Situation Assessment in Everyday Life

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1 ABSTRACT.

Currently, theoretical and applied approaches related to such a concept as "Situation Assessment" have as a rule strong military character. It is evident from simple analysis of conferences and workshops dedicated to this subject. The paper represents an attempt of developing methodology and system of instruments for analysis and help in resolving everyday life situations - from simple life situations up to business situations. As an analytic instrument *Aggregated Preference Indices Method for considered alternatives* is proposed. As an example a case study of cars preference estimation by a consumer is considered. An example of computer prototype realization as a web-service (available by reference www.polyidea.com) is given

Key words. Situation Assessment, Situation Awareness, Immunocomputing, Bayesian Approach, Decision Support Systems.

2 INTRODUCTION

Current paper represents an attempt of developing methodology and tool for helping ordinary people or businessman to make not intuitive but substantiated quantitative choice in a range of situations which cannot be reduced to simple enumeration of alternatives or calculation of coefficients.

"The *understanding* of the situation gained from the sum total of the relevant information provided to make a correct decision regarding the allocated objectives and/or desired end state" [9]. "Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" [9].

As a rule, problem of choice forms a basis of ordinary situation. A person faces above problem almost every day. And the main feature of problem of choice is a price. One case if you need choosing a loaf of bread, and quite another - if you are choosing a car or a cottage. In this context concept "system" can have widest interpretation: it can be used to describe relatively inexpensive articles of domestic utility as well as complex financial and economic objects.

Thus, situation recognition represents analysis of mentioned criteria on the matter of getting validated conclusion about current system state and probable system state in the near future. [1].

By-turn, under situation control is understood a purposeful influence on system with a view of changing situation in our favour. The above influence can be realized by performing certain activities aimed at changing system attributes that are characterized by revealed criteria

Traditionally problem of situation assessment is considered as research area relating to defense or military aspects. Interest in above problem has appeared relatively not long ago. In spite of a great number of available papers being of methodological or statement character, there's quite difficult to find approaches suggesting quantitative methods for situation assessment.

Formerly, the authors of this paper proposed method of Immunocomputing for assessment of complex tactic situations appearing in global monitoring systems. As the problem consists in situations assessment in everyday life, there was necessity in another, easier for ordinary people, approach that takes into account not only numerical but also uncertain and nonnumerical user information .

In view of the aforesaid, as an analytic instrument an *Aggregated Preference Indices Method* for considered alternatives is proposed. This method is developed by scientists of Saint-Petersburg State University and Saint-Petersburg Institute for Informatics and Automation of the Russian Academy of Sciences. The method is based on Bayesian model of uncertainty randomization allowing to process nonnumeric, uncertain and incomplete information being available for decision-maker or user. Method's realization for user is suggested in a form of decision support system's (DSS) interface. DSS (demo can be downloaded from www.www.www) is tested by example of solving a problem of reliable commercial bank choice and a problem of car preference estimating. Above method is adaptable by user to solve a great number of standard situations occurring everywhere in everyday life.

Research structure. In the 2nd part a concept of situation in the wide sense and assessment approaches are given. General concept of situation is defined in everyday sense understandable to real user being unacquainted with special subject area and research. In the 3rd part well-known techniques that can be applied to situation assessment problem on everyday level, that is to say in everyday life, are analyzed. The idea of immunocomputing method is given.

In the 4th part the suggested method based on Bayes approach is described. General mathematical problem statement and general solution method are given.

The 5th part represents a computer prototype for above method and set of services being available to user. Meanwhile a wide spectrum of services is implied: local computer, thin or thick client and mobile device. In the 6th part some examples for case of choosing a car are considered. Alternatives for realization and promotion of this technology in EU and other countries are proposed. Besides, a numerical estimate for economic effect from widespread adoption of above technology is given. Conclusion represents general findings, nearest development and adoption programmes for above technology, as well as discussion questions.

3 SITUATION ASSESSMENT

In everyday life and service activities a person regularly has to make decisions – to choose one or another behaviour type among several alternatives. Various decisions differ by complexity of decision-making as well as by character of probable consequences. The more complex controlled system is, the greater number of factors influence on ultimate choice of decision-maker, and the more scale are results of proper or wrong decision. Management science states that decision process diagram doesn't depend on subject area the decision is made in. Although man have been making decisions since his appearance on Earth, awareness of this simple idea came to us relatively not long ago – soon after Second World War when theory of games and theory of random process control were developed.

Situations (as it is often said – patterns, objects, signals, events or processes) assessment or, that is to say, recognition, - is the most widespread problem a person has to solve almost every second from first till last day of his life. Let's consider some examples of pervasive recognition mechanism.

