}}{a_j^*} w_{j3}\right), \forall_j, \tilde{x}_j \text{ is a benefit criterion} \\ \left(\dfrac{a_j^-}{c_{ij}} w_{j1}, \dfrac{b_j^-}{b_{ij}} w_{j2}, \dfrac{c_j^-}{a_{ij}} w_{j3}\right), \forall_j, \tilde{x}_j \text{ is a cost criterion} \end{cases} \tag{4.15}$$

The result of Eq. (4.15) can be summarized as:

$$\tilde{\mathbf{V}} = \begin{bmatrix} \tilde{v}_{11} & \cdots & \tilde{v}_{1j} & \cdots & \tilde{v}_{1n} \\ \vdots & & \vdots & & \vdots \\ \tilde{v}_{i1} & \cdots & \tilde{v}_{ij} & \cdots & \tilde{v}_{in} \\ \vdots & & \vdots & & \vdots \\ \tilde{v}_{m1} & \cdots & \tilde{v}_{mj} & \cdots & \tilde{v}_{mn} \end{bmatrix} \tag{4.16}$$

In **Step 4**, we now define the fuzzy positive ideal solution (FPIS), i.e., $\tilde{A}^* = [\tilde{v}_1^*, ..., \tilde{v}_n^*]$ and fuzzy negative ideal solution (FNIS), i.e., $\tilde{A}^- = [\tilde{v}_1^-, ..., \tilde{v}_n^-]$. The $\tilde{v}_j^*$ and $\tilde{v}_j^-$ are the fuzzy numbers with the largest generalized mean and the smallest generalized mean, respectively. The generalized mean for fuzzy number $\tilde{v}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, $\forall j$, is defined as:

$$M(\tilde{v}_{ij}) = \frac{-a_{ij}^2 + c_{ij}^2 - a_{ij}b_{ij} + b_{ij}c_{ij}}{[3(-a_{ij} + c_{ij})]} \tag{4.17}$$

For each column *j*, we find the greatest generalized mean as $\tilde{v}_j^*$ and the lowest generalized mean as $\tilde{v}_j^-$. Consequently, the FPIS ($\tilde{A}^*$) and FNIS ($\tilde{A}^-$) are obtained.

In order to acquire the Separation Measures $\tilde{S}_i^*$ and $\tilde{S}_i^-$ in **Step 5**, we have to compute the Euclidean distance $\tilde{D}_{ij}^*$ and $\tilde{D}_{ij}^-$ firstly. For fuzzy data, the difference between two fuzzy numbers $\mu_{v_{ij}}(x)$ and $\mu_{v_j^*}(x)$ (based on Zadeh, 1965) is calculated as:

$$\tilde{D}_{ij}^* = 1 - \{\sup_x [\mu_{v_{ij}}(x) \wedge \mu_{v_j^*}(x)]\} = 1 - L_{ij}, \forall i, j \tag{4.18}$$

where L_{ij} is the highest degree of similarity of $\tilde{v}_{ij}$ and $\tilde{v}_j^*$. The value of L_{ij} is depicted in Figure 4-3.

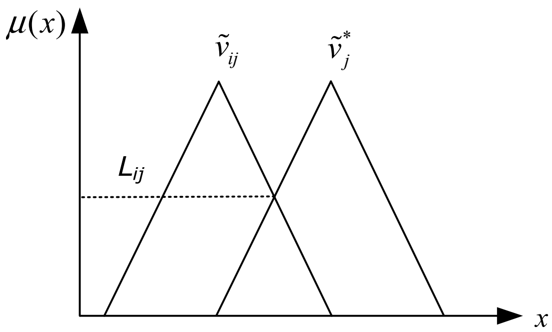

Figure 4-3 The derivation of L_{ij}

Similarly, the difference between $\mu_{v_{ij}}(x)$ and $\mu_{v_j^-}(x)$ is defined as:

$$\tilde{D}_{ij}^- = 1 - \{\sup_x [\mu_{v_{ij}}(x) \wedge \mu_{v_j^-}(x)]\} = 1 - L_{ij}, \forall i, j \tag{4.19}$$

More specifically, $\tilde{D}_{ij}^*$ and $\tilde{D}_{ij}^-$ are calculated as below, where $\tilde{v}_j^* = (a^*, b^*, c^*)$ and $\tilde{v}_j^- = (a^-, b^-, c^-)$ are the fuzzy numbers with the largest generalized mean and the smallest generalized mean, respectively.

$$\tilde{D}_{ij}^{*} = \begin{cases} 1 - \dfrac{c_{ij} - a^{*}}{b^{*} + c_{ij} - a^{*} - b_{ij}} & for\, b_{ij} < b^{*} \\ 1 - \dfrac{c^{*} - a_{ij}}{b_{ij} + c^{*} - a_{ij} - b^{*}} & for\, b^{*} < b_{ij} \end{cases} \quad \forall i, j \tag{4.20}$$

$$\tilde{D}_{ij}^{-} = \begin{cases} 1 - \dfrac{c^{-} - a_{ij}}{b_{ij} + c^{-} - a_{ij} - b^{-}} & for\, b^{-} < b_{ij} \\ 1 - \dfrac{c_{ij} - a^{-}}{b^{-} + c_{ij} - a^{-} - b_{ij}} & for\, b_{ij} < b^{-} \end{cases} \quad \forall i, j \tag{4.21}$$

Note that both $\tilde{D}_{ij}^{*}$ and $\tilde{D}_{ij}^{-}$ are crisp values now. Therefore, the Separation Measures $\tilde{S}_{i}^{*}$ and $\tilde{S}_{i}^{-}$ can be calculated according to Eq. (3.8) and Eq. (3.9), and the relative closeness index C_i obtained as Eq. (3.12). Accordingly, the set of alternatives can be ranked from the most preferred to the least preferred feasible solutions.

4.3 Creating a composite road safety performance index by applying fuzzy TOPSIS method

To handle the situations that the importance weights and/or the criteria values are probably given by linguistic terms in the road safety context, in this section, two applications of the fuzzy TOPSIS method (i.e., only weights need to be fuzzified and both weights and indicator values are fuzzified) are conducted to combine the six individual SPIs (the same as in Section 3.3) into an overall index for the 21 European countries. In this respect, the source data (the indicator values shown in Table 3-1, and the weight scores in Table 3-3) which are expressed in crisp values are firstly converted into linguistic terms, and then represented by triangular fuzzy numbers. Subsequently, fuzzy calculations are executed with the purpose of creating a composite road safety performance index.

4.3.1 Application 1 --- fuzzy weights and crisp indicator values

In this study, we assume that the indicator weights given by the eight experts are expressed in linguistic terms. This is realized by converting the crisp values (see Table 3-3) using a transformation mapping. Specifically, given the indicator weights ranged from 0 to 10, based on the triangular membership function presented in Fig. 4-4, the weight scores are sorted into seven groups (Absolutely unimportant $\tilde{\alpha}_1$, Unimportant $\tilde{\alpha}_2$, Less important $\tilde{\alpha}_3$, Important $\tilde{\alpha}_4$, More important $\tilde{\alpha}_5$, Strongly important $\tilde{\alpha}_6$, Absolutely important $\tilde{\alpha}_7$) as in Table 4-1. Hence, the corresponding relationship between the crisp values and the linguistic terms can be described as the transformation mapping presented in Eq. (4.22).

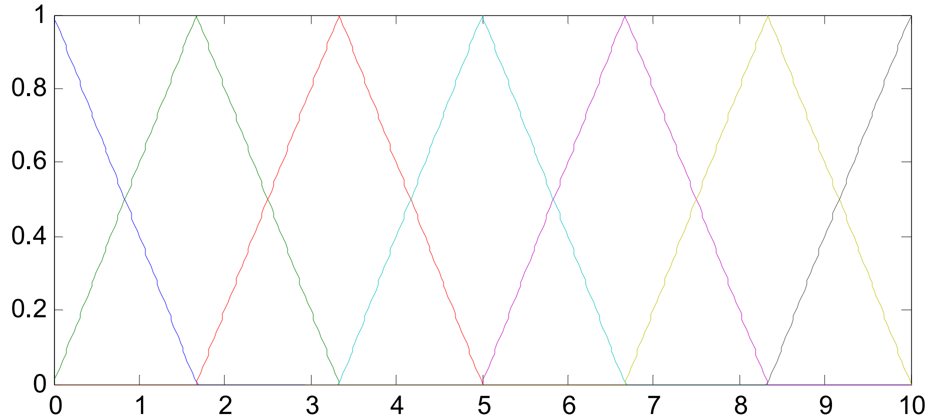

Figure 4-4 Triangular membership function with seven classes ranged from 0 to 10

$$f(w)=\begin{cases}\tilde{\alpha}_1 & if \quad w=0\\ \tilde{\alpha}_2 & if \quad w=1,2\\ \tilde{\alpha}_3 & if \quad w=3,4\\ \tilde{\alpha}_4 & if \quad w=5\\ \tilde{\alpha}_5 & if \quad w=6,7\\ \tilde{\alpha}_6 & if \quad w=8,9\\ \tilde{\alpha}_7 & if \quad w=10\end{cases} \tag{4.22}$$

Moreover, these linguistic variables can be expressed in positive triangular fuzzy numbers as listed in Table 4-3.

