DOMINANCE-BASED ROUGH SET APPROACH: AN APPLICATION CASE STUDY FOR SETTING SPEED LIMITS FOR VEHICLES IN SPEED CONTROLLED ZONES

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Abstract

Speed management represents an important strategy in order to improve road safety, because a strong relationship is between speed and crash occurrence and severity. Speed limits enforcement is the main measure to control operating speeds but to obtain the compliance of drivers, the limits must be safe but also credible.
This means that road users have to regard the speed limit as logical under given conditions and so a speed limit is credible if it fits the image evoked by the road.
This paper describes the development of a Decision Support System (DSS) for the selection of safe and credible speed limits for speed zones. The proposed DSS is based on Dominance-based Rough Set Approach (DRSA), which presents interesting advantages in terms of transparency and manageability with respect to many other decision support competitive methodologies. In fact DRSA, after getting the preferred information necessary to set up the decision model, in terms of exemplary decisions, allows to build a multi-criteria model expressed in terms of *"if..., then ..."* decision rules.
The proposed multi-criteria decision approach aims to suggest to decision-makers a safe and credible speed limit for speed zones, taking into consideration many factors such as accident rate, roadway geometry, roadway development, traffic and others.

Keywords

Speed limits; Decision Support System; Dominance-based Rough Set.

1. Introduction

Over the past five decades, individuals and societies have greatly benefited from a rapid improvement in road infrastructure. At the same time, industry has manufactured motor vehicles able to travel at increasingly higher speeds.
High-speed vehicle transportation has facilitated the economic development of countries and also it has improved the quality of life. However, these high-speeds have considerably adverse impact, mainly in terms of road accidents (and consequent fatalities, injuries, and material damages), but also in environmental terms, including noise and exhaust emissions, and finally in terms of the comfort of residential and urban areas.
Recently, the demand for strategies that reduce such adverse impacts of speed has increased. A growing portion of the population has required increasing road safety, reducing adverse environmental impacts and improving general quality of life.
Speed management policies have become a high priority in many countries. Speed limits enforcement represents the core of every speed management policy and so a tool that helps the decision-makers to choose the most suitable speed limit for each speed zone can be useful in order to obtain the compliance of the drivers with limit.
A method for setting speed limits with a Decision Support System (DDS) based on Dominance-based Rough Set Approach (DRSA) (Greco, Matarazzo and Slowinski 2001, 2005, 2014) is presented in this paper. We have approached the assessment of speed limits in the context of newly emerging approach to knowledge discovery and data mining, called rough–granular computing (Stepaniuk 2008). Indeed DRSA can be seen as a specific methodology for rough-granular computing (see Greco, Matarazzo and Slowinski 2008). In fact, the advantage of DRSA for decision support originated by its rough-granular computing nature is in its use a specific non-Boolean logic (Greco, Matarazzo and Slowinski 2012) which generalize to consideration of preference order the non-Bolean logic of rough sets (Cattaneo and Nisticò 1989, Cattaneo and Ciucci 2004).
The proposed methodology suggests to the decision makers a safe and credible speed limit based on a decision model set up by means of preference information in terms of exemplary decisions provided by an expert panel. At the same time, the methodology produces some easily understandable decision rules that can help the decision makers to explain the reasons for the suggested speed limit.
This paper has been divided into seven sections. Section 2 introduces the speed management question and presents a brief literature review of the expert systems for setting speed limits; Section 3 explains the aim of the present work, the methodology and the data used for the decision model development; Section 4 presents the DRSA multi-criteria decision model for setting speed limits developing; Section 5 describes the application of the decision model; Section 6 reports a discussion on the presented methodology; finally, Section 7 provides the conclusions and some recommendations.

2. Methods for Setting Speed Limits: a review

The speed limit system is the basis of every speed management.
Establishing a set of speed limits represents a complex trade-off between several factors - such as crash and injury risks, enforceability, travel time, societal attitudes, environmental concerns and political considerations - and the relative importance assigned to everyone.
These different trades-off are variously reflected in a range of different philosophies (TRB, 1998; Elvik & Vaa, 2004; Fildes at al., 2005; Aarts et al., 2009):

- Engineering: speed limit system based on engineering and traffic characteristics (design speed); safety considerations are taken into account but not always explicitly.

- Drivers' choice: speed limit system based on the 85th percentile speed that is driven on the road (V_{85}); safety as well as a kind of credibility is taken into account.
- Economic optimization: speed limit system based on the optimal trade-off between costs and benefits of different speed related issues and policy fields; safety is one of the many issues that is or can be considered.
- Harm minimization: speed limit system based on the concept that life and health cannot be measured or traded in terms of monetary costs, and that human trauma as a crash's consequence is considered unacceptable.
- Expert systems: speed limits determined by computer programs employing decision rules operating off a well-defined knowledge base relating to road conditions, to generate speed recommendations.

The most common approach for setting speed limits is to determine them after conducting an engineering study of the road and traffic environment on the road section and surrounding roads. In an engineering study, a lot of information is collected such as traffic speeds, crash data, type and amount of roadside development, road geometry, and the number of type of road users. These factors allow engineers to define a road design speed.

Alternative and very common, is the philosophy of setting speed limits by drivers' choice of speed, which is otherwise known as the "basic law limit". This approach leaves it up to drivers to determine what represents a reasonable and safe travel speed. This has been an accepted speed limit practice because it is politically popular, it appeals to road users and the public in general, and it is obeyed by the majority of drivers. However, speed limits arising from this philosophy often incorporate various engineering considerations, which may result in modified speeds if the speed chosen by drivers was not appropriate.

The various economic optimization approaches are based on setting a dollar value to all the costs associated with travel and to the burden of injury and fatality from motor vehicle crashes. The method relies heavily on the quality of the data used to determine the costs of each of the factors involved. The lack of a universally accepted method for determining the economic costs of each transport factor has limited the objectiveness of these approaches, which have been rarely used to determine speed limit policy. Nevertheless, the approach has gained some recognition by virtue of its emphasis on what mobility factors are actually costing society, particularly in terms of injury costs.

If economic optimizations approaches assume that it is legitimate to put a fiscal cost on human trauma, some alternative approaches are based on the argument that life and health are beyond the monetary costs associated with safety and good health is beyond the other benefits of transport. These approaches, known as harm minimization approaches, recognize that while it may not be possible to eliminate road trauma, it may be possible to create a transport system that does not view casualties and fatalities as an acceptable and inevitable cost of mobility. Examples of these philosophies are the *Swedish Vision Zero* (Tingvall & Haworth, 1999) and *Dutch Sustainable Safety* (Wegman & Aarts, 2006).

Finally, the expert-based systems aim to develop a uniform and consistent approach to setting speed limits while still accounting for situation specific criteria that may not be incorporated into a standard engineering analysis. Let us remember that expert systems are computer programs used to solve complex problems in a given field by employing decision rules operating on a well-defined knowledge base.