1. Let's assume, that you need certain section of mathematics field. Your actions are as follows:

a) weigh up where you can find manual you're interested in;

b) recognize manual on bookshelf by spines (against other books – by reading, recognizing titles in consecutive order or by appearance that you're keeping in your memory according to prior use of this manual);

c) leaf over and recognize page with table of contents (you know from previous experience that table of contents is in the beginning or in the end of book);

d) recognize headline texts of table of contents (read);

e) leaf over manual and recognize required number from page numbering;

f) read the found page and evaluate relevance of search results. If found material doesn't suit you for some reasons, you either repeat the described above procedure beginning from one of the items a)…e), or make some other decision, e.g. betake to Internet etc.

2. Let's consider an example from economics field. Through economic indices head of a certain region reveals (recognizes) change for the worse of food supply in some region, town etc. Having turned to another group of economic indices, he recognizes the origin of such undesirable phenomenon (e.g. lack of fuel for motor transport). Finally he makes decision on additional supply agreement for petrol or diesel fuel with suppliers, or new suppliers are found and dispatch of tanks consist or refuelers for delivery is organized etc.

Over a long period of time problem of situation recognition had been considered from a position of biology and psychology methods only. And just cybernetics allowed to introduce quantitative methods into study of psychological recognition process underlying any decision making that opened up new possibilities in automatic recognition systems' research and engineering, as well as to introduce mathematical presentation into recognition domain.

The algorithms underlying recognition are quite evident. In classic statement of recognition problem all existing object (situation) set is decompounded into classes, or patterns. The pattern of any object is specified by set of its particular manifestations. Technique of element assigning to some pattern is called a decision rule. One more important concept "metric" is a method of determining spacing between elements of universal set. The less spacing is, the more resembling symbols, sounds, situations (what we are recognizing) are. Usually elements are given in a number set form, and metric is specified in a functional form. Efficiency of recognition algorithm depends on choice of patterns presentation and metric realization. Algorithms with different metrics make mistakes with different frequency (right of mistake for recognizers is as typical as for people).

Principle of situation recognition process can be well illustrated by elementary algorithm that is based on a method of etalons set. On its entry there are learning sample (a certain set of examples $A'_{i,j}$ for each pattern A_i), metric d and object x being recognized. With the use of metric we calculate distance from x to each element $d(x, a_{i,j})$ of learning sample and find relative distance $d(x, A_{i,j})$ as a distance from x to the nearest element from A_i. Element x relates to the nearest pattern.

Method of k-nearest neighbours is another elementary algorithm. Everything is even easier here - k nearest to x elements of learning sample are taken and number of related to each pattern elements is estimated. X relates to the same pattern that majority of elements does.

There exists a great number of other much more complex techniques, and theoretic issues on this subject may be awe-inspiring by there monumental character. However, the given simple algorithms allow to see basic principle of recognition theory, namely, object (situation) being recognized relates to a more *similar* class, and all recognition techniques differs one from another exactly by method of similarity measure determining.

In view of the aforesaid, situation assessment purposes making a certain decision or choosing from several alternatives. What does singularity of situation assessment problem consist in? Or, in other words, how does it differ from decision theory problems and from aforesaid routine problems of pattern recognition?

Let's specialize the matter of concept "situation" in order to answer the above question. As stated above, situation is a combination of some parameters (indices, criteria) that directly or indirectly define system (object) state at a certain moment.

Objective of routine problem of pattern recognition theory consists in ***recognition*** of one object from many others, for example, recognition of letters in penscript, recognition of faces in a crowd, sounds in a choir, ballistic warheads in assemblage of space objects etc.

Routine problem of decision theory implies ***choice*** of an alternative from several ones based on analysis of parameters characterizing these alternatives.

Special feature of situation assessment problem is that choice objective consists in ***action*** aimed at situation change in our favour. The second feature of situation assessment problem is that as a rule the whole list of all possible situations is very large, not to say endless. Therefore, the list of possible "responses" to existing situation is equally large. Finally, the third problem's feature is that situation changes in course of time and the action being preferable at present may become baneful in a short time.

Chess is the most illustrative example of situation assessment. Play of chess opening is an example of situation assessment with its further step-by-step realization. But first and foremost chess is a game being played by strict rules, and set of chess-pieces on chessboard is quite limited. However, developing of process-specialized supercomputer Deep Blue had been needed to more or less successful "situations analysis" in match with G. Kasparov.

Usually situation analysis in real life is manifold complex in contrast to chess, because there may be several players, the whole list of "chesspieces" on "chessboard" may be unknown, and each of "chesspieces" commonly has backup "move" unforeseen by rules. Theory of situations recognition specializes in solving tasks of that very type.