Table 4-3 Triangular fuzzy numbers for the linguistic terms of indicator weights

Linguistic terms	Triangular fuzzy numbers
Absolutely unimportant	(0, 0, 1/6)
Unimportant	(0, 1/6, 2/6)
Less important	(1/6, 2/6, 3/6)
Important	(2/6, 3/6, 4/6)
More important	(3/6, 4/6, 5/6)
Strongly important	(4/6, 5/6, 1)
Absolutely important	(5/6, 1, 1)

Thus, the converted linguistic weight matrix (*LW*) and the fuzzified weight matrix are obtained in Table 4-4 and Table 4-5, respectively. And the fuzzy weight vector (*FW*) computed by geometric mean method (see Eq. (4.11)) is also listed in the last row of Table 4-5.

Since the indicator values are crisp in this case (the same as in Section 3.3), the weighted normalized fuzzy decision matrix $\tilde{\mathbf{V}}$ could be derived by multiplying the normalized decision matrix **D'** (see Table 3-2) with the fuzzy weight vector *FW* based on Eq. (4.7) directly.

It should be mentioned here that each element in $\tilde{\mathbf{V}}$ is fuzzy number $\tilde{v}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, so its generalized mean $M(\tilde{v}_{ij})$ should be figured out according to Eq. (4.17). The largest generalized mean and the smallest generalized mean of each indicator could then be picked out, and the countries corresponding to the extremes of $M(\tilde{v}_{ij})$ are the relevant $\tilde{v}_j^*$ and $\tilde{v}_j^-$ for each indicator. Now, the Euclidean distance $\tilde{D}_{ij}^*$ and $\tilde{D}_{ij}^-$ could be calculated as Eq. (4.20) and Eq. (4.21), and the separation measures $\tilde{S}_i^*$ and $\tilde{S}_i^-$, as well as the relative closeness index C_i are subsequently obtained.

Table 4-4 Linguistic weight matrix *LW*

Experts	ALC. & DRUGS	SPEED	PROTECT SYSTEMS	VEHICLE	ROADS	TRAUMA CARE
E1	Absolutely Important	Absolutely Important	Strongly Important	More Important	More Important	More Important
E2	Strongly Important	Absolutely Important	Absolutely Important	Absolutely Important	Strongly Important	Absolutely Important
E3	Strongly Important	Strongly Important	Strongly Important	More Important	Strongly Important	More Important
E4	Absolutely Important	Absolutely Important	Strongly Important	Strongly Important	Strongly Important	Absolutely Important
E5	Absolutely Important	Strongly Important	More Important	Strongly Important	More Important	Important
E6	Strongly Important	Absolutely Important	Strongly Important	More Important	Absolutely Important	Strongly Important
E7	Strongly Important	Absolutely Important	Strongly Important	Strongly Important	Strongly Important	Strongly Important
E8	Absolutely Important	Absolutely Important	Absolutely Important	Strongly Important	Strongly Important	Strongly Important

Table 4-5 The fuzzified weight matrix and the geometric mean *FW*

Experts	ALC. & DRUGS			SPEED			PROTECT SYSTEMS			VEHICLE			ROADS			TRAUMA CARE		
E1	5/6	1	1	5/6	1	1	2/3	5/6	1	1/2	2/3	5/6	1/2	2/3	5/6	1/2	2/3	5/6
E2	2/3	5/6	1	5/6	1	1	5/6	1	1	5/6	1	1	2/3	5/6	1	5/6	1	1
E3	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1	1/2	2/3	5/6	2/3	5/6	1	1/2	2/3	5/6
E4	5/6	1	1	5/6	1	1	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1	5/6	1	1
E5	5/6	1	1	2/3	5/6	1	1/2	2/3	5/6	2/3	5/6	1	1/2	2/3	5/6	1/3	1/2	2/3
E6	2/3	5/6	1	5/6	1	1	2/3	5/6	1	1/2	2/3	5/6	5/6	1	1	2/3	5/6	1
E7	2/3	5/6	1	5/6	1	1	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1
E8	5/6	1	1	5/6	1	1	5/6	1	1	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1
Geometric Mean	0.745	0.913	1.000	0.788	0.955	1.000	0.680	0.848	0.977	0.615	0.784	0.934	0.638	0.806	0.955	0.602	0.774	0.908

The final index scores for the 21 European countries under study and their corresponding ranking results are listed in the following Table 4-6.

Table 4-6 The index scores and ranking results for the 21 European countries based on the fuzzy TOPSIS (fuzzy weights) and the classical TOPSIS

Country	*C* (fuzzy TOPSIS (FW))	Fuzzy TOPSIS (FW) Ranking	*C* (TOPSIS)	TOPSIS Ranking
Austria	0.549	10	0.325	12
Belgium	0.523	11	0.412	9
Cyprus	0.303	21	0.204	19
Czech Republic	0.471	15	0.220	18
Denmark	0.691	1	0.528	2
Estonia	0.308	20	0.096	21
Finland	0.514	12	0.335	11
France	0.566	9	0.397	10
Germany	0.617	6	0.466	7
Greece	0.442	17	0.236	16
Hungary	0.413	18	0.165	20
Ireland	0.597	8	0.479	6
Italy	0.452	16	0.266	15
Netherlands	0.639	5	0.524	3
Poland	0.404	19	0.233	17
Portugal	0.497	13	0.308	13
Slovenia	0.600	7	0.423	8
Spain	0.472	14	0.290	14
Sweden	0.688	2	0.605	1
Switzerland	0.656	3	0.522	4
United Kingdom	0.650	4	0.481	5

It can be seen that based on the fuzzy TOPSIS (fuzzy weight) method, Denmark is now the best performing country, while Cyprus the worst, which rank second and third-to-last respectively in the TOPSIS method. Moreover, comparing the composite index values of the 21 European countries based on the two methods, we find that they are highly correlated with a Pearson's correlation coefficient of 0.952, and a relatively high value is derived for each country by using the fuzzy TOPSIS method, which is mainly owing to the use of fuzzy numbers for representing the importance of each indicator instead of precise numbers. Furthermore, by checking the two ranking results, almost all the countries have a difference in rank with a maximum of two positions except for Czech Republic, which ranks three positions ahead of the one from the classical TOPSIS method. In other words, the linguistic expressions from the experts can be well handled by integrating the fuzzy logic in the TOPSIS method without losing any important information.

4.3.2 Application 2 --- fuzzy weights and fuzzy indicator values

In this application, we further consider the situation that the indicator values of the 21 European countries also need to be expressed in linguistic terms. The same kind of transformation mapping is used to describe the relationship between the crisp values (see Table 3-1) and the linguistic terms. Taking speed domain as an example, which has the indicator values ranged from 3 to 12. The following transformation mapping is utilized.

$$f(x) = \begin{cases} \tilde{\beta}_1 & 3 \le x < 3.75 \\ \tilde{\beta}_2 & 3.75 < x < 5.25 \\ \tilde{\beta}_3 & 5.25 < x < 6.75 \\ \tilde{\beta}_4 & 6.75 < x < 8.25 \\ \tilde{\beta}_5 & 8.25 < x < 9.75 \\ \tilde{\beta}_6 & 9.75 < x < 11.25 \\ \tilde{\beta}_7 & 11.25 < x \le 12 \end{cases} \tag{4.23}$$

Analogously, the indicator values of the other six risk domains are all categorized into seven groups (very low $\tilde{\beta}_1$, low $\tilde{\beta}_2$, medium low $\tilde{\beta}_3$, medium $\tilde{\beta}_4$, medium high $\tilde{\beta}_5$, high $\tilde{\beta}_6$, very high $\tilde{\beta}_7$). Moreover, these linguistic variables are further converted into positive triangular fuzzy numbers as shown in Table 4-7.

Table 4-7 Triangular fuzzy numbers for the linguistic terms of indicator values

Linguistic terms	Triangular fuzzy numbers
Very low (VL)	(0, 0, 1/6)
Low (L)	(0, 1/6, 2/6)
Medium low (ML)	(1/6, 2/6, 3/6)
Medium (M)	(2/6, 3/6, 4/6)
Medium high (MH)	(3/6, 4/6, 5/6)
High (H)	(4/6, 5/6, 1)
Very high (VH)	(5/6, 1, 1)

As a result, the fuzzy decision matrix (**FD**) is obtained in Table 4-8.