Expert systems and algorithms in setting speed limits in last years become very famous. In the next sub-paragraphs SaCredSpeed algorithm and the USLIMITS expert system are described.

2.1 Harm minimization approach: SaCredSpeed algorithm

The *Dutch Sustainable Safety* have been developed in 1992 and updated on 2006 (Wegman & Aarts, 2006) by the SWOV, the Institute of Road Safety Research.

One of the key concepts in a Sustainably Safe Traffic System is safe, credible limits and good information about them. First of all safe driving speed needs to be determined in order to set the corresponding speed limit; the safe speeds assessment depends on the legal traffic situation and further road design details. Speed limits also need to be credible - *'credible speed limits'* (SWOV, 2007) - that means that the speed limit has to meet the expectations evoked by the road image, defined by the road's features and its surroundings. Road users also always have to be aware of the current speed limit, so information must be applied very consistently and, also, speed limits must be convincing for the road users.
Recently the SWOV have presented the initial elaboration of an algorithm that concretizes its own speed management vision based on harm minimization (Aarts et al., 2009), (Aarts et al., 2010). This algorithm, called *'SaCredSpeed'* (Safety and Credible Speed), is based on scientific knowledge about safe speed, speed management and credibility and is focused on the issues that are considered the most relevant on this; other variables such as traffic flow, environment and health are not taken into consideration.
The SaCredSpeed algorithm consists in three separate algorithms, respectively for safety, for credibility and enforcement of speed limit (Aarts et al., 2009). First algorithm uses input data of a particular stretch of road - i.e. data about road construction, road layout, legal traffic situation – and assess, applying its logical rules, a safe speed and speed limit for that particular situation. The second part of the algorithm - stating that a speed limit is credible when the limit in force is conforms to what the road user considers to be reasonable for that particular road section - determines the credibility of speed limit by a broad range of road design and road layout characteristics based on existing studies (Aarts et al., 2009). The third part of the algorithm assesses the need for additional police enforcement checking existing police enforcement situation and speed data, when available.
Finally the outcome of the three algorithms is combined resulting in possible directions for speed management, and precisely:

- an indication of the safety of the speed limit and operation speed;
- an indication of the credibility of the current speed limit on a road section;
- a set of measures to be taken in order to improve the safety and credibility of the speed limit.

SaCredSpeed nowadays is the unique approach in safe speed limits settings based on harm minimization, and is the only one that includes credibility of speed limit assessment.
The algorithm permits to evaluate safety and credibility of speed limits and, moreover, its suggestions gives a useful support for their adaptation. Its logical rules in setting safe speed limits - based on national guidelines on infrastructure design - only take into account road design and users, and does not consider operative conditions (i.e. traffic volume, percentage of heavy vehicles, accident rate) and maintenance conditions (i.e. status of pavement and road signs), that in different national politics can have a great importance and need to be considered.
Furthermore, although users - i.e. managing authorities - know the decisional process, they cannot easily change or update it basing on their current policies, engineering criteria, practices, and experience if necessary.

2.2 Expert-based systems: USLIMITS2

The first expert-system based approach for setting speed limits in speed zones was developed in 1987 in the state of Victoria (Australia) (Jarvis & Hoban, 1988). This was a DOS-based program, called VLIMITS, developed by ARRB for Victoria State using decision rules for different road and traffic conditions, developed by a panel of experts using field measurements at 60 locations. In 1992 VLIMITS was updated (TRB, 1998) and was developed for all Australian state roads authorities and for New Zealand, modifying the name and the rules: collectively, they are called XLIMITS.

Based on the Australian XLIMITS example, the USLIMITS expert system has been developed in United States by ARRB for FHWA, adapting decision rules to North American policies and practices. All the systems developed by ARRB are considered proprietary and their logic and decision rules are not available for the user, so users are not permitted to know which, and how many, variables influence the final recommendation.

In 2006 the Final Report of NCHRP Project No. 3-67 "Expert System for recommending speed limits in speed zones" (Srinivasan et al., 2006) was presented: the Project was designed to develop an expert system to succeed USLIMITS. In contrast to all previous versions, USLIMITS2 (Srinivasan et al., 2006) (Lemer, 2007) (Srinivasan et al., 2008) is open source, available with complete information about the system's logic and factors influencing speed limits recommendations, provided by the system. The Study Report, the User Guide and the Decision Rules are available on the official website (http://www2.uslimits.org). When logging in, it is possible to question the system about the most appropriate speed limit for a specific speed zone.

In this system, although complete information about the system's logic, factors influencing speed limits and the decision rules are known, the output is only a recommended speed limit for the new road section, basing on its characteristics, putted as input. With this type of output users has difficulty to understand which road section characteristics have influenced the result or which is the cause that runs to it, because the decision process is not evident and it is not possible to evaluate or update it.

3. Problem definition

Considering the lacks of the presented algorithms and expert-systems in terms of transparency and adaptability to different situations, the aim of the present work is the definition of a decision-support tool that can assist the decision makers in setting speed zone limits using a multi-criteria decision model.

The basic idea of the presented research is to develop an intelligible and user friendly tool that can suggests to users a safe speed limit and can easily explains them the reasons of the recommendation, in order to avoid the "*black box*" effects of many alternative decision support methods. More precisely our aim is to represent the experience of one or more experts in a set of *"if …, then …"* decision rules that synthesize some exemplary decisions about speed limits supplied by them.

Furthermore, in order to consider multiple attributes in the decision process for setting speed limits in speed zone, a multi-criteria decision model has been used.

3.1 Methodology

The multi-criteria decision model adopted in this study is based on the Dominance-based Rough Set Approach (DRSA) (Greco et al., 1999) (Greco et al., 2001) (Greco et al., 2002b) (Greco et al., 2005) (Slowinski et al., 2005). This approach is an evolution of Classical Rough Set approach (CRSA) developed by Pawlak (Pawlak, 1991) that allows applying it in multi-criteria decision problems. We shall come back on the advantages of DRSA with respect to classical rough set approach at the end of the Section 4, after presenting the basic concepts of DRSA.

DRSA has been chosen because it has two important advantages over other approaches:

- DRSA requires the preference information in terms of exemplary decisions which are very natural and easy to be provided by the decision maker (contrary to some quite technical parameters required by other competitive multiple criteria methods, such as weights of criteria, trade-offs between criteria, thresholds, and so on) (Fishburn, 1967) (Mousseau, 1993);

- DRSA produces a decision model expressed in terms of easily understandable "*if…, then…*" decision rules which permits to control the decision process and to avoid the *"black box"* effects of many alternative decision support methods (Greco et al., 2005) (Slowinski et al., 2009).