4 SITUATION ASSESSMENT BY IMMUNOCOMPUTING

The research done showed that results received in the field of artificial intelligence can be used to elaborate real SAW work algorithms.

There exists a set of technologies for knowledge manipulation, known as knowledge engineering. Application of the results received from knowledge engineering where strict rules are determined and modern computers exceed human brain capacity (calculation tasks, exhaustive search of alternatives, etc.) looks quite promising.

As for trends in biological AI , it can be used to model thought biological mechanisms in order to arrive at a better understanding with further progress through technical devices. The best developed fields here are artificial neural nets (ANN) and genetic algorithms (GA).

New progress and research in informatics, based on information processing implementing protein molecules' immune networks [8], processing principles appeared under the term of "immunocomputing" (IC). The principal difference between IC and other calculation methods lies in the functions of their basic components and matches their biological prototypes and mathematic models. The basic premise here is the arbitrary IC basic components (formal proteins) interconnection within a formal immune network (FIN).

IC proposes the following new approach to AI problems as a new series of calculations:

- • pattern recognition and data analysis based on molecular recognition principles;
- • language representation and task solving based on analogues between words and bio molecules;
- • natural and technical systems modeling based on bio molecules interactions.

Let us consider a description (in pseudo code) of the basic IC pattern recognition algorithm using such a transformation.

```
Learning // data mapping into FIN space
{
to receive a learning sample;
to form a learning matrix;
to calculate SVD of the learning matrix; // SVD–singular value decomposition//
}
Recognition // data classification in FIN
{
to receive a situation vector; //pattern
to map a vector in FIN space;
to find the closest FIN point;
to assign a vector the closest FIN point class;
}
```

Using an IC basic algorithm of pattern recognition consider the description (in pseudo code) of the developed algorithm for recognition of a situation emerging in the process of decision making.

```
//Standard interface module;
forming subject domain model of Situation
{
determine Situation as a set of parameters;
determine number coding of parameters; //parameters' vector
Form learning matrix;
}
// Module "Situation"
```

learning //data mapping into FIN space
{
to receive a learning matrix;
calculate the SVD of the learning matrix;
store first three singular numbers and matching vectors;
}
recognition //data classification in space FIN
{
receive parameters' vector of Situation; //pattern
to project the pattern into a point FIN $[w_1,w_2,w_3]$;
to find *n* closest points FIN; //*n* is given in interface module
to determine codes SS for these points; //classes SS
to determine probabilities SS for each point;
to forward results into interface module;
}

The above IC-algorithm has been used for SAW learning and the solution of Situation for end user.

5 SITUATION ASSESSMENT BY BAYESIAN APPROACH

The main component of the theoretical basis for the suggested decision support system (DSS) is *Aggregated Indices Method* (AIM) (e.g., see [8,13,14,18]). In the method's framework it is supposed that all possible *alternatives* (synonyms: variants, solutions, courses of action, objects, etc.) of a decision are fixed by a *decision-maker* (DM). Also, it is assumed that some *attributes* (synonyms: characteristics, features, properties, parameters, etc.) are selected by the DM for the alternatives description. Thus, the alternatives of the decision-making may be named *multi-attribute alternatives*.

A numerical value of an attribute for a given alternative determines an estimation of the alternative's preference, this estimation being a numerical function of the attribute's value. Such functions of the attributes' values are named *single preference indices* (synonyms: specific, special, particular, peculiar, individual, elementary, etc.). Any single preference index may be treated as a *single criterion of preference*. Thus, a collection of all single criteria's values for a given alternative plays a role of a *multi-criteria estimation* of the alternative's preference.

It is supposed that each of the constructed single preference criterion is necessary, and the whole set of them is sufficient for a numerical estimation of any alternative's preference. In other words, it is supposed that a numerical estimation of an entire alternative's preference is a numerical function of the set of all single preference criteria. Such numerical function of all single criteria of preference is named *aggregated preference index*, and is treated as an *aggregated criterion* of the alternatives' preference. Value of an aggregated preference index for a given alternative is its preference estimation which takes into account the whole set of single estimations of the alternative's preference.

Additionally it is assumed that an *aggregative function* (i.e. function which determines a corresponding aggregated index) makes allowance for *significance* (synonyms: importance, influence, weight, etc.) of different single performance indices for the aggregated preference index. Namely, the aggregative function is supposed to be determined by appropriate non-negative parameters which are named *weight-coefficients* ("*weights*"), and which play role of single indices' significance estimations.

To distinguish between many single indices (which estimate alternatives' preference by different single criteria) and an only one aggregated index (which evaluates alternatives' preference by an aggregated criterion) we'll use the pair of antonyms "single-aggregated", but an user has a wide selection to pick from the large set of English antonyms pairs: local-global, particular-common, specific-general, individual-collective, isolated-joint, analytic-synthetic, and so on.