Table 4-8 Fuzzy decision matrix *FD*

Country	ALC. & DRUGS			SPEED			PROTECT SYSTEMS			VEHICLE			ROADS			TRAUMA CARE		
Austria	0	1/6	1/3	1/6	1/3	1/2	1/2	2/3	5/6	1/3	1/2	2/3	1/6	1/3	1/2	1/6	1/3	1/2
Belgium	1/6	1/3	1/2	5/6	1	1	1/3	1/2	2/3	1/2	2/3	5/6	5/6	1	1	1/2	2/3	5/6
Cyprus	5/6	1	1	5/6	1	1	1/2	2/3	5/6	0	0	1/6	1/3	1/2	2/3	0	1/6	1/3
Czech	0	1/6	1/3	1/6	1/3	1/2	1/2	2/3	5/6	0	0	1/6	0	1/6	1/3	1/6	1/3	1/2
Denmark	0	0	1/6	0	1/6	1/3	2/3	5/6	1	1/2	2/3	5/6	1/6	1/3	1/2	1/2	2/3	5/6
Estonia	0	0	1/6	5/6	1	1	1/2	2/3	5/6	0	0	1/6	0	0	1/6	0	0	1/6
Finland	0	0	1/6	1/6	1/3	1/2	2/3	5/6	1	1/6	1/3	1/2	0	0	1/6	1/6	1/3	1/2
France	0	1/6	1/3	1/3	1/2	2/3	5/6	1	1	1/3	1/2	2/3	1/6	1/3	1/2	2/3	5/6	1
Germany	0	1/6	1/3	1/3	1/2	2/3	5/6	1	1	1/3	1/2	2/3	1/3	1/2	2/3	5/6	1	1
Greece	1/6	1/3	1/2	1/6	1/3	1/2	0	0	1/6	1/3	1/2	2/3	0	1/6	1/3	1/2	2/3	5/6
Hungary	0	0	1/6	5/6	1	1	1/6	1/3	1/2	1/6	1/3	1/2	0	1/6	1/3	1/3	1/2	2/3
Ireland	0	1/6	1/3	0	0	1/6	2/3	5/6	1	5/6	1	1	0	0	1/6	1/6	1/3	1/2
Italy	1/6	1/3	1/2	5/6	1	1	1/3	1/2	2/3	1/3	1/2	2/3	1/6	1/3	1/2	1/3	1/2	2/3
Netherlands	0	1/6	1/3	1/3	1/2	2/3	2/3	5/6	1	1/2	2/3	5/6	5/6	1	1	1/2	2/3	5/6
Poland	0	0	1/6	1/3	1/2	2/3	1/3	1/2	2/3	0	1/6	1/3	0	0	1/6	0	1/6	1/3
Portugal	0	1/6	1/3	2/3	5/6	1	2/3	5/6	1	1/6	1/3	1/2	1/6	1/3	1/2	1/2	2/3	5/6
Slovenia	0	1/6	1/3	1/6	1/3	1/2	1/2	2/3	5/6	2/3	5/6	1	1/6	1/3	1/2	1/3	1/2	2/3
Spain	1/6	1/3	1/2	2/3	5/6	1	2/3	5/6	1	1/3	1/2	2/3	1/6	1/3	1/2	1/6	1/3	1/2
Sweden	0	0	1/6	0	1/6	1/3	2/3	5/6	1	1/2	2/3	5/6	0	0	1/6	1/2	2/3	5/6
Switzerland	0	1/6	1/3	0	1/6	1/3	1/2	2/3	5/6	1/2	2/3	5/6	1/3	1/2	2/3	5/6	1	1
United Kingdom	0	0	1/6	0	1/6	1/3	5/6	1	1	1/2	2/3	5/6	0	1/6	1/3	1/3	1/2	2/3

After normalizing the fuzzy decision matrix (**FD**) according to Eq. (4.13), the weighted normalized fuzzy decision matrix $\tilde{\mathbf{V}}$ could be derived by computing the product of the normalized **FD** and the geometric mean of fuzzy weight scores *FW* (see Table 4-5) based on Eq. (4.15). Afterwards, following the same fuzzy TOPSIS procedure as in application 1, the relative closeness index C_i can be worked out. The final composite index scores for the 21 European countries and their corresponding ranking results produced by both applications are indicated in Table 4-9.

Table 4-9 The index scores and ranking results for the 21 European countries based on the two fuzzy TOPSIS applications

Country	*C* (fuzzy TOPSIS (FW&FD))	Fuzzy TOPSIS (FW&FD) Ranking	*C* (fuzzy TOPSIS (FW))	Fuzzy TOPSIS (FW) Ranking
Austria	0.560	13	0.549	10
Belgium	0.584	11	0.523	11
Cyprus	0.297	20	0.303	21
Czech Republic	0.490	15	0.471	15
Denmark	0.793	1	0.691	1
Estonia	0.294	21	0.308	20
Finland	0.578	12	0.514	12
France	0.695	8	0.566	9
Germany	0.730	5	0.617	6
Greece	0.424	19	0.442	17
Hungary	0.471	17	0.413	18
Ireland	0.701	7	0.597	8
Italy	0.472	16	0.452	16
Netherlands	0.744	4	0.639	5
Poland	0.441	18	0.404	19
Portugal	0.604	10	0.497	13
Slovenia	0.667	9	0.600	7
Spain	0.524	14	0.472	14
Sweden	0.714	6	0.688	2
Switzerland	0.774	2	0.656	3
United Kingdom	0.764	3	0.650	4

It can be seen that Denmark is the best performing country, while Cyprus and Estonia are the two countries with worst performance in the two cases. Moreover, comparing the index scores of the 21 European countries based on these two applications, we find that they are highly correlated with a Pearson's correlation coefficient of 0.974, which implies the effectiveness of solving expert subjective judgments on indicator values by using fuzzy set theory. In addition, taking a close look at the two ranking results, we find that six countries (BE, CZ, DK, FI, IT and ES) remain their ranking positions unchanged, ten countries (CY, FR, DE, HU, IR, NL, PL, PT, CH and UK) move their positions up and five countries (AT, EE, EL, SL and SE) decline. It means that substitutions of the linguistic terms (further triangular fuzzy numbers) for the crisp indicator values will impact on the final results to a certain extent. In this case, Sweden has a biggest decrease in its ranking position, which suggests that the indicator values of Sweden have been underestimated by using the linguistic variables.

4.4 Comparison and discussion

To make an overall comparison, the ranking results derived from the classical TOPSIS method in Section 3.3 and the fuzzy TOPSIS method (both applications in Section 4.3), together with the ones based on the number of fatalities per million inhabitants are presented in Table 4-10.

Table 4-10 Ranking results based on TOPSIS method, fuzzy TOPSIS method and fatalities

Country	TOPSIS Ranking	Fuzzy TOPSIS Ranking (FW)	Fuzzy TOPSIS Ranking (FW&FD)	Fatality Ranking
Austria	12	10	13	11
Belgium	9	11	11	12
Cyprus	19	21	20	17
Czech Republic	18	15	15	18
Denmark	2	1	1	6.5
Estonia	21	20	21	13.5
Finland	11	12	12	4
France	10	9	8	9
Germany	7	6	5	6.5
Greece	16	17	19	19
Hungary	20	18	17	16

Ireland	6	8	7	8
Italy	15	16	16	10
Netherlands	3	5	4	3
Poland	17	19	18	21
Portugal	13	13	10	20
Slovenia	8	7	9	13.5
Spain	14	14	14	15
Sweden	1	2	6	1
Switzerland	4	3	2	5
United Kingdom	5	4	3	2

From an overall perspective, the three index ranking results from the (fuzzy) TOPSIS methods are quite similar, and most of the countries (except Sweden) have an average difference in rank with a maximum of two positions. Moreover, by comparing the ranking results with the ones based on the number of fatalities per million inhabitants, the highest disagreements are found to lie in the following six countries, Denmark, Estonia, Finland, Italy, Portugal and Slovenia, with an average difference in rank more than four positions.

Furthermore, the correlation analysis is conducted to quantitatively assess the above ranking results. The Pearson's correlation coefficients among the above four ranking results are given in Table 4-11.

Table 4-11 The Pearson's correlation coefficients among the four ranking results

	TOPSIS Ranking	**Fuzzy TOPSIS Ranking (FW)**	**Fuzzy TOPSIS Ranking (FW&FD)**	**Fatality Ranking**
TOPSIS Ranking	1.000	0.969	0.942	0.804
Fuzzy TOPSIS Ranking (FW)	0.969	1.000	0.966	0.794
Fuzzy TOPSIS Ranking (FW&FD)	0.942	0.966	1.000	0.752
Fatality Ranking	0.804	0.794	0.752	1.000

The high correlation coefficients achieved among the first three rankings (i.e., the three TOPSIS applications) verifies the above discussions that the linguistic terms given by experts (either for the indicator values or the corresponding weights) can be well handled by integrating the fuzzy logic in the classical TOPSIS method without losing any important information.