The proposed multiple criteria decision support system aims to suggest the managing authority the most appropriate speed limit for every speed zone taking into account its geometric and operative characteristics and maintenance conditions, on the basis of a safety police described using a set of decision rules induced from some exemplary decisions taken by one or more experts.

3.2 Data

The first step in the decision-support system development was data selection.
In the presented work, data is composed by a set of 100 road sections of Italian rural roads network, and specifically two lane roads with statutory speed limit of 90km/h. Road sections have been selected taking into account geometric, operative, maintenance characteristics and accident rate, obtaining speed zones with homogeneous characteristics and at least 300 meters extended.
Speed zone features have been defined by a set of attributes that can well describe the real conditions of every road section. These features have been registered by field observations and data collection.
The considered attributes are reported in the following together with their value scales, within parentheses:

A_1= Traffic Volume (high, moderate and low);
A_2= Percentage of heavy vehicles (high, moderate and low);
A_3= Lane width (in meters);
A_4= Shoulder width (in meters);
A_5= Road Signs (yes or no);
A_6= Pavement Condition (high, moderate and low);
A_7= Roadside Hazard Rating (1,2,3 or 4);
A_8= Accident Rate (high or low);
A_9= Adverse Alignment (yes or no).

It is important to remark that other and different attributes can be considered in speed zone definition, in relation to available data and/or Decision Maker (DM) choice.
Every attribute and its classification are described here in the following.
The attribute *"Traffic Volume"* describes the traffic level on the investigated road section. It has been obtained from managing authorities' data and it is classified as low, moderate and high considering as threshold 6,000 ad 20,000 vehicles/day. (Traffic Volume is low if lower than 6,000 vehicles/day, it is medium if it is not smaller than 6,000 and lower than 20,000 vehicles/day, and it is high if it is not smaller than 20,000 vehicles/day).
The attribute *"Percentage of heavy vehicles*" is classified into low, medium and high, considering low a percentage of heavy vehicles lower than 10% of the traffic volume, medium a percentage of heavy vehicles included between 10% and 20% of the traffic volume and high a value higher than 20%.
The attributes *"Lane width"* and *"Shoulder width"* describe the lane and the shoulder size (in meters).
The attribute *"Road signs"* indicates the presence or absence of pavement markings on the investigated road section.
The attribute *"Pavement Condition"* describes the pavement condition as high, moderate and low.
The *"Roadside Hazard Rating (RHR)"* is a measure of the roadside conditions including shoulder wide and type, side slope and presence/absence of fixed objects on the roadside

(Zegeer et al., 1988). Roadside hazard defined by Zegeer is ranked on a seven-point categorical scale from 1 (best) to 7 (worst). This scale has been adapted to Italian Roads and a four-point scale has been used.
The four categories of roadside hazard rating are defined as follows:

- RHR=1

  Presence of roadside barriers if required, correctly installed and by law.
  Roadside free from obstacles (trees, poles, etc.) or embankments.
  Recoverable in a run-off-road situation.

- RHR=2

  Presence of roadside barriers if required, but either not properly or not legally installed.
  Possible presence of exposed trees, poles or other objects.
  Marginally recoverable in a run-off-road situation.

- RHR=3

  Limited presence of roadside barriers in flyover, steep and high slope, etc.
  Exposed rigid obstacles (trees, poles, etc.) and embankments.
  Virtually non-recoverable in a run-off-road situation.

- RHR=4

  Absence of roadside barriers.
  Cliff or vertical rock cut.
  Non-recoverable in a run-off-road situation.

The attribute *"Accident rate*" describes the safety conditions of each section. For each section the accident rate is defined as the ratio between the observed number of accidents (only fatal and injury crashes are taken into account) and the risk exposure (given by the product of all traffic flows in the observed period for the section length); the investigated period has to be at least two years long to be significant and no longer than five years in order to avoid non stationary phenomena. In this study a five years long period is used. The evaluation of safety level is based on a statistical procedure and it is classified as low hazardous section or high hazardous section.
Finally, the *"Adverse Alignment"* attribute includes road features with vertical and/or horizontal alignment, which differs significantly from the alignment of the general road. Adverse alignment segments typically reduce operating speeds below the general speed limit for the section. Examples of adverse alignment segments are: small radius curve, winding road, curve after long straight, narrow pavement widths and shoulders, road bumps, etc. The presence or the absence of an adverse alignment in the measured section has been marked.

3.3 Expert Panel selection

The set of the 100 road sections selected on Italian rural roads, each one described by the set of chosen attributes, has been submitted to an Expert Panel.
The Expert Panel function is to assess a safe speed limit for every investigated speed zone, basing only on its features (classified as described above) and some photos. Every Expert Panel component has to select the most appropriate speed limit (in terms of safety) among 60, 70, 80 and 90 km/h. The last one is the statutory speed limit for the investigated type of roads and so the chosen limit may not exceed this one.
Different participants, with different priorities and purposes in speed limits selection, can be included in the Expert Panel. For example, it can be made-up by members of managing authority, road safety experts, road users, government delegates, and so on.

The final decision, in this case the safer speed limit for each selected speed zone, can be the mean of every Expert Panel member selected value or can be selected as the value on which they agree.
In the present case study the Expert Panel was composed by three safety experts among professors of the Department of Civil and Environmental Engineering of the University of Catania.
The final decision about the safe speed limit for every selected speed zone has been taken by common agreement.
It is important to remark that, using DRSA, it is also possible to consider at the same time multiple decision makers (Greco et al. 2006) with different priorities and purposes in speed limits selection, and use the decision of every decision maker (or decision maker group) in the decision table to assess decision rules.

4. Dominance Rough Set Approach to develop a multi-criteria decision model for setting speed limits

In the following subsections, the application of DRSA in multi-criteria decision model for setting speed limits is presented.

4.1 Information table and Dominance Relation

The base of a Rough Set analysis is an *information table*. The rows of the table are labelled by *objects*, whereas columns are labelled by *attributes* and entries of the table are *attribute-values*, called *descriptors*.
In the present example, every row of the table is a road section, and every column contains technical and functional parameters conveniently selected to describe road sections.
Formally, by an *information table* we understand the 4-tuple $S=<U,Q,V,f>$, where U is a finite set of objects, Q is a finite set of *attributes*, $V=\bigcup_{q\in Q} V_q$ and V_q is a value set of the attribute q, and $f:U\times Q\rightarrow V$ is a total function such that $f(x,q)\in V_q$ for every $q\in Q$, $x\in U$, called *information function* (Pawlak, 1991).
The set Q is, in general, divided into set C of *condition attributes* and set D of *decision attributes*. The notion of attribute differs from that of *criterion*, because scale of a criterion (its value set) has to be ordered according to decreasing or increasing preference, while the scale of a regular attribute does not have to be ordered.
In the presented example, U is a set of 100 road sections on Italian rural roads, (two lane roads with statutory speed limit of 90km/h) and Q is composed by the attributes that describe them. *C* are the condition attributes and the speed limit recommended by an expert panel as the most appropriate, among 60, 70, 80 and 90 km/h, is the decision attribute *D*. The information table and the expert recommended speed limit that constitute the exemplary decision are shown in Table 1 (The complete table of experimental data is reported in attachment).
In this case, all the condition attributes are criteria. For example, where the problem is to determine speed limits, considering the RHR a road section with good pavement condition will be preferable to a road section with bad ones, and therefore the higher speed limit will be assigned to the first one instead of the second one.
It is important to observe that the criteria preference-order used in the presented case study are fixed by the expert panel but these can be modified according to the preference and knowledge of expert components.
Assuming that all condition attributes $q\in C$ are criteria, let $\succeq_q$ be a *weak preference* relation on U with respect to criterion q such that $x\succeq_q y$ means "*x is at least as good as y with respect*