In more formalized mode Aggregated Preference Indices method may be represented as a series of the following four steps: (0) alternatives and attributes fixation; (1) single preference indices construction; (2) aggregative function selection; (3) weight-coefficients estimation.

Suppose that $\boldsymbol{k}$ *multi-attribute alternatives* $\boldsymbol{A(1),\ldots,A(k)}$ are described by vectors $\boldsymbol{a(i)=(a_1(i),\ldots,a_m(i))}$, where $\boldsymbol{a_j(i)}$ is a numerical value of *attribute* $\boldsymbol{a_j}$ for alternative $\boldsymbol{A(i)}$, $\boldsymbol{j=1,\ldots,m}$; $\boldsymbol{i=1,\ldots,k}$ ($\boldsymbol{m}$ – number of attributes, $\boldsymbol{k}$ – number of alternatives under consideration). In other words, multi-attribute alternative $\boldsymbol{A(i)}$ is described by a vector $\boldsymbol{a(i)=(a_1(i),\ldots,a_m(i))}$ which is a value of the $\boldsymbol{m}$-dimensional variable vector $\boldsymbol{a=(a_1,\ldots,a_m)}$ of the alternatives' attributes. All alternatives under consideration compose finite set $\boldsymbol{A=\{A(i),\ i=1,\ldots,k\}}$.

A decision-maker (DM) evaluates preference of the alternatives from the set $\boldsymbol{A}$ by many *single preference indices* $\boldsymbol{q_1,\ldots,q_m}$, each of them being a function $\boldsymbol{q_j=q_j(a_j)}$ of a correspondent attribute $\boldsymbol{a_j}$, $\boldsymbol{j=1,\ldots,m}$. A function $\boldsymbol{q_j=q_j(x_j)}$ may be treated as a *single preference criterion*: a value $\boldsymbol{q_j(i)=q_j(a_j(i))}$ of function $\boldsymbol{q_j=q_j(a_j)}$ is a *single estimation of preference* of alternative $\boldsymbol{A(i)}$. Without the loss in generality it may be supposed that all single indices are *normalized*, i.e., any single index $\boldsymbol{q_j=q_j(x_j)}$ meets the inequality $\boldsymbol{0<=q_j<=1}$. As this normalization takes place, the minimal value $\boldsymbol{q_j(r)=q_j(a_j(r))=0}$ of single index $\boldsymbol{q_j=q_j(x_j)}$ is correlated with alternative $\boldsymbol{A(r)}$ which has the minimal degree of preference, and the maximal value $\boldsymbol{q_j(s)=q_j(a_j(s))=0}$ – with alternative $\boldsymbol{A(s)}$ which has the maximal degree of preference. So, multifunction $\boldsymbol{q(a)=(q_1(a_1),\ldots,q_m(a_m))}$ sets up a correlation between alternative $\boldsymbol{A(i)}$ with attributes values $\boldsymbol{a(i)=(a_1(i),\ldots,a_m(i))}$ and its *multi-criteria estimation* $\boldsymbol{q(i)=(q_1(i),\ldots,q_m(i))}$, where $\boldsymbol{q_j(i)=q_j(a_j(i))}$ is a value of *normalization function* (single preference index) $\boldsymbol{q_j=q_j(a_j)}$, $\boldsymbol{j=1,\ldots,m}$; $\boldsymbol{i=1,\ldots,k}$.

Single preference indices $\boldsymbol{q_1,\ldots,q_m}$ being fixed, alternatives' preference may be compared with the help of *component-wise order relation*, which is determined for alternatives $\boldsymbol{A(r)}$, $\boldsymbol{A(s)}$ by the condition: $\boldsymbol{A(r)>>A(s)}$ (read: alternative $\boldsymbol{A(r)}$ dominates alternative $\boldsymbol{A(s)}$ by multi-criteria estimation $\boldsymbol{q=(q_1,\ldots,q_m)}$ of preference) if and only if for any $\boldsymbol{j=1,\ldots,m}$ it takes place unstrict inequality $\boldsymbol{q_j(r)>=q_j(s)}$, and for a $\boldsymbol{l}$ from the set $\boldsymbol{\{1,\ldots,m\}}$ it takes place strict inequality $\boldsymbol{q_l(r)>q_l(s)}$. In other words: alternative $\boldsymbol{A(r)}$ is more preferable as a whole entity (by the aggregated set $\boldsymbol{q=(q_1,\ldots,q_m)}$ of single criteria) than alternative $\boldsymbol{A(s)}$ ($\boldsymbol{A(r)>>A(s)}$) if and only if alternative $\boldsymbol{A(s)}$ is not more preferable than $\boldsymbol{A(r)}$ from the point of view of each single criterion $\boldsymbol{q_j}$ ($\boldsymbol{q_j(r)>=q_j(s)}$, $\boldsymbol{j=1,\ldots,m}$) and there exists a criterion $\boldsymbol{q_l}$, such that $\boldsymbol{A(r)}$ is more preferable than $\boldsymbol{A(s)}$ from the point of view of the criterion ($\boldsymbol{q_l(r)>q_l(s)}$).