Moreover, concerning the last column of Table 4-11, which contains the correlation coefficients of the first three ranking results relative to the ranking based on the number of road fatalities per million inhabitants, respectively. We can see that the classical TOPSIS ranking produces the best fit with the fatality ranking (0.804) followed by the fuzzy TOPSIS ranking in which the weights are fuzzified (0.794). Although the fuzzy TOPSIS ranking considering both fuzzy weights and fuzzy indicator values results in the lowest correlation coefficient (0.752), it is still acceptable, and further validate the feasibility of using this fuzzy TOPSIS method to handle qualitative problems such as linguistic variables which are usually used to assess the weights of all criteria and the ratings of each alternative with respect to each criterion.

4.5 Summary

Due to the uncertainty of human cognition and imprecise/vague judgements, linguistic assessments rather than crisp numerical values are usually given by experts. In such cases, the classical TOPSIS method may not be used directly. Therefore, the fuzzy TOPSIS method is developed by integrating the fuzzy set theory into TOPSIS method, which embodies the fuzzy nature of the comparison or evaluation process and strengthens the comprehensiveness and rationality of the decision-making process. In this chapter, the fuzzy TOPSIS method is applied to create a composite road safety performance index for 21 European countries, and two situations are considered, i.e., only weights need to be fuzzified and both weights and indicator values are fuzzified. Comparisons of the results with the ones from the classical TOPSIS method as well as the road safety final outcome (i.e., fatalities) indicate that the fuzzy TOPSIS method could provide a promising solution to handle the problems that the weight scores and/or the indicator values are given in linguistic terms instead of crisp values.

In the previous chapters, both the classical TOPSIS method and the fuzzy TOPSIS method are used to combine the individual SPIs into an overall index. In these applications, however, relatively small number of basic indicators are considered (i.e., one indicator for each risk domain), which might be insufficient in reflecting the entire situation of the risk domains. To this end, more indicators are developed, and a hierarchical structure of the indicators is constructed. Correspondingly, the realization of a hierarchical TOPSIS method which enables taking the layered hierarchy of the indicators into account is valuable, which will be specified in the next chapter.

Chapter 5 Hierarchical Fuzzy TOPSIS Analysis

In the previous two chapters, six individual safety performance indicators, i.e., one --- best available --- indicator representing each of the six road safety risk domains developed by Hermans (2009), were used to create a composite index by means of both the classical TOPSIS method and the fuzzy TOPSIS method. However, since the selection of one SPI for each risk domain might be insufficient in reflecting the entire feature of that domain, and moreover, the collection of additional data on the best needed indicators is also ongoing, thus, a hierarchical structure of the indicators should and could be taken into account. Currently, some other best available indicators have been formulated to represent some of the six risk domains and served as the complements of the existing six SPIs. Correspondingly, a hierarchical (fuzzy) TOPSIS model is needed to combine the multilayer indicators into one overall road safety performance index.

In this chapter, we firstly specify the adjustments of the fuzzy TOPSIS algorithm which can take the layered hierarchy of the indicators into account in Section 5.1. Then, the application of this new model to combine the hierarchical SPIs into an overall safety performance index is carried out (Section 5.2), and comparisons of the ranking results with the ones obtained in the previous chapters as well as the final outcome are subsequently conducted (Section 5.3), which validate the use of this model in road safety performance evaluation. Finally, a summary is given in Section 5.4.

5.1 The hierarchical fuzzy TOPSIS method procedure

Development of a hierarchical fuzzy TOPSIS method can be treated as a nature extension of the fuzzy TOPSIS method due to the ever increasing complexity of today's performance evaluation activities. It can be realized by taking multilayer structures of the performance indicators into account. Based on the main procedure of the fuzzy TOPSIS method (see Section 4.2.2), the computation process of applying the hierarchical fuzzy TOPSIS method is presented as follows:

Step 1 Consider a two-layer situation of m alternatives, each including n main criteria (MC), r sub-criteria (SC). Assume each main criterion has r_j sub-criteria, thereby the total number of sub-criteria r is equal to the sum of r_j ($j = 1, 2, \ldots, n$). $\tilde{x}_{ijk}$ represents the value of the kth sub-criteria within the jth main criteria of the ith alternative, which can be linguistic variables, and can be further represented by triangular fuzzy numbers, i.e., $\tilde{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk})$. Thus, a hierarchical fuzzy multi-criteria decision-making problem can be concisely expressed in matrix format as:

$$\begin{array}{c} \\ \\ \tilde{\mathbf{D}} = \begin{array}{c} \\ \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \end{array} \begin{array}{c} \begin{array}{cccccccccccc} & MC_1 & & & MC_2 & & \cdots\cdots & & MC_n & \\ SC_{11} & SC_{12} & \cdots & SC_{1r_1} & SC_{21} & SC_{22} & \cdots & SC_{2r_2} & \cdots\cdots & SC_{n1} & SC_{n2} & \cdots & SC_{nr_n} \end{array} \\ \begin{bmatrix} \tilde{x}_{111} & \tilde{x}_{112} & \cdots & \tilde{x}_{11r_1} & \tilde{x}_{121} & \tilde{x}_{122} & \cdots & \tilde{x}_{12r_2} & \cdots\cdots & \tilde{x}_{1n1} & \tilde{x}_{1n2} & \cdots & \tilde{x}_{1nr_n} \\ \tilde{x}_{211} & \tilde{x}_{212} & \cdots & \tilde{x}_{21r_1} & \tilde{x}_{221} & \tilde{x}_{222} & \cdots & \tilde{x}_{22r_2} & \cdots\cdots & \tilde{x}_{2n1} & \tilde{x}_{2n2} & \cdots & \tilde{x}_{2nr_n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m11} & \tilde{x}_{m12} & \cdots & \tilde{x}_{m1r_1} & \tilde{x}_{m21} & \tilde{x}_{m22} & \cdots & \tilde{x}_{m2r_2} & \cdots\cdots & \tilde{x}_{mn1} & \tilde{x}_{mn2} & \cdots & \tilde{x}_{mnr_n} \end{bmatrix} \end{array} \quad (5.1)$$

Step 2 Convert the decision making matrix ($\tilde{\mathbf{D}}$) to a dimensionless matrix ($\tilde{\mathbf{D}}'$). In doing so, the linear scale transformation is used as shown in Eq. (5.2).

$$\tilde{r}_{ijk} = \begin{cases} \tilde{x}_{ijk}(:)\tilde{x}^*_{jk} = \left(\dfrac{a_{ijk}}{c^*_{jk}}, \dfrac{b_{ijk}}{b^*_{jk}}, \dfrac{c_{ijk}}{a^*_{jk}}\right), \forall_{jk}, \tilde{x}_{jk}\ is\ a\ benefit\ criterion \\ \tilde{x}^-_{jk}(:)\tilde{x}_{ijk} = \left(\dfrac{a^-_{jk}}{c_{ijk}}, \dfrac{b^-_{jk}}{b_{ijk}}, \dfrac{c^-_{jk}}{a_{ijk}}\right), \forall_{jk}, \tilde{x}_{jk}\ is\ a\ cost\ criterion \end{cases} \quad (5.2)$$

where $\tilde{x}^*_{jk} = (a^*_{jk}, b^*_{jk}, c^*_{jk})$ and $\tilde{x}^-_{jk} = (a^-_{jk}, b^-_{jk}, c^-_{jk})$ present the largest and the lowest value of each sub-criterion, respectively.

Step 3 Construct the weight score matrix of the main criteria with respect to the final objective.

$$\tilde{w}_{MC} = \begin{array}{c} MC_1 \\ MC_2 \\ \vdots \\ MC_j \\ \vdots \\ MC_n \end{array} \begin{bmatrix} \tilde{w}_1 \\ \tilde{w}_2 \\ \vdots \\ \tilde{w}_j \\ \vdots \\ \tilde{w}_n \end{bmatrix} \quad (5.3)$$

where $\tilde{w}_j \left(j = 1, 2, \ldots, n \right)$ is the geometric mean of the main criteria weight scores assigned by the *K* experts, which is calculated according to Eq. (4.11).

Step 4 Obtain the importance weight scores of the sub-criteria with respect to the corresponding main criteria. The sub-criteria weight matrix is presented in Eq. (5.4).

$$\tilde{w}_{SC} = \begin{array}{cc} & \begin{array}{cccccc} \tilde{w}_1 & \tilde{w}_2 & \cdots & \tilde{w}_j & \cdots & \tilde{w}_n \\ MC_1 & MC_2 & \cdots & MC_j & \cdots & MC_n \end{array} \\ \begin{array}{c} SC_{11} \\ SC_{12} \\ \vdots \\ SC_{1r_1} \\ SC_{21} \\ SC_{22} \\ \vdots \\ SC_{2r_2} \\ \vdots \\ SC_{j1} \\ SC_{j2} \\ \vdots \\ SC_{jr_j} \\ \vdots \\ SC_{n1} \\ SC_{n2} \\ \vdots \\ SC_{nr_n} \end{array} & \left[\begin{array}{cccccc} \tilde{w}_{11} & 0 & \cdots & 0 & \cdots & 0 \\ \tilde{w}_{12} & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{w}_{1r_1} & 0 & \cdots & 0 & \cdots & 0 \\ 0 & \tilde{w}_{21} & \cdots & 0 & \cdots & 0 \\ 0 & \tilde{w}_{22} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \tilde{w}_{2r_2} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tilde{w}_{j1} & \cdots & 0 \\ 0 & 0 & \cdots & \tilde{w}_{j2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tilde{w}_{jr_j} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & \cdots & \tilde{w}_{n1} \\ 0 & 0 & \cdots & 0 & \cdots & \tilde{w}_{n2} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & \cdots & \tilde{w}_{nr_n} \end{array} \right] \end{array} \tag{5.4}$$

where $\tilde{w}_{jr_j} \left(j = 1, 2, \ldots, n \right)$ is the geometric mean of the sub-criteria weight scores with respect to the corresponding main criteria given by the *K* experts.