to criterion q". It is supposed that $\succeq_q$ is a total pre-order, i.e. a strongly complete and transitive binary relation, defined on U on the basis of evaluations f(·,q).
Furthermore, assuming that the set of decision attributes D (possibly a singleton {d}) makes a partition of U into a finite number of classes, let Cl={Cl_t, t∈T}, T={1,...,n}, be a set of these classes such that each x∈U belongs to one and only one Cl_t∈Cl. Assuming that the classes are ordered, i.e., for all r, s∈T, such that r>s, the objects from Cl_r are preferred to the objects from Cl_s.
More formally, if $\succeq$ is a *comprehensive preference* relation on U, i.e., if for all x,y∈U, x$\succeq$y means "x is at least as good as y": [x∈Cl_r, y∈Cl_s, r>s] ⇒ [x$\succeq$y and *not* y$\succeq$x]. For example, an object *x* dominating object *y* on all considered criteria (i.e. *x* having evaluations at least as good as *y* on all considered criteria) should also dominate *y* on the decision (i.e. *x* should be assigned to at least as good class as *y*). Objects satisfying the dominance principle are called *consistent*, and those which are violating the dominance principle are called *inconsistent*.
The above assumptions are typical for consideration of a *multiple-criteria sorting problem* (also called *ordinal classification problem*) (Greco et al., 2002a).
In the present case the set of decision D attributes is a singleton given by the attribute "recommended speed limit" which partitions the set U of the 100 road sections in the classes:

- Cl_1 composed of road sections with recommended speed limit of 60 km/h;
- Cl_2 composed of road sections with recommended speed limit of 70 km/h;
- Cl_3 composed of road sections with recommended speed limit of 80 km/h;
- Cl_4 composed of road sections with recommended speed limit of 90 km/h.

4.2 Dominance based approximation

These classes are ordered according to the preference of recommended speed limit, such that x≻y whenever x∈Cl_r, y∈Cl_s and r≥s.
Partition of the set U in classes, respecting dominance relationship, allows to approximate sets in unions of classes, called *upward union* and *downward union* of classes, respectively:

$$Cl_t^{\geq} = \bigcup_{s \geq t} Cl_s$$
$$Cl_t^{\leq} = \bigcup_{s \leq t} Cl_s$$

with *t*={1,2,…n}.
Thus, the statement $x \in Cl_t^{\geq}$ means "*x* belongs to at least class Cl_t", while $x \in Cl_t^{\leq}$ means "*x* belongs to at most class Cl_t".
In the case study the *upward union of classes* are:

- $Cl_1^{\geq}$ composed of road sections with recommended speed limit "at least" 60 km/h;
- $Cl_2^{\geq}$ composed of road sections with recommended speed limit "at least" 70 km/h;
- $Cl_3^{\geq}$ composed of road sections with recommended speed limit "at least" 80 km/h;
- $Cl_4^{\geq}$ composed of road sections with recommended speed limit "at least" 90 km/h;

The *downward union of classes* are:

- $Cl_1^{\leq}$ composed of road sections with recommended speed limit "at most" 60 km/h;
- $Cl_2^{\leq}$ composed of road sections with recommended speed limit "at most" 70 km/h;
- $Cl_3^{\leq}$ composed of road sections with recommended speed limit "at most" 80 km/h;
- $Cl_4^{\leq}$ composed of road sections with recommended speed limit "at most" 90 km/h.

Let us remark that $Cl_1^{\geq}$ = $Cl_n^{\leq}$ =*U*, $Cl_n^{\geq}$ =*Cl*$_n$ and $Cl_1^{\leq}$ =*Cl*$_1$.

In this application, the upward union classes $Cl_1^{\geq}$ and the downward union classes $Cl_4^{\leq}$ contain all the 100 road sections considered: in fact for all considered road sections the speed limit is always at least 60 km/h and at most 90 km/h.

Furthermore, for *t=2,...,n*, we have: $Cl_{t-1}^{\leq}$ = $U - Cl_t^{\geq}$ and $Cl_t^{\geq}$ = $U - Cl_{t-1}^{\leq}$.

The key idea of rough sets is approximation of knowledge expressed in terms of decision attributes by knowledge expressed in terms of condition attributes. This means to explain the partition of the decision attribute, according to the recommended speed limits, in terms of technical and functional parameters expressed by the conditional attributes.

In DRSA, where condition attributes are criteria and classes are preference-ordered, the knowledge approximated is a collection of *upward and downward unions of classes* and the "*granules of knowledge*" are sets of objects defined using *dominance relation*.

That is *x dominates y* with respect to $P \subseteq C$ if $x \in U$, the "*granules of knowledge*" used for approximation in DRSA are:

- a set of objects dominating x, called *P-dominating set*, $D_P^+(x) = \{y \in U : yD_Px\}$
- a set of objects dominated by x, called *P-dominated set*, $D_P^-(x) = \{y \in U : xD_Py\}$

Moreover, above dominating sets and dominated sets are "*granules of knowledge*" in the sense that it is supposed that road sections dominating x should be classified with at least the same recommended speed limit than x as well as road sections dominated by x should be classified with at most the same recommended speed limit.

For instance, if the considered criteria are "*traffic volume*" and "*percentage of heavy vehicles*", both of them evaluated on three levels scale with high, moderate and low, and road section x is evaluated as moderate with respect to traffic volume as well as with respect to percentage of heavy vehicles, then:

- $D_P^+(x)$ is composed of all road sections moderate or low with respect to traffic volume and percentage of heavy vehicles,

and

- $D_P^-(x)$ is composed of all road sections moderate or high with respect to traffic volume and percentage of heavy vehicles.