The component-wise order relation usually gives a *partial order* only: there exists a pair of alternatives $\boldsymbol{A(r)}$, $\boldsymbol{A(s)}$ from set $\boldsymbol{A}$ such that all three relations $\boldsymbol{A(r)>>A(s)}$, $\boldsymbol{A(s)>>A(r)}$, and $\boldsymbol{A(s)=A(r)}$ are not fulfilled. Often, these pairs of *component-wise order incomparable alternatives* form an overwhelming majority among all possible pairs of alternatives from set $\boldsymbol{A}$. So, multi-criteria comparison of multi-attribute alternatives meets *the problem of alternatives' preference incomparability*. For a solution of the problem may be used so called "linearization" of a component-wise strict order relation >> by a scalar-valued *aggregative function* (synonyms: synthesizing function, convolution, etc.) $\boldsymbol{Q=Q(q)=Q(q_1,\ldots,q_m)}$ which meets the *condition of monotony*: if $\boldsymbol{A(r)>>A(s)}$, then $\boldsymbol{Q(q(r))>=Q(q(s))}$. Also, it is supposed that *aggregated preference index* $\boldsymbol{Q(q;w)}$ meets some other obvious conditions: $\boldsymbol{0<=Q(q;\ w)<=1}$ – *normalization condition*, and $\boldsymbol{Q(0,\ldots,0)=0}$, $\boldsymbol{Q(1,\ldots,1)=1}$ – *edge conditions*. A value $\boldsymbol{Q(q(i))=Q(q_1(i),\ldots,q_m(i))}$ of synthesizing function $\boldsymbol{Q(q)}$ for alternative $\boldsymbol{A(i)}$ is a measure of preference of the alternative (*aggregated estimation of preference*).

To make allowance for *significance* of different single performance indices it is supposed that aggregative function $\boldsymbol{Q(q)}$ is determined by vector $\boldsymbol{w=(w_1,\ldots,w_m)}$ of parameters $\boldsymbol{w_1,\ldots,w_m}$: $\boldsymbol{Q(q)=Q(q;w)=Q(q_1,\ldots,q_m;w_1,\ldots,w_m)}$. These parameters are named *weight-coefficients* ("*weights*"), and play role of single indices' significance estimations. Weight-coefficients meet the two conditions: $\boldsymbol{w_j>=0}$ – *condition of non-negativity*, and $\boldsymbol{w_1+\ldots+w_m=1}$ – *normalization condition*. Weight-coefficient $\boldsymbol{w_j}$ is a measure of single preference index' significance (importance, influence, etc.) for aggregated estimation $\boldsymbol{Q(q;w)=Q(q_1,\ldots,q_m;w_1,\ldots,w_m)}$ of alternatives preference.

After selection of a concrete *weight-vector* $\boldsymbol{w=(w_1,\ldots,w_m)}$ of parameters $\boldsymbol{w_1,\ldots,w_m}$, aggregative function $\boldsymbol{Q(q)=Q(q;w)}$ is completely determined, and may be used for construction of the required estimations $\boldsymbol{Q(q(i);w)=Q(q_1(i),\ldots,q_m(i);w_1,\ldots,w_m))}$, $\boldsymbol{i=1,\ldots,k,}$ of preference's degrees for alternatives $\boldsymbol{A(1),\ldots,A(k)}$.

As alternatives of a decision-making are frequently some "*objects*" amongst which a decision-maker must choose a most preferable one, a correspondent process of alternatives' preference estimation may be interpreted as a process of estimation of objects' *quality*. Here the term "*object*" means a tangible or intangible thing (entity) whose quality may be described by a totality of the object's attributes (by an attribute-vector $a=(a_1,\ldots,a_m)$). Examples of objects: a *device*; a *commercial bank*; a *machine*; a *model of development*; an *investment contract*, etc. Examples of quality: *usability* of a device; *reliability* of a commercial bank; *maintainability* of a machine; *sustainability* of a model of development; *availability* of an investment contract, etc. Examples of attributes: *maximal speed* of a vehicle; *equity capital* of a commercial bank; *power* of an engine; *pay-back period* of an investment contract, etc.