Step 5 Calculate the final weight score for each sub-criterion, which is the product of the main criterion weight score and the sub-criterion weight score with respect to the corresponding main criterion.

$$\tilde{W}_{SCj} = \tilde{w}_{MCj}\left(\cdot\right)\tilde{w}_{SCj} = \tilde{w}_{j}\left(\cdot\right)\begin{bmatrix}\tilde{w}_{j1}\\ \tilde{w}_{j2}\\ \vdots \\ \tilde{w}_{jr_j}\end{bmatrix} = \begin{bmatrix}\tilde{w}_{SCj1}\\ \tilde{w}_{SCj2}\\ \vdots \\ \tilde{w}_{SCjr_j}\end{bmatrix},\ \ \left(j = 1,2,\ldots,n\right) \tag{5.5}$$

where $\tilde{W}_{SCj}$ represents the final sub-criteria weight matrix concerning the *j*th main criterion. $\tilde{w}_{MCj}$ and $\tilde{w}_{SCj}$ denote the *j*th main criterion weight score and the sub-criteria weight scores of this main criterion, respectively.

Step 6 By multiplying the fuzzy criteria values and the fuzzy weight scores of each sub-criterion, the weighted normalized fuzzy decision matrix $\tilde{\mathbf{V}}$ could be achieved as calculated in Eq. (4.15).

$$\begin{array}{cc} & \begin{array}{ccccccccccccc} & MC_1 & & & & MC_2 & & & \cdots\cdots & & MC_n & & \\ SC_{11} & SC_{12} & \cdots & SC_{1r_1} & SC_{21} & SC_{22} & \cdots & SC_{2r_2} & \cdots\cdots & SC_{n1} & SC_{n2} & \cdots & SC_{nr_n} \end{array} \\ \tilde{\mathbf{V}} = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} \tilde{v}_{111} & \tilde{v}_{112} & \cdots & \tilde{v}_{11r_1} & \tilde{v}_{121} & \tilde{v}_{122} & \cdots & \tilde{v}_{12r_2} & \cdots\cdots & \tilde{v}_{1n1} & \tilde{v}_{1n2} & \cdots & \tilde{v}_{1nr_n} \\ \tilde{v}_{211} & \tilde{v}_{212} & \cdots & \tilde{v}_{21r_1} & \tilde{v}_{221} & \tilde{v}_{222} & \cdots & \tilde{v}_{22r_2} & \cdots\cdots & \tilde{v}_{2n1} & \tilde{v}_{2n2} & \cdots & \tilde{v}_{2nr_n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{m11} & \tilde{v}_{m12} & \cdots & \tilde{v}_{m1r_1} & \tilde{v}_{m21} & \tilde{v}_{m22} & \cdots & \tilde{v}_{m2r_2} & \cdots\cdots & \tilde{v}_{mn1} & \tilde{v}_{mn2} & \cdots & \tilde{v}_{mnr_n} \end{bmatrix} \end{array} \tag{5.6}$$

Subsequently, the fuzzy addition principle (see Eq. (4.2)) is used to aggregate the values within each main criterion as follows.

$$\tilde{v}_{ij}^{'} = \sum_{k=1}^{r_j} \tilde{v}_{ijk},\ \ j = 1,2,\ldots,n. \tag{5.7}$$

Thus, the matrix $\tilde{\mathbf{V}}$ is converted into $\tilde{\mathbf{V}}^{'}$:

$$\tilde{\mathbf{V}}' = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} MC_1 & MC_2 & \cdots & MC_n \end{array} \\ \begin{bmatrix} \tilde{v}'_{11} & \tilde{v}'_{12} & \cdots & \tilde{v}'_{1n} \\ \tilde{v}'_{21} & \tilde{v}'_{22} & \cdots & \tilde{v}'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{v}'_{m1} & \tilde{v}'_{m2} & \cdots & \tilde{v}'_{mn} \end{bmatrix} \end{array} \tag{5.8}$$

By now, the hierarchical algorithm is ready to be included in the computation process of the fuzzy TOPSIS method. Followed by the Step 4 described in Section 4.2.2, the final index score C_i as well as the ranking order of the alternatives can be obtained.

5.2 Combining multilayer road safety performance indicators by applying hierarchical fuzzy TOPSIS method

As described in Section 2.4, currently, apart from the existing six SPIs (one represents each of the six road safety risk domains), some other indicators have been formulated, and thus a hierarchical structure of road safety performance indicators has been developed as shown in Figure 5-1 (a representation of Figure 2-2), which includes 11 SPIs with three layers.

In this section, the developed hierarchical fuzzy TOPSIS method is applied to combine these 11 layered SPIs into an overall road safety performance index for the same set of 21 European countries. In this respect, the indicator values are collected in Table 2-1, which construct the decision matrix of this study. Moreover, the fuzzy weight scores of the main criteria with respect to the road traffic safety are the ones used in the fuzzy TOPSIS method, which are shown in Table 4-5. Based on the same transformation approach as in Section 4.3.1, we obtain the fuzzy weight scores of the sub-criteria with respect to the corresponding main criteria. The linguistic weight matrix given by the same eight experts and the corresponding fuzzified weight matrix with the combined weight for each sub-criterion derived from the geometric mean method are presented in Table 5-1 and Table 5-2, respectively[1].

[1] In the survey, experts are not required to assign weight to every (sub-)criterion. In other words, only those they think relevant to road safety will be assigned non-null weights. Thereby, the combined weight for a particular criterion using the geometric mean method only consider the experts who assign a non-null weight