For any *P*⊆*C*, we say that *x*∈*U* belongs to $Cl_t^{\geq}$ *without any ambiguity* if *x*∈ $Cl_t^{\geq}$ and, for all objects *y*∈*U* dominating *x* with respect to *P*, we have *y*∈ $Cl_t^{\geq}$, i.e. $D_P^+(x) \subseteq Cl_t^{\geq}$. For example, considering the above road section *x* and *P*={"*traffic volume*", "*percentage of heavy vehicles*"}, if *x* has a speed limit of 80 km/h, i.e. x∈*Cl*$_3$, and all road sections y belonging to $D_P^+(x)$ (because evaluated moderate or low with respect to traffic volume and percentage of heavy vehicles) have a speed limit of at least 80 km/h (i.e. $y \in Cl_3^{\geq}$ and consequently $D_P^+(x) \subseteq Cl_3^{\geq}$) then x is classified with recommended speed limit at least 80 km/h without ambiguity. In simple words, this means that according to the objects in the universe U, not worse conditions than x with respect to the two criteria "*traffic volume*" and "*percentage of heavy vehicles*" imply a recommended speed limit of at least 80 km/h. Therefore, it is reasonable to recommend a speed limit of at least 80 km/h for any new road section not originally present in the universe, if it satisfies the same conditions, i.e. it is not worse than x with respect to the two criteria "*traffic volume*" and "*percentage of heavy vehicles*".

Instead, we say that *x*∈*U could belong* to $Cl_t^{\geq}$ if there would exist at least one object *y*∈ $Cl_t^{\geq}$ such that *y* is dominated by *x* with respect to P, i.e. *y*∈ $D_P^-(x)$. For example, if considering again the above road section *x* and *P*={"*traffic volume*", "*percentage of heavy vehicles*"}, there exists at least one road sections y belonging to $D_P^-(x)$ (because evaluated moderate or high with respect to traffic volume and percentage of heavy vehicles) has a recommended speed limit of at least 90 km/h (i.e. $y \in Cl_4^{\geq}$ and consequently $D_P^-(x) \cap Cl_4^{\geq} \neq \emptyset$) and then x could be classified with recommended speed limit at least 90 km/h. In simple words, this means that according to the objects in the universe U, a recommended speed limit of at least 90 km/h could be taken into consideration in case of not worse conditions than x on the two criteria "*traffic volume*" and "*percentage of heavy vehicles*", because in the universe there is road section y that is not better than x with respect to considered criteria but has a speed limit of 90km/h. This is due to the fact that there is an ambiguity between x and y with respect to criteria from P.

Thus, with respect to $P \subseteq C$, the set of all objects belonging to $Cl_t^{\geq}$ without any ambiguity constitutes the *P-lower approximation* of $Cl_t^{\geq}$, denoted by $\underline{P}(Cl_t^{\geq})$, and the set of all objects that could belong to $Cl_t^{\geq}$ constitutes the *P-upper approximation* of $Cl_t^{\geq}$, denoted by $\overline{P}(Cl_t^{\geq})$:

$$\underline{P}(Cl_t^{\geq}) = \{x \in U:\ D_P^+(x) \subseteq Cl_t^{\geq}\}$$
$$\overline{P}(Cl_t^{\geq}) = \{x \in U:\ D_P^-(x) \cap Cl_t^{\geq} \neq \emptyset\}$$

for t=1,...,n.

Analogously, one can define *P-lower approximation* and *P-upper approximation* of $Cl_t^{\leq}$:

$$\underline{P}(Cl_t^{\leq}) = \{x \in U:\ D_P^-(x) \subseteq Cl_t^{\leq}\}$$
$$\overline{P}(Cl_t^{\leq}) = \{x \in U:\ D_P^+(x) \cap Cl_t^{\leq} \neq \emptyset\}$$

for t=1,...,n.

Observe that $\underline{P}(Cl_t^{\geq}) \subseteq \overline{P}(Cl_t^{\geq})$, for all $P \subseteq C$ and for all t=1,...,n.

4.3 Decision Rules and procedures for generation of decision rules

The dominance-based rough approximations of *upward and downward unions of classes* can help to induce a generalized description of objects contained in the information table in terms of "*if..., then...*" decision rules (Greco et al., 2002a) (Greco et al., 2005) (Slowinski et. al., 2005).

In DRSA, for a given *upward or downward union of classes*, $Cl_t^{\geq}$ or $Cl_s^{\leq}$, the decision rules induced under a hypothesis that objects belonging to $\underline{P}(Cl_t^{\geq})$ or $\underline{P}(Cl_s^{\leq})$ are *positive* and all the others *negative*, suggest a *certain* assignment to "at least class Cl_t" or to "at most class Cl_s", respectively; on the other hand, the decision rules induced under a hypothesis that objects belonging to the intersection $\overline{P}(Cl_s^{\leq}) \cap \overline{P}(Cl_t^{\geq})$ are *positive* and all the others *negative*, are suggesting an *approximate* assignment to some classes between Cl_s and Cl_t ($s<t$).

Assuming that, for each $q \in C$, $V_q \subseteq$R (i.e. V_q is quantitative) and that, for each $x,y \in U$, $f(x,q) \geq f(y,q)$ implies $x \succeq_q y$ (i.e. V_q is preference-ordered), the following three types of decision rules can be considered:

1) D$_{\geq}$-*decision rules* with the following syntax:

   if $f(x,q_1) \geq r_{q1}$ *and* $f(x,q_2) \geq r_{q2}$ *and …* $f(x,q_p) \geq r_{qp}$, *then* $x \in Cl_t^{\geq}$,

   where $P=\{q_1,...,q_p\} \subseteq C$, $(r_{q1},...,r_{qp}) \in V_{q1} \times V_{q2} \times ... \times V_{qp}$ and $t \in \{2,…,n\}$;

   for example:

   if lane width is ≥ "3.75 m", road signs are "present", pavement condition are "high" and Roadside Hazard Rating is ≤ "3", then recommended speed limit have to be "at least" 80 km/h, i.e. road section x $\in Cl_3^{\geq}$.

2) D$_{\leq}$-*decision rules* with the following syntax:

if $f(x,q_1) \le r_{q1}$ *and* $f(x,q_2) \le r_{q2}$ *and ...* $f(x,q_p) \le r_{qp}$, *then* $x \in Cl_t^{\le}$,

where $P=\{q_1,...,q_p\} \subseteq C$, $(r_{q1},...,r_{qp}) \in V_{q1} \times V_{q2} \times ... \times V_{qp}$ and $t \in \{1,...,n-1\}$;

for example:

if shoulder width is ≤ "0.50 m", Roadside Hazard Rating is ≥ "2", accident rate is ≥ "high" and adverse alignment are present, then recommended speed limit have to be "at most" 70 km/h, i.e. road section x $\in Cl_2^{\le}$.

An object $x \in U$ *supports* decision rule *r* if its description is matching both the condition part and the decision part of the rule. The decision rule *r covers* object *x* if it matches the condition part of the rule.