Different objects may possess of different or equal degrees (gradations, extents, measures, etc.) of any of their attribute and of a fixed quality. Therefore, an object's degree of quality is determined by value of a correspondent attribute-vector $a=(a_1,\ldots,a_m)$. Thus, any process of alternatives' preference estimation with help of an aggregated preference index may be put into terminological shape of correspondent *objects quality estimation* by use of an *aggregated quality index*.

6 COMPUTER PROTOTYPE DEVELOPMENT

A flexible interactive decision support system (DSS) APIS (APIS – Aggregated Preference Indices System) is proposed as software for decision-making under uncertainty. The structure of Aggregated Preference Indices method (which is realized in DSS APIS) is a special case of general structure of Aggregated Indices Method (AIM) and consists in four successive steps (stages). Such sequence of operations (steps) for constructing of general estimations of alternatives' preference is named *APIS Project*. The steps of a APIS Project are special cases of above-stated general case, and may be interpreted in a analogous manner: (0) alternatives, attributes, and attributes values fixation; (1) monotone single preference indices construction; (2) additive aggregative function selection; (3) weight-coefficients estimation by uncertain information. The final step of getting of output data of an APIS Project may be marked out: (4) Calculation of aggregated preference estimations for alternatives.

A decision-maker (DM) starts to work with DSS APIS by fixing a list (vector) $a=(a_1,\ldots,a_m)$ of attributes and a list $A(1),\ldots,A(k)$ of decision alternatives under consideration. Then the DC must enter a $m*k$-dimensional rectangular matrix $(a_j(i))$ of attributes values with m rows and k columns ($j=1,\ldots,m$; $i=1,\ldots,k$), where m is a number of attributes, and k – number of alternatives under consideration. Element $a_j(i)$ of the matrix is a numerical value of attribute a_j for alternative $A(i)$. So, multi-attribute alternative $A(i)$ is described by a row-vector $a(i)=(a_1(i),\ldots,a_m(i))$ which is a value of the m-dimensional variable vector $a=(a_1,\ldots,a_m)$ of the alternatives' attributes. In the same way, values of attribute a_j form column-vector $(a_j(1),\ldots,a_j(k))^T$ (T is the mark of transposition operation) of matrix $(a_j(i))$ of attributes' values.

Sometimes an attribute has non-numerical gradations of its value (e.g., values of an attribute are an expert committee's scores with ordered gradations ***"bad"***, ***"neutral"***, ***"good"***). In such case, the non-numerical gradations must be previously arithmetizated, i.e. they must be transformed into numeric form by a monotone transformation f (e.g., $f(\text{"bad"})=-1$, $f(\text{"neutral"})=0$, $f(\text{"good"})=1$, or $f(\text{"bad"})=0$, $f(\text{"neutral"})=1/2$, $f(\text{"good"})=1$, etc.). After such arithmetization an attribute may be treated as a usual numerical variable.

Any single preference index q_j, $j=1,\ldots,m,$ in DSS APIS is determined on a finite numerical interval $[MIN_j,MAX_j]$ by an increasing or decreasing power normalization function with a positive exponent ($Exponent(j) > 0$).

If degree of preference q_j is increasing when value of attribute a_j is increasing on interval $[MIN_j,MAX_j]$, then non-decreasing normalization function $q_j=q_j(a_j)$ is determined by formulas:

$q_j=q_j(a_j)=0$, when $a_j < MIN_j$;

$q_j(a_j)=q_j(a_j;Exponent(j)) = [(a_j-MIN_j)/(MAX_j-MIN_j)]^{Exponen(j)t}$, when $MIN_j<=a_j<= MAX_j$;

$q_j=q_j(a_j)=1$, when $a_j>MAX_j$.

When parameter $Exponent(j)$ meets condition $Exponent(j)>1$ (condition $Exponent(j)<1$), then function $q_j = q_j(a_j)$ is convex downwards (convex upwards) on the interval $[MIN_j,MAX_j]$. When parameter $Exponent(j)$ meets condition $Exponent(j)=1$, then function $q_j = q_j(a_j)$ is linear on the interval $[MIN_j,MAX_j]$. So, a DM can take into account information on type and degree of normalization function's convexity by choosing an appropriate value of parameter $Exponent(j)$.

Minimal value $q_j=q_j(a_j)=0$ (maximal value $q_j=q_j(a_j)=1$) of single preference index $q_j=q_j(a_j)$ is arrived for such values of attribute a_j that are no more than MIN_j (no less than MAX_j). So, in case when an attribute takes for an alternative value which is less than MIN_j (which is more than MAX_j), this alternative has the least (the most) degree of preference estimation from the point of view of the attribute.