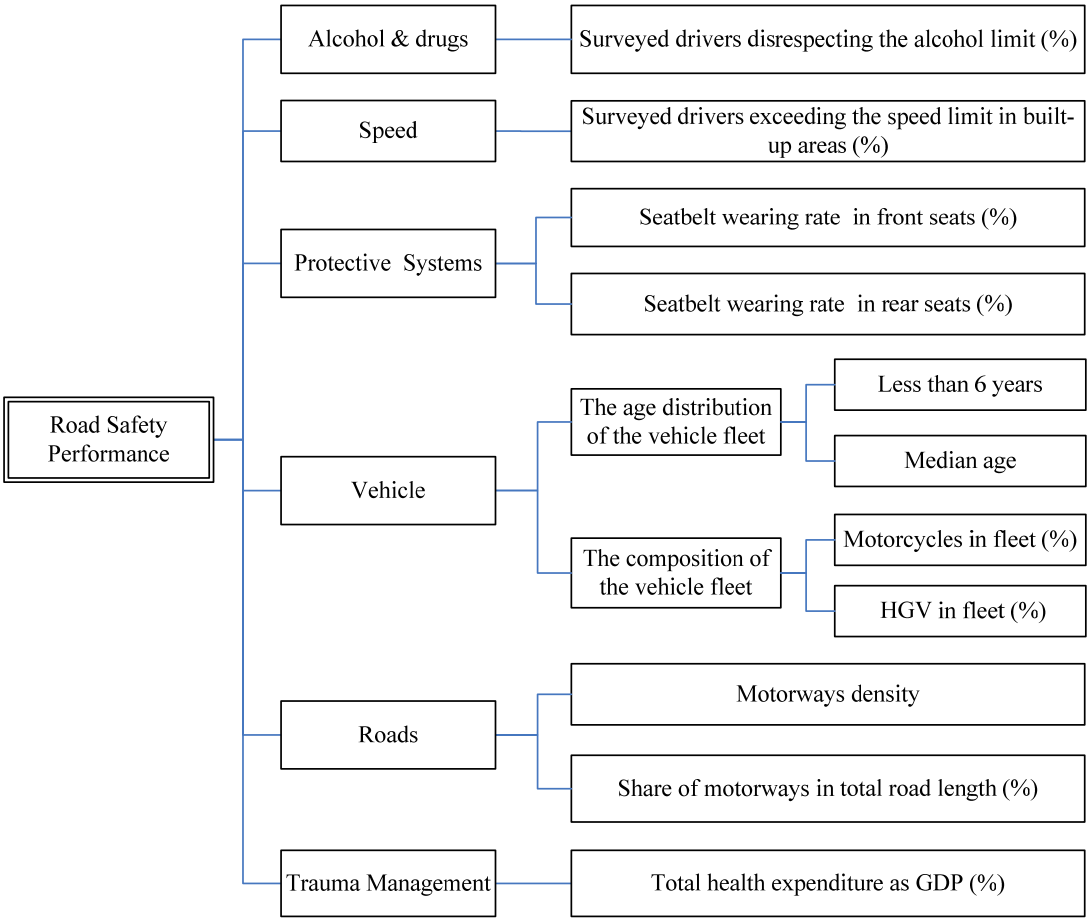

Figure 5-1 The hierarchical structure of the developed SPIs

To convert the hierarchical decision making matrix to a dimensionless one, the criteria values presented in Table 2-1 are normalized according to the linear scale transformation function shown in Eq. (5.2). In this case, five out of 11 SPIs, (i.e., the percentage of surveyed car drivers disrespecting the alcohol limit (A1); the percentage of surveyed car drivers exceeding the speed limit in built-up areas (S1); the median age of the passenger car fleet (V2); the share of motorcycles in the vehicle fleet (V3) and the share of heavy goods vehicles (HGV) in the vehicle fleet (V4)) are the cost criteria, while the remaining six indicators are benefit ones. The normalized hierarchical decision matrix $\tilde{\mathbf{D}}'$ is shown in Table 5-3, where all the indicator values are expected to be the higher the better.

Table 5-1 Linguistic weight matrix of sub-criteria *LW*

Country	Alcohol & drugs	Speed	Protective Systems		Vehicle				Roads		Trauma management
	% surveyed drivers > BAC limit	% surveyed drivers > speed limit in built-up areas	seat belt wearing rate in front seats	seat belt wearing rate in rear seats	% passenger cars < 6 years	median age of passenger cars	% Motor-cycles in vehicle fleet	% HGV in vehicle fleet	density of motorways	share of motorways in total	% total health expenditure as GDP
	A1	S1	P1	P2	V1	V2	V3	V4	R1	R2	T1
E1	Absolutely important	More important	Absolutely important	Absolutely important	—	—	Strongly important	Strongly important	—	—	—
E2	Strongly important	Strongly important	Absolutely important	Absolutely important	—	—	—	—	Absolutely important	Strongly important	Absolutely important
E3	Absolutely important	Strongly important	Absolutely important	Strongly important	More important	More important	Strongly important	Strongly important	Less important	Less important	—
E4	—	—	—	Strongly important	—	—	—	—	—	—	—
E5	More important	Strongly important	More important	Strongly important	Strongly important	Strongly important	More important	More important	—	—	More important
E6	Strongly important	Absolutely important	Strongly important	Strongly important	Strongly important	Strongly important	More important	More important	More important	—	—
E7	Absolutely important	Absolutely important	Absolutely important	Absolutely important	Strongly important	Strongly important	Strongly important	Strongly important	Strongly important	Strongly important	Important
E8	Absolutely important	Strongly important	Absolutely important	Absolutely important	Less important	Less important	Strongly important	Strongly important	Strongly important	Less important	—

Table 5-2 The fuzzified weight matrix and the geometric mean values of the sub-criteria

Country	Alcohol & drugs			Speed			Protective Systems						Trauma management		
	% surveyed drivers > BAC limit			% surveyed drivers > speed limit in built-up areas			seat belt wearing rate in front seats			seat belt wearing rate in rear seats			% total health expenditure as GDP		
	A1			S1			P1			P2			T1		
E1	5/6	1	1	1/2	2/3	5/6	5/6	1	1	5/6	1	1	—	—	—
E2	2/3	5/6	1	2/3	5/6	1	5/6	1	1	5/6	1	1	5/6	1	1
E3	5/6	1	1	2/3	5/6	1	5/6	1	1	2/3	5/6	1	—	—	—
E4	—	—	—	—	—	—	—	—	—	2/3	5/6	1	—	—	—
E5	1/2	2/3	5/6	2/3	5/6	1	1/2	2/3	5/6	2/3	5/6	1	1/2	2/3	5/6
E6	2/3	5/6	1	5/6	1	1	2/3	5/6	1	2/3	5/6	1	—	—	—
E7	5/6	1	1	5/6	1	1	5/6	1	1	5/6	1	1	1/3	1/2	2/3
E8	5/6	1	1	2/3	5/6	1	5/6	1	1	5/6	1	1	—	—	—
Geometric Mean	0.756	0.908	0.977	0.715	0.868	0.977	0.778	0.929	0.977	0.745	0.913	1.000	0.781	0.872	0.929

Country	Vehicle												Roads					
	% passenger cars < 6 years			Median age of passenger cars			% Motor- cycles in vehicle fleet			% HGV in vehicle fleet			density of motorways			share of motorways in total		
	V1			V2			V3			V4			R1			R2		
E1	—	—	—	—	—	—	2/3	5/6	1	2/3	5/6	1	—	—	—	—	—	—
E2	—	—	—	—	—	—	—	—	—	—	—	—	5/6	1	1	2/3	5/6	1
E3	1/2	2/3	5/6	1/2	2/3	5/6	2/3	5/6	1	2/3	5/6	1	1/6	1/3	1/2	1/6	1/3	1/2
E4	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
E5	2/3	5/6	1	2/3	5/6	1	1/2	2/3	5/6	1/2	2/3	5/6	—	—	—	—	—	—
E6	2/3	5/6	1	2/3	5/6	1	1/2	2/3	5/6	1/2	2/3	5/6	1/2	2/3	5/6	—	—	—
E7	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1
E8	1/6	1/3	1/2	1/6	1/3	1/2	2/3	5/6	1	2/3	5/6	1	2/3	5/6	1	1/6	1/3	1/2
Geometric Mean	0.630	0.774	0.896	0.630	0.774	0.896	0.687	0.825	0.955	0.687	0.825	0.955	0.647	0.792	0.896	0.577	0.726	0.841

Table 5-3 Normalized hierarchical decision matrix $\tilde{\mathbf{D}}'$

COUNTRY	A1	S1	P1	P2	V1	V2	V3	V4	R1	R2	T1
Austria	0.038	0.500	0.794	0.557	0.655	0.664	0.129	0.729	0.328	0.250	0.652
Belgium	0.017	0.250	0.680	0.455	0.761	0.751	0.267	0.459	0.934	0.185	0.817
Cyprus	0.005	0.250	0.825	0.341	0.317	0.537	0.211	0.235	0.475	0.365	0.557
Czech Republic	0.050	0.500	0.773	0.466	0.362	0.454	0.106	0.567	0.115	0.065	0.652
Denmark	0.333	0.750	0.866	0.716	0.729	0.682	0.239	0.273	0.393	0.228	0.783
Estonia	0.063	0.250	0.773	0.773	0.319	0.392	0.842	0.364	0.033	0.029	0.461
Finland	0.333	0.500	0.918	0.909	0.536	0.547	0.152	0.440	0.033	0.101	0.643
France	0.020	0.429	1.000	0.932	0.693	0.600	0.250	0.372	0.311	0.166	0.878
Germany	0.042	0.429	0.969	1.000	0.705	0.832	0.152	1.000	0.557	0.833	0.965
Greece	0.013	0.500	0.412	0.284	0.685	0.624	0.093	0.293	0.098	0.048	0.861
Hungary	0.077	0.250	0.608	0.386	0.490	0.624	0.432	0.408	0.098	0.054	0.730
Ireland	0.040	1.000	0.876	0.523	1.000	0.972	1.000	0.347	0.049	0.029	0.635
Italy	0.014	0.250	0.732	0.341	0.657	0.635	0.078	0.586	0.361	0.127	0.730
Netherlands	0.053	0.429	0.887	0.727	0.725	0.832	0.246	0.451	1.000	0.279	0.852
Poland	0.333	0.429	0.732	0.511	0.415	0.423	0.340	0.354	0.016	0.017	0.565
Portugal	0.024	0.273	0.907	0.511	0.535	0.516	0.178	0.239	0.361	0.160	0.835
Slovenia	0.037	0.500	0.835	0.557	0.933	1.000	0.333	0.810	0.377	0.199	0.765
Spain	0.014	0.273	0.887	0.784	0.673	0.657	0.110	0.305	0.328	1.000	0.670
Sweden	1.000	0.600	0.948	0.909	0.735	0.713	0.167	0.554	0.066	0.182	0.817
Switzerland	0.024	0.750	0.845	0.602	0.738	0.688	0.128	0.797	0.525	0.303	1.000
United Kingdom	0.167	0.750	0.959	0.955	0.828	0.998	0.432	0.477	0.246	0.137	0.696

Table 5-4 The derived fuzzy weight scores for the sub-criteria

	A1			S1			P1		
$\tilde{W}_{SC}$	0.564	0.829	0.977	0.564	0.829	0.977	0.529	0.788	0.955
	P2			**V1**			**V2**		
$\tilde{W}_{SC}$	0.507	0.774	0.977	0.387	0.607	0.837	0.387	0.607	0.837
	V3			**V4**			**R1**		
$\tilde{W}_{SC}$	0.423	0.647	0.892	0.423	0.647	0.892	0.413	0.638	0.856
	R2			**T1**					
$\tilde{W}_{SC}$	0.368	0.585	0.803	0.470	0.675	0.844			

Next, by multiplying the main criteria weight scores (see Table 4-5) and the sub-criteria weight scores with respect to each main criterion in Table 5-2 using Eq. (5.5), we obtain the final weight scores for each sub-criterion listed in Table 5-4.