Each decision rule is characterized by its *strength*, defined as the number of objects supporting the rule. In the case of approximate rules, the strength is calculated for each possible decision class separately.

Procedures for generation of decision rules from a decision table use an inductive learning principle. The objects are considered as examples of classification. In order to induce a decision rule with an univocal and certain conclusion about assignment of an object to decision class *X*, the examples belonging to the *C*-lower approximation of *X* are called *positive* and all the others *negative*.

Analogously, in case of a possible rule, the examples belonging to the *C*-upper approximation of *X* are positive and all the others negative. Possible rules are characterized by a coefficient, called *confidence*, telling to what extent the rule is consistent, i.e. what is the ratio of the number of positive examples supporting the rule to the number of examples belonging to set *X* according to decision attributes. Finally, in case of an approximate rule, the examples belonging to the *C*-boundary of *X* are positive and all the others negative.

With respect to Table 1 (*information table*) the DRSA gives back 391 decision rules in the *"if….then…"* form, and more precisely:

- ✓ 89 decisions recommend a speed limit ≥ 90 km/h;
- ✓ 63 decisions recommend a speed limit ≥ 80 km/h;
- ✓ 53 decisions recommend a speed limit ≥ 70 km/h;
- ✓ 67 decisions recommend a speed limit ≤ 60 km/h;
- ✓ 59 decisions recommend a speed limit ≤ 70 km/h;
- ✓ 60 decisions recommend a speed limit ≤ 80 km/h.

Every decision rule specifies the recommended speed limit and the reasons why it has been suggested; for every rule it is also possible to know which objects (example cases on information table) support the rule. The possibility of recognizing the examples supporting specific decision rules allows the authority' managers to understand and discuss the set of decision rules, which can be also revised easily if necessary. For example, taking into account the following decision rule:

*if Traffic Volume is ≤ "low", Shoulder Width is ≥ "1.00 m", Pavement Con*dition *is ≤ "medium" and Accident Rate is ≤ "low" then recommended speed limit have to be "at least" 90 km/h*

it is possible to know that it is supported by the exemplary cases n. 7, 31, 44, 46, 47, 51 and 70 of the information table. In Table 2 some examples of the 391 decision rules have been reported, indicating also the road sections from Table 1, which support the considered rule.

It is worthy noting that an algorithm specifically developed by the authors has implemented the induction of decision rules, which is based on the DRSA methodology. For the induction of decision rules it is also available a free software, called jMAF (Błaszczyński, Greco, Matarazzo, Słowiński, Szeląg 2013), free of charge at the web address: http://idss.cs.put.poznan.pl/site/139.html. For other methodologies to induce DRSA decision rules see Susmaga, Słowiński, Greco, Matarazzo 2000, Greco, Matarazzo, Slowinski, Stefanowski 2001, Li, Li, Zhang, Chen, Zhang 2015.

4.4. Advantages of DRSA with respect to the classical rough set approach

We conclude this section by pointing out the advantages of the DRSA with respect to the classical rough set approach. The first basic advantage is that classical rough set approach in its basic formulation is not able to deal with criteria because it does not take into consideration order relations on the set of values taken by attributes. Indeed, classical rough set approach is based on indiscernibility relations being equivalence relations, that is reflexive, symmetric and transitive binary relations, instead of the preorder relations, that is reflexive and transitive relations in general not symmetric, used by DRSA. Without entering into technical the details, let us explain this point with a simple didactic example. Suppose that the decision of the speed limit is taken considering criteria "*traffic volume*" and "*percentage of heavy vehicles*". Suppose also to have the decision table showed in the following Table 3.

Using classical rough set approach one can induce the following decision rules:

Rule 1: *if Percentage of heavy vehicles is "low", then recommended speed is 70 km/h* (indeed, there is one road section, R1, which satisfies the condition of the rule and its recommended speed is 70 km/h);

Rule 2: *if Percentage of heavy vehicles is "medium", then recommended speed is 80 km/h* (indeed, there are two road sections, R2 and R4, which satisfy the condition of the rule and their recommended speed is 80 km/h.

It is apparent that the two rules are not coherent between them. In fact, one would expect that if the percentage of heavy vehicles passes from "low" to "high", then the recommended speed should not increase, how instead is suggested by the two rules. The reason of the inadequate recommendation given by Rule 1 and Rule 2 is the indiscernibility relation according to which rules are induced considering conditions «*Percentage of heavy vehicles is "low"*» or «*Percentage of heavy vehicles is "medium"*», instead of «*Percentage of heavy vehicles is "at most low"*» or «*Percentage of heavy vehicles is "at most medium"*». DRSA induce perfectly coherent rules such as

Rule 3: *if Traffic volume is (at most) "low", then recommended speed is (at least) 80 km/h* (indeed, there are two road sections, R4 and R5, which satisfy the condition of the rule and their recommended speed is (at least) 80 km/h);

Rule 4: *if Traffic volume and Percentage of heavy vehicles are both is (at most) "medium", then recommended speed is 80 km/h* (indeed, there are two road sections, R2 and R4, which satisfy the condition of the rule and their recommended speed is (at least) 80 km/h.
Greco, Matarazzo and Slowinski (2007) proved that decision rules obtained by classical rough seta approach can be obtained by DRSA when the original information is recoded in a specific form. One could ask if also the inverse is not possible, i.e. if there is some recodification of the original information that permits to induce DRSA decision rules using classical rough set approach. Observe that this recodification would have the advantage to permit to use the rule induction algorithms of the classical rough set approach also in presence of criteria with its value set ordered according to decreasing or increasing preferences.
Such a recodification there exists and consists in the substitution of the original criteria with a new set of attributes that for each possible value of original attributes, with the exclusion of the worst one, assigns value 1 if the considered object has a not worse value and 0 in the opposite case. For example the above Table 3 should be recoded as shown in Table 4.

Using the classical rough set approach applied to the decision table presented in Table 4 following decision rules would be induced:

Rule 5: *if "Traffic volume not worse than low" = 1, then recommended speed is (at least) 80 km/h* (indeed, there are two road sections, R4 and R5, which satisfy the condition of the rule and their recommended speed is (at least) 80 km/h);

Rule 6: *if "Traffic volume not worse than medium" = 1 and "Percentage of heavy vehicles not worse than medium"=1, then recommended speed is 80 km/h* (indeed, there are two road sections, R2 and R4, which satisfy the condition of the rule and their recommended speed is (at least) 80 km/h).