If degree of preference q_j is decreasing when value of attribute a_j is increasing on interval $[MIN_j,MAX_j]$, then non-increasing normalization function $q_j=q_j(a_j)$ is determined by formulas:

$q_j=q_j(a_j)=1$, when $a_j < MIN_j$;

$q_j(a_j)=q_j(a_j;Exponent(j)) = [(MAX_j-a_j)/(MAX_j-MIN_j)]^{Exponen(j)t}$, when $MIN_j<=a_j<= MAX_j$;

$q_j=q_j(a_j)=0$, when $a_j>MAX_j$.

When parameter $Exponent(j)$ meets condition $Exponent(j)>1$ (condition $Exponent(j)<1$), then function $q_j = q_j(a_j)$ is convex downwards (convex upwards) on the interval $[MIN_j,MAX_j]$. When parameter $Exponent(j)$ meets condition $Exponent(j)=1$, then function $q_j = q_j(a_j)$ is linear on the interval $[MIN_j,MAX_j]$. So, a DM can take into account information on type and degree of normalization function's convexity by choosing an appropriate value of parameter $Exponent(j)$.

Minimal value $q_j=q_j(a_j)=0$ (maximal value $q_j=q_j(a_j)=1$) of single preference index $q_j=q_j(a_j)$ is arrived for such values of attribute a_j that are no less than MAX_j (no more than MIN_j). So, in case when an attribute takes for an alternative value which is more than MAX_j (which is less than MIN_j), this alternative has the least (the most) degree of preference estimation from the point of view of the attribute.

After formation of monotone normalization functions $q_j=q_j(a_j)$, $j=1,\ldots,m$, values of all single preference indices for all alternatives under consideration may be calculated. These values form a $m*k$-dimensional rectangular matrix $(q_j(i))$ of single preference indices values with m rows and k columns ($j=1,\ldots,m$; $i=1,\ldots,k$), where m is a number of attributes, and k – number of alternatives under consideration. Element $q_j(i)$ of the matrix is a numerical value of single preference index q_j for alternative $A(i)$. So, multi-attribute alternative $A(i)$ is described by a row-vector $q(i)=(q_1(i),\ldots,q_m(i))$ which is a value of the m-dimensional variable vector $q=(q_1,\ldots,q_m)$ of the alternatives' single preference indices. In the same way, values of single preference index q_j form column-vector $(q_j(1),\ldots,q_j(k))^T$ (T is the mark of transposition operation) of matrix $(q_j(i))$ of single preference indices' values. Thus, any alternative A(i) has now a multi-criteria estimation $q(i)=(q_1(i),\ldots,q_m(i))$ of its preference.

As it was stated in the foregoing sketchy overview of general Aggregated Indices method, any synthesizing function $Q=Q(q)=Q(q_1,\ldots,q_m)$, that gives for alternative $A(i)$ aggregated estimation $Q(q(i))$ of its preference, must meet certain conditions:

(1)*condition of monotony* – if alternative $A(s)$ is not more preferable than $A(r)$ from the point of view of each single preference criterion q_j (i.e., nequalities $q_j(r)>=q_j(s)$, $j=1,\ldots,m$, take place) and there exists a single preference criterion q_l, such that $A(r)$ is more preferable than $A(s)$ from the point of view of the criterion (i.e., inequality $q_l(r)>q_l(s)$ takes place), then $Q(q(r))>=Q(q(s))$;

(2)*condition of normalization* – value of aggregated preference estimation $Q(q)$ varies from the minimal value 0 (for the least preferable alternatives) to the maximal value 1 (for the most preferable alternatives) (another way, values of aggregated preference index $Q(q)$ meet inequality $0<= Q(q)<= 1$);

(3)*edge condition* – if all arguments (single performance indices $q_1,\ldots,q_m$) of aggregative function $Q(q_1,\ldots,q_m)$ take on the minimal value, i.e. the "worst" single preference estimation, $q_j=0$ (the maximal value, i.e. the "best" single preference estimation, $q_j=1$), then aggregated preference index takes on the minimal value, i.e. the "worst" preference estimation, $Q(q_1,\ldots,q_m)=Q(0,\ldots,0)=0$ (the maximal value, i.e. the "best" aggregated preference estimation, $Q(q_1,\ldots,q_m)=Q(1,\ldots,1)=1$).