Subsequently, the weighted normalized fuzzy decision matrix $\tilde{\mathbf{V}}$ could be achieved by computing the product of the normalized hierarchical decision matrix $\tilde{\mathbf{D}}'$ and the above fuzzy weight scores. After aggregating the values within each main criterion by the fuzzy addition principle, we obtain the final weighted normalized fuzzy decision matrix $\tilde{\mathbf{V}}'$.

Table 5-5 The results derived from the hierarchical fuzzy TOPSIS and the fatality ranking

Country	*C* (Hierarchical Fuzzy TOPSIS)	Hierarchical Fuzzy TOPSIS Ranking	No. of fatalities per mln inhab.	Fatality Ranking
Austria	0.544	10	115	11
Belgium	0.501	12	117	12
Cyprus	0.297	21	134	17
Czech Republic	0.463	15	142	18
Denmark	0.672	3	80	6.5
Estonia	0.355	20	121	13.5
Finland	0.540	11	73	4
France	0.560	9	101	9
Germany	0.679	2	80	6.5
Greece	0.396	18	146	19
Hungary	0.413	17	131	16
Ireland	0.562	8	84	8
Italy	0.420	16	105	10
Netherlands	0.630	6	63	3
Poland	0.395	19	149	21
Portugal	0.469	14	148	20
Slovenia	0.592	7	121	13.5
Spain	0.499	13	130	15
Sweden	0.715	1	59	1
Switzerland	0.653	5	74	5
United Kingdom	0.654	4	61	2

By now, following the same fuzzy TOPSIS procedure as in Section 4.3 (from Step 4 on), the relative closeness index C_i can be calculated. The final composite index scores for the 21 European countries and the corresponding ranking results together with their fatality ranking are presented in Table 5-5.

The ranking results derived from the hierarchical fuzzy TOPSIS method show that Sweden is the best performing country, while Cyprus the worst. By comparing the results with the ones based on the number of fatalities per million inhabitants, we find that over half of the countries have the difference in rankings with no more than two positions, and about two thirds are no more than three positions, which indicates the high similarity between the derived road safety performance index and the final outcomes. The main disagreements exist in five countries, which are Estonia, Finland, Italy, Portugal, and Slovenia, with the first three underestimated while the last two overestimated. Furthermore, the Pearson's correlation analysis reveals that the composite road safety performance index score of the 21 European countries is highly (negatively) correlated with their number of fatalities per million inhabitants, which is -0.810.

5.3 Comparison and discussion

In this section, we put the results derived from the classical TOPSIS method (in Chapter 3), the fuzzy TOPSIS method (in Chapter 4) and the hierarchical fuzzy TOPSIS method together to gain insight into their similarity and difference, and further explore the degree of correlation between each of the above three results and the road safety final outcomes.

As shown in Table 5-6, the ranking results based on the fuzzy TOPSIS method and the hierarchical fuzzy TOPSIS method take on an overall high resemblance, since most of the countries have a difference in rank with a maximum of one position. Nevertheless, they disagree most on the first six rankings of countries, which are Sweden, Germany, Denmark, United Kingdom, Switzerland, and the Netherlands. It implies that incorporation of new SPIs will influence the ranking position more on those countries with high rankings, rather than those low ranking ones. Moreover, by comparing the ranking results with the ones based on the number of fatalities per million inhabitants, we can see that most of the countries' ranking positions are going towards the fatality

Table 5-6 Ranking results based on the classical TOPSIS, fuzzy TOPSIS (weight fuzzified), hierarchical fuzzy TOPSIS and fatalities

Country	***C* (TOPSIS)**	**TOPSIS Ranking**	***C* (Fuzzy TOPSIS (FW))**	**Fuzzy TOPSIS (FW) Ranking**	***C* (Hierarchical Fuzzy TOPSIS)**	**Hierarchical Fuzzy TOPSIS Ranking**	**No. of fatalities per mln inhab.**	**Fatality Ranking**
Austria	0.325	12	0.549	10	0.544	10	115	11
Belgium	0.412	9	0.523	11	0.501	12	117	12
Cyprus	0.204	19	0.303	21	0.297	21	134	17
Czech Republic	0.220	18	0.471	15	0.463	15	142	18
Denmark	0.528	2	0.691	1	0.672	3	80	6.5
Estonia	0.096	21	0.308	20	0.355	20	121	13.5
Finland	0.335	11	0.514	12	0.540	11	73	4
France	0.397	10	0.566	9	0.560	9	101	9
Germany	0.466	7	0.617	6	0.679	2	80	6.5
Greece	0.236	16	0.442	17	0.396	18	146	19
Hungary	0.165	20	0.413	18	0.413	17	131	16
Ireland	0.479	6	0.597	8	0.562	8	84	8
Italy	0.266	15	0.452	16	0.420	16	105	10
Netherlands	0.524	3	0.639	5	0.630	6	63	3
Poland	0.233	17	0.404	19	0.395	19	149	21
Portugal	0.308	13	0.497	13	0.469	14	148	20
Slovenia	0.423	8	0.600	7	0.592	7	121	13.5
Spain	0.290	14	0.472	14	0.499	13	130	15
Sweden	0.605	1	0.688	2	0.715	1	59	1
Switzerland	0.522	4	0.656	3	0.653	5	74	5
United Kingdom	0.481	5	0.650	4	0.654	4	61	2

rankings based on the hierarchical fuzzy TOPSIS method, except for Germany, the Netherlands, and Spain. In order to make a quantitative comparison and provide a clear insight into the relationship among different columns, the correlation analysis is adopted. In Table 5-7, the Pearson's correlation coefficients among the composite index scores (*C*) and the number of fatalities per million inhabitants are presented, and Table 5-8 displays the Pearson's correlation coefficients among the corresponding ranking results.

Table 5-7 The Pearson's correlation coefficients among three *C*s and the number of fatalities per million inhabitants

	***C* (TOPSIS)**	***C* (Fuzzy TOPSIS (FW))**	***C* (Hierarchical Fuzzy TOPSIS)**	**No. of fatalities per mln inhab.**
C (TOPSIS)	1.000	0.952	0.929	-0.802
C (Fuzzy TOPSIS (FW))	0.952	1.000	0.974	-0.763
C (Hierarchical Fuzzy TOPSIS)	0.929	0.974	1.000	-0.810
No. of fatalities per mln inhab.	-0.802	-0.763	-0.810	1.000

Table 5-8 The Pearson's correlation coefficients among the different sets of ranking results

	TOPSIS Ranking	**Fuzzy TOPSIS Ranking (FW)**	**Hierarchical Fuzzy TOPSIS Ranking**	**Fatality Ranking**
TOPSIS Ranking	1.000	0.969	0.942	0.804
Fuzzy TOPSIS Ranking (FW)	0.969	1.000	0.979	0.794
Hierarchical Fuzzy TOPSIS Ranking	0.942	0.979	1.000	0.814
Fatality Ranking	0.804	0.794	0.814	1.000

As shown in Table 5-7, the composite index scores (*C*) derived from the classical TOPSIS method, the fuzzy TOPSIS method and the hierarchical fuzzy TOPSIS method present a highly positive-correlated relationship with the highest correlation coefficient of 0.974. Moreover, the index scores and the number of the fatalities per million inhabitants are also highly negative-correlated, and the one generated from the hierarchical fuzzy

TOPSIS method produces the highest correlation with the fatalities (-0.810). It means that the development of multilayer SPIs to represent a country's road safety situation is desirable, and the application of the hierarchical fuzzy TOPSIS method is also valuable in creating an overall road safety performance index. The same conclusions can be drawn by considering the corresponding ranking results as in Table 5-8.

5.4 Summary

In this chapter, some more safety performance indicators are identified for each road safety risk domain so as to reflect the characters of road safety system of a country in a more comprehensive way. As a result, a hierarchical structure of the indicators is created. To combine these multilayer indicators into one overall road safety performance index, a hierarchical fuzzy TOPSIS method is developed in this study. The derived composite index scores show a relatively higher correlation with the number of fatalities per million inhabitants than the ones from the classical TOPSIS method and single layer fuzzy TOPSIS method. Therefore, we conclude that development of a hierarchical structure of indicators is valuable, which can capture more information on road crash and injury causation, thereby better understand the complex character of the road safety phenomenon. Moreover, as a new MCDM methodology, the proposed hierarchical fuzzy TOPSIS method could serve as a feasible approach to combine the multilayer indicators into one overall index. At the same time, it effectively handles the problems of linguistic expression instead of crisp values given by experts.