It is straightforward to verify that Rule 5 and Rule 6 are equivalent to Rule 3 and Rule 4, respectively. Thus this example seems to suggest to handle decision table with criteria by recoding the information and after applying the classical rough set approach algorithm to induce decision rules taking into account preference order in the values taken by criteria. Unfortunately, this is not an efficient procedure from computational point of view. Indeed the algorithm to induce decision rules are exponential in the number of attributes and it is clear that the above recodifications transforms the original decision table with m=card(C) criteria, to another decision table with $\sum_{j=1}^{m}(n_j - 1)$ dichotomic attributes, with n_j being the cardinal of values taken by criterion q_j (for example decision table in Table 4 recoded the 2 criteria of the decision table in Table 3 by 4 dichotomic attributes because each one of the two original criteria in Table 3 take 3 values). It is clear that this multiplication of attributes due to the recodification makes the application of rule induction algorithms of classical rough set approach highly inefficient and suggests to apply the rule induction algorithms developed for DRSA.

5. Application of the decision model

After discussion, the expert panel accepted the set of the 391 decision rules to be the decision model for setting speed limits on speed zone. Several methodologies can be used to apply the DRSA decision rules to classify new objects taking into account some goodness measures of the considered rules (see e.g. Błaszczyński, Greco and Słowiński 2007, Ko,Fujita and Tzeng 2013a, 2013b and 2014). In the proposed Decision Support System (DSS) the following original methodology is used.
Giving as input the characteristics of the new road section, the procedure uses decision rules generated by DRSA and gives back a recommended speed limit, providing the most important decision rules that can help decision makers to understand the reasons of the suggested speed limit.
An example on a road section is presented herein.
The features of the considered road section have been listed below:

- Traffic Volume (A_1) = High
- Percentage of heavy vehicles (A_2) = Low
- Lane width (A_3) = 3.50 m
- Shoulder width (A_4) = 1.00 m
- Road Signs (A_5) = Yes
- Pavement Condition (A_6) = Moderate
- Roadside Hazard Rating (A_7) = 3
- Accident Rate (A_8)= Low

- Adverse Alignment (A_9) = Yes

The DSS suggests 70 km/h as speed limit and returns 20 decision rules (Table 5):

- 8 of them recommend a speed limit ≥ 70 km/h;
- 2 of them recommend a speed limit ≤ 70 km/h
- 10 of them recommend ≤ 80 km/h.

The speed limit value is calculated as the value that satisfy all decision rules returned by the DRSA: for the example case, the speed limit satisfying all the three suggestions is 70 km/h, because 70 km/h is not smaller than 70 km/h, not larger than 70 km/h and not larger than 80 km/h.

If it is not possible to satisfy all decision rules, then the rules supported by larger and larger numbers of road section in the original data base need to be considered, until the set of remaining rules becomes consistent with a unique value of the speed limit. For example, let us consider a road section with the following characteristics:

- Traffic Volume (A_1) = High
- Percentage of heavy vehicles (A_2) = Low
- Lane width (A_3) = 3.50 m
- Shoulder width (A_4) = 1.00 m
- Road Signs ($A_{5)}$ = Yes
- Pavement Condition (A_6) = Moderate
- Roadside Hazard Rating (A_7) = 3
- Accident Rate (A_8)= Low
- Adverse Alignment (A_9) = No

The DSS gives 25 rules matching the considered case and more precisely:

- 13 decision rules suggesting speed limit ≥ 70 km/h,
- 5 decision rules suggesting speed limit ≥ 80 km/h,
- 2 decision rules suggesting speed limit ≥ 90 km/h,
- 1 decision rules suggesting speed limit ≤ 70 km/h,
- 4 decision rules suggesting speed limit ≤ 80 km/h.

In this case, no speed limit is able to satisfy all the rules. Indeed there is not an unique speed limit value that can satisfy all the five suggestions. In fact, a value that is at the same time not smaller than 70 km/h, not smaller than 80 km/h, and not smaller then 90 km/h, and not greater than 70 km/h, and not greater than 80 km/h does not exists.

The set of rules according to their support therefore needs to be reduced, taking progressively into account decision rules more and more supported. Considering decision rules supported by at least 21 road sections, the software returns:

- 11 decision rules suggesting speed limit ≥ 70 km/h,
- 1 decision rules suggesting speed limit ≥ 80 km/h,
- 1 decision rules suggesting speed limit ≤ 70 km/h,
- 4 decision rules suggesting speed limit ≤ 80 km/h.

Also, in this case there is not a unique speed limit value that can satisfy all suggestions. Indeed, a value that is at the same time not smaller than 70 km/h, not smaller than 80 km/h, not greater than 70 km/h, and not greater than 80 km/h does not exists.

Taking into account decision rules supported by at least 22 road sections, the software returns:

- 7 decision rules suggesting speed limit ≥ 70 km/h,
- 1 decision rules suggesting speed limit ≥ 80 km/h,
- 4 decision rules suggesting speed limit ≤ 80 km/h.

In this case, the speed limit that can satisfy all the three suggestions is 80 km/h.

The decision rules aim to explain to the decision-maker the reasons why the expert panel suggests a specific speed limit for the considered road section. Obviously it is not reasonable

to submit too many decision rules to the decision maker, so only the most supported rules recommending the exact value of the speed limit (and precisely the lower and the upper limit) are presented to the decision maker.
For the first example case, the final output is presented in table 6.

The proposed methodology can be used also if the information of some road section feature is not available (for example traffic or crash data) as explained by the following examples.
Let us consider a road section, for which accident rate data is not available, with characteristics listed below:

- Traffic Volume (A_1) = High
- Percentage of heavy vehicles (A_2) = Low
- Lane width (A_3) = 3.50 m
- Shoulder width (A_4) = 1.00 m
- Road Signs (A_5) = Yes
- Pavement Condition (A_6) = Moderate
- Roadside Hazard Rating (A_7) = 3
- Accident Rate (A_8)= **not available**
- Adverse Alignment (A_9) = Yes

In this case, it is necessary to assign a value to the accident rate data. We decide to work in behalf of security, putting the less favorable value (in terms of road security) of accident rate, i.e. A_8= High. In this case our methodology suggests a 60 km/h speed limit and returns 21 decision rules:

- 2 of them recommend a speed limit ≤ 60 km/h;
- 3 of them recommend a speed limit ≤ 70 km/h;
- 16 of them recommend ≤ 80 km/h.

If we decide to put in the other possible value of accident rate (i.e. A_8= Low) we return at the first example case, where recommended speed limit is 70 km/h.
So, it is possible to insert some conjectured value for the characteristics with missing data and apply the proposed procedure. However, it is clear that the solution suggested by the software is strongly dependent on the conjectured values. Instead it could be interesting to try to get a result that, maintaining a cautionary principle, accepts that there is some missing value.
Observe that in some cases, assigning different values to the missing data, the results may change (as in the above example), or may not change as in the following example:

- Traffic Volume (A_1) = **not available**
- Percentage of heavy vehicles (A_2) = **not available**
- Lane width (A_3) = 3.50 m
- Shoulder width (A_4) = 1.00 m
- Road Signs (A_5) = Yes
- Pavement Condition (A_6) = Moderate
- Roadside Hazard Rating (A_7) = 3
- Accident Rate (A_8)= Low
- Adverse Alignment (A_9) = Yes

Using the less favorable values (in terms of road security) of both attributes, i.e. A_1= High and A_2= High, our methodology suggests 70 km/h as speed limit and returns 21 decision rules:

- 8 of them recommend a speed limit ≤ 70 km/h;
- 4 of them recommend a speed limit ≥ 70 km/h;
- 18 of them recommend ≤ 80 km/h.

Therefore, in this case, the recommended speed limit does not depend on the value assigned to the missing data (although the corresponding decision rules are different).

6. Discussion

The conceptual model in figure 1 represents, in a simple way, the proposed methodology to assess speed limits.

Figure 1. Conceptual model of the DRSA methodology to assess speed limits

Thus, on the basis of some speed limits assigned by one or more experts for a sample of road sections, the presented model get some decision rules in the following form: *"if road section characteristics are …, then the recommended speed limit have to be at least/at most …"*. That means that, taking into account a new road section, every time that the antecedents, i.e. the *"if-part*" conditions, are satisfied, also the consequence, i.e. the "*then-part*", is satisfied.
Moreover, for each decision rule, it is possible to know which are the exemplary decisions that the given rule is describing. This information is very useful because it allows the DM to evaluate critically the decision rules. If some decision rule is not convincing for the DM, possibly there is some example to which should correspond a different decision in terms of recommended speed limits. Therefore, after revising the not convincing exemplary decisions, a new set of decision rules can be induced and submitted again to the DM until (s)he is satisfied. This is concordant with posterior rationality of March (March, 1978), which advocates discovery of intentions of a decision maker instead of the interpretation of a priori position. In simple words for the experts is easier to give some examples of good decisions rather than explain the reasons for which a decision is good.
So, using the proposed methodology, is asked to the experts what for them is easier, i.e. a set of exemplary decisions, and is given them what for them is more difficult, i.e. a set of explanations about the goodness of the decisions. Moreover this explanation is expressed in a clear way that permits the experts to see what are the exact relations between the provided information and the final recommendation. In fact, a lot of statistical methods such as the regression approach, express their results through a technical formulation that the users cannot understand without a specific background and consequently those results are perceived, very often, as a *black box* whose recommendations have to be accepted because the "scientific authority" of the model guarantees that the result is "right". In this context, the aspiration of the DM to find good reasons to make decision is frustrated and (s)he feels the need of a more transparent methodology in which the relation between the original information and the final recommendation is shown clearly. Such a transparent methodology searched for has been called *glass box* (Slowinski et al., 2009) and DRSA has proved to be its typical representative.
So, we developed a decision-support tool that can provide decision rules, synthesizing some exemplary decisions about speed limits supplied by the experts, in a very natural and clear form (like the *"if… then…"* form), easy to understand without a specific statistical background.
Periodically the system can be evaluated and updated if necessary, basing on the managing authority's current policies, engineering criteria, practices, and experience.
In fact, the DRSA permits a simple and transparent system revision because it only requires updating the set of exemplary decisions from which the "*if…, then…"* decision rules are induced. The rules explain the decision policy adopted in the examples and, after acceptance, can be used to support new decisions.
In the speed assessment problem based on DRSA, hierarchies of criteria (as proposed in Dembczynski, Greco and Slowinski 2002) can be taken into account also. For example,

geometry of the road can be considered as criterion having as sub criteria radius of horizontal and vertical curves, sight distances, etc. Moreover, let us observe that a new paradigm emerging in the domain of expert systems is the hierarchical modeling of structural granules permitting to represent sensory information systems (see e.g. Skowron, Stepaniuk, Jankowski, Bazan and Swiniarski 2012). In our context this means that one could consider as data of the model not only the measured speed, but we could take into account some more comprehensive information related to the behavior of the drivers in different contexts, such as weather conditions, traffic, different times in a day, different seasons. However, we defer the research on such more complex models for future investigation.

7. Conclusions

The first version of a multi-criteria decision support system to suggest the most appropriate speed limits for speed zones to managing authority has been presented in this paper.

The model developed herein provides to decision makers a safe speed limit using geometric and operative characteristics and maintenance conditions; it provides also some easily understandable decision rules that can help to explain the reasons for the suggested speed limit for each investigated road section.

The developed Decision Support System is based on Dominance-based Rough Set Approach (DRSA) which requires basic input information in terms of evaluation examples, i.e. exemplary decision about speed limits, and express the results of the decision analysis in a very understandable way using *"if… then…"* rules.

The adopted Dominance-based Rough Set Approach presents several advantages over other approaches in terms of transparency and manageability and has permitted to develop an intelligible and user-friendly multi-criteria decision model for setting speed limits in speed zone.

In fact DRSA produces a decision model expressed in terms of easily understandable "*if… then…*" decision rules which permits to control the decision process and to avoid the "black box" effects of many alternative decision support methods, ensuring a high degree of transparency. The DRSA also permits a simple revision of the decision model because it only requires to update the set of exemplary decisions from which the "*if… then…"* decision rules are induced. So, on the basis of the managing authority's current policies, engineering criteria, practices, and experience, the system can be evaluated and updated periodically. Moreover the model can be easily changed using different "condition attributes", or using a "decision attribute" suggested by different decision makers with different purposes and priorities. In this way the system can be adapted to every approach, such us harm minimization, economic optimization, driver's choice, etc…

In this paper a sample application of the built Decision Support System is also developed using a software which can easily interface with the DRSA output. Putting as input the investigated road section features, the software gives back a recommended speed limit and only the more important decision rules that can help decision makers to understand the reasons of the suggested speed limit. The obtained results are very encouraging and were found to be very interesting for decision makers, because they are clear and very helpful in decision-making process.

The developed Decision Support System aims the similar purpose of the above-mentioned models, i.e. USLIMITS and SaCredSpeed, but presents some important difference with them.

The first difference is the adopted method for the DSS developing, because in the presented model a Dominance-based Rough Set Approach (DRSA) has been used, which offers the numerous advantages presented above in terms of transparency and manageability.

In the final output the developed DSS, besides recommending a speed limit value (like USLIMITS), also provides some decision rules that can help decision makers to understand

the reasons of the suggested speed limit and, consequently, to discover the most appropriate measure to improve road safety and drivers' compliance with speed limits.
Finally, because of its versatility, the methodology we are proposing can be adapted to every road management strategy only changing the attributes and/or the decision examples that form the information table.

Acknowledgement
We thank the Reviewers and the Editor for all constructive remarks throughout the reviewing process. The third author wishes to acknowledge funding by the "Programma Operativo Nazionale. Ricerca & Competitività 2007-2013" within the project "PON04a2 E SINERGREEN-RES-NOVAE".

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