Chapter 6 Conclusions

Due to the ever increasing traffic volume in the past decades, the road traffic injuries and fatalities have been recognized as one of the most important but preventable public health issues. Currently, with the gradually growing awareness of the complexity of road safety phenomenon, it has been acknowledged that the traditional way in assessing a country's road safety situation that only concentrates on the road safety final outcomes (such as the number of crashes and injuries) is insufficient in explaining more detailed aspects of crash causation and injury prevention. Therefore, to better understand the processes that lead to crashes, to identify corresponding interventions, and to make progress in road safety as the final purpose, more and more safety performance indicators, also known as the intermediate outcomes in the road safety management system, are continuously developed and increasingly used as a supportive instrument for national or sub-national comparisons.

However, a simple comparison per indicator only shows a small piece of the road safety picture, and it can be misleading since different countries may operate in different circumstances with different focal points. Consequently, to measure the multi-dimensional concept of road safety which cannot be captured by a single indicator, the exploration of a composite road safety performance index is attractive and desirable. The index thus presents the overall road safety picture by capturing a multitude of risk information in one index score, and offers advantages in terms of communication, benchmarking, and prioritizing road safety actions.

In this manuscript, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, as one of the well known classical multi-criteria decision making techniques, was investigated in combining individual safety performance indicators into an overall index for a set of European countries. To justify the feasibility and effectiveness of this method in road safety area under different requirements, we explored a series of extensions and applications in the previous chapters. In this chapter, the key research findings are formulated in Section 6.1, followed by the prospects for the further research topics in Section 6.2.

6.1 Key findings

Based on the different sets of road safety performance indicators and the corresponding data collected for 21 European countries, we investigated the application of the classical TOPSIS method and its extensions (i.e., the fuzzy TOPSIS method and the hierarchical fuzzy TOPSIS method) in creating an overall road safety performance index. The three main research findings are elaborated as follows:

1 The classical TOPSIS method can be effectively used as an alternative way to combine individual safety performance indicators/criteria into an overall index with the purpose of comparing and ranking given alternatives (countries).

In this manuscript, based on the six best available SPIs used in Hermans (2009)' research (one indicator for each road safety risk domain) and the relative importance of each indicator (i.e., the indicator weights) assigned by the eight road safety experts from seven European countries (each expert was considered to be of similar importance), the TOPSIS method was applied to create a composite road safety performance index for the 21 European countries. By comparing the derived final index scores with the relevant point of reference (i.e., the number of road fatalities per million inhabitants), a relatively high Pearson's correlation coefficient is generated, and a similar result was achieved by considering the corresponding ranking results based on the TOPSIS method with the ones from the fatalities ranking. Moreover, comparing the ranking results with the ones from the other five widely used methods (i.e., FA, AHP, BA, DEA, and EW) applied in Hermans (2009), we find that they are highly correlated with one another, and the TOPSIS ranking produces an even higher correlation coefficient when the final outcome ranking is taken into account. Consequently, the TOPSIS method can be regarded as an effective alternative way in creating a composite road safety performance index for a given set of countries.

2 As a nature extension of the classical TOPSIS method, the fuzzy TOPSIS method that integrates fuzzy logic into TOPSIS provides a promising solution to handle the subjective kind of uncertainty on data, which in this study is the problem that the indicator weights and/or the indicator values are given in linguistic terms instead of crisp values.

Under the circumstances that all the indicators and their respective weights are expressed in crisp values, the classical TOPSIS method can be directly used without any problem. However, in practice, crisp data are inadequate or inappropriate to model real-life situations. Specifically, experts prefer to give linguistic valued judgements based on human experience rather than crisp values. Moreover, in the decision matrix, probably only part of the indicators can be constructed on the basis of measurable quantitative parameters, and the others need to be specified with either ordinal measures or the help of expert subjective judgments. In such cases, the application of the classical TOPSIS method may face serious practical problems. As a result, the fuzzy TOPSIS method is developed by integrating the fuzzy logic into the TOPSIS method, which embodies the fuzzy nature of the comparison or evaluation process and strengthens the rationality of the decision-making process.

In this study, after conducting two applications (i.e., only weights need to be fuzzified and both weights and indicator values are fuzzified) to combine the same six individual SPIs into an overall index based on the fuzzy TOPSIS method, the highly correlated index scores with the ones from the classical TOPSIS method were derived, and the acceptable Pearson's correlation coefficients between the ranking results from the fuzzy TOPSIS method and the number of road fatalities per million inhabitants were also obtained. All these justify the feasibility of using the fuzzy TOPSIS method to handle the subjective kind of uncertainty on data (linguistic terms given by experts in this study) without losing important information.

3 The realization of the hierarchical fuzzy TOPSIS method further extends the use of the TOPSIS method by taking the layered hierarchy of the indicators into account, which is seldom considered in the current index research and difficult to realize in other traditional weighting methods.

Since the selection of one SPI for each road safety risk domain is obviously insufficient in reflecting the entire feature of that domain, it is reasonable to question the comprehensiveness of the composite road safety performance index derived from both the classical TOPSIS method and the fuzzy TOPSIS method. Therefore, more indicators need to be developed for each risk domain, and they might also be linked to one another constructing a layered hierarchy. In order to take this kind of hierarchical structure of the indicators into account when creating the composite road safety performance index, the extension of the one-layer TOPSIS methods to a multilayer one is pressingly needed.

In this study, we therefore developed a hierarchical fuzzy TOPSIS method, and then applied this model to combine the multilayer indicators into one overall road safety performance index. The derived composite index scores show a relatively higher correlation with the number of fatalities per million inhabitants than the ones from the single layer TOPSIS methods (both classical and fuzzy), which validates the necessary of developing multilayer SPIs to entirely represent each of the road safety risk domain, and also implies the usefulness and effectiveness of applying the developed hierarchical fuzzy TOPSIS method to create a composite index by integrating the indicators with hierarchical structures.

6.2 Topics for further research

Road traffic injuries and fatalities will continue to be an important public health issue within the next decade. Since more and more countries are taking steps to improve their road safety situation, there is a growing need for a country to evaluate its own road safety performance and compare it with other countries. In this respect, research on safety performance indicators and further combining them into one composite index has proven valuable. In the future, more aspects with regard to the index research could be investigated.

1 Creating the composite road safety performance index based on more available indicators

Since the collection and searching for additional data on the best needed indicators is an ongoing process, it is worthwhile to take more safety performance indicators into account so as to capture the characters of road safety in a more comprehensive way. However, selection of more indicators means more complexity of the system structure, and also more difficult in collecting experts' opinion. Therefore, it is necessary to balance the number of indicators selected for each risk domain with the costs in using these indicators.

2 Validating the composite index values using different references

In this study, the number of fatalities per million inhabitants as one of the road safety final outcomes was utilized as the only reference in validating the created composite index values. In the future, it is also possible to employ other final outcomes, such as the number of crashes, and different severity of injuries. Moreover, except for the population size, other more appropriate measures of exposure, such as the number of vehicles, distance travelled, or the total road length, can be used to make countries comparable. However, in doing so, the data availability, reliability, and comparability should be taken into account.

3 Assessing the road safety performance over time

In this study, due to data limitations, only the data for 2003 was adopted to create the composite road safety performance index. It will be valuable if time series data could be collected. Thus, countries' road safety performance over time can be assessed, and the robustness of their ranking results guaranteed. Moreover, the current road safety progress of a country can then be monitored, and the future development trends predicted. However, the extension of the data set used for time series analysis inevitably leads to missing data issue. Therefore, a proper methodology is expected to be able to deal with this uncertainty factor and further be incorporated into the hierarchical fuzzy TOPSIS framework. In addition, considering the reliability of the final results, it is necessary to conduct uncertainty and sensitivity analysis to reveal the impact of a change in indicator set, corresponding weights, or hierarchical structure.

4 Developing a comprehensive road safety index by combining indicators in different layers of the road safety management system simultaneously

By now, the index research attention in this study has been only paid to the layer of safety performance indicators in the road safety management system. To further take other layers into account, which include road safety final outcomes, policy performance indicators, and background information, a more comprehensive road safety index can be constructed reflecting the overall road safety situation of a country. In doing so, appropriate indicators for each of these layers should be developed, and moreover, importance weights for different layers of the system and for different indicators need to be specified. Nevertheless, due to the complexity of the road safety system, new challenges will arise, for instance, to allocate an appropriate weight to each layer of the road safety management system, only the experts with sufficient knowledge about the entire road safety system will be asked for opinions. However, it is not easy in practice since experts may be only familiar with one or several of all these layers, which will to a certain extent increase the uncertainty of the final composite index.

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