In many existing now decision support systems *additive aggregative function* (*weighted arithmetical mean*) $Q(q;w)=Q(q_1,\ldots,q_m;w_1,\ldots,w_m)=q_1*w_1+\ldots+q_m*w_m$ is selected as a synthesizing function. It is obvious, that the additive aggregative function meets all abovementioned conditions (condition of monotony, condition of normalization, and edge condition). Thus, additive aggregated preference index $Q(q;w)$ may be used as an appropriate tool for getting of aggregated preference estimations $Q(q(i);w)=Q(q_1(i),\dots,q_m(i);w_1,\dots,w_m)=q_1(i)*w_1+\dots+q_m(i)*w_m$ of alternatives $A(i)$, $i=1,\dots,k$. Weighted arithmetical mean $Q(q;w)$ is the most popular type of synthesizing functions. And there are some reasons for such popularity of this additive aggregative function. First of all, it is the most simple and easy interpretable synthesizing function. Then, weighted arithmetical mean is, as psychological experiments and practice of decision making show, a quite natural form of single criteria aggregation for majority of real decision-makers (e.g., see works [4,5]). Therefore, just additive aggregative function is using in DSS APIS for aggregated preference estimations construction.

Weight-coefficients estimation is the most subtle and delicate stage in Aggregated Indices Method because of usual *shortage of information* ("*information deficiency*") about *exact numerical values* of weight-coefficients. As a rule, a decision-maker has only *non-numeric information* on weights, this information being represented by comparative propositions of the type: "single preference index q_r is more significant for aggregated preference index' value determination than single preference index q_s", "degree of significance of single preference index q_r for aggregated preference index' value determination is equal to analogous degree of significance of single index q_s", and so on. Sometimes, a decision-maker can additionally determine intervals for the weight-coefficients values. The noted shortage of information implies the *problem of weight-coefficients estimation on the base of uncertain information*.

The main advantage of DSS APIS over another well known decision support systems just consists in its ability to take into account different types of uncertain information on weight-coefficients. Namely, ASPIS works with the next types of uncertain information.

Non-numeric information on weights – non-numeric information (*ordinal information*) on weight-coefficients values is determined by a system $OI(w)=\{w_r=w_s;w_u>w_v;\dots\}$ of equalities and inequalities for weight-coefficients (marks r, s, u, v take values from set $\{1,2,\dots,m\}$).

Non-exact information on weights – non-exact information (*interval information*) on weight-coefficients values is determined by a system $II(w)=\{a_j<=w_j<=b_j;\dots\}$ of inequalities and equalities (when $a_j=b_j$) for weight-coefficients (mark j takes values from set $\{1,2,\dots,m\}$).

NNN-information on weights – non-numeric, non-exact (inexact), and non-complete (incomplete) information on weights is a combination $I(w)$ of non-exact information (interval information) $II(w)$ on weights and non-numeric information (ordinal information) $OI(w)$ on weights. As a weight-vector may be ambiguously determined by a combination of these two types of information, modifier "non-complete" may be added to the name of the joint information, which is represented in the form of a system $I(w)=\{w_r=w_s;w_u>w_v;a_j<=w_j<=b_j;\dots\}$ of equalities and inequalities for weight-coefficients (marks r, s, u, v, j take values from set $\{1,2, \dots ,m\}$).

Moreover, DSSS ASPIS works with *indirect uncertain information* on weight-coefficients, this information being obtained from the analogous information on aggregated preference indices $Q(q(i);w)$, $i=1,\dots,k$, for different alternatives under consideration. For example, consider that it is obtained ordinal (non-numeric) information that alternative $A(r)$ of a decision is more preferable than alternative $A(s)$. It means that inequality $Q(q(r);w)>Q(q(s);w)$ takes place. As ASPIS uses additive aggregative function $Q(q;w)=q_1*w_1+\dots+q_m*w_m$, the abovementioned inequality for the aggregated preference estimations $Q(q(r);w)$, $Q(q(s);w)$ may be transformed into linear inequality for weight-coefficients: $q_1(r)*w_1+\dots+q_m(r)*w_m>q_1(s)*w_1+\dots+q_m(s)*w_m$. Types of uncertain information on aggregated preference estimations (with which ASPIS works) are outlined below.

Non-numeric information on aggregated preference estimations – non-numeric information (ordinal information) on aggregated preference index' values is determined by a system $OI(Q)$ of equalities and inequalities for different alternatives: $OI(Q)=\{Q(q(r);w)=Q(q(s);w);Q(q(u);w)>Q(q(v);w);\dots\}$ (marks r, s, u, v take values from set $\{1,2,\dots,k\}$).

Non-exact information on aggregated preference estimations – non-exact information (interval information) on aggregated preference index' values is determined by a system $II(Q)=\{A_i<=Q(q(i);w)<=B_i;\ldots\}$ of equalities (when $A_j=B_i$) and inequalities for different alternatives' aggregated preference estimations (mark i takes values from set $\{1,2,\ldots,k\}$).

NNN-information on aggregated preference estimations – non-numeric, non-exact (inexact), and non-complete (incomplete) information on aggregated preference index' values for different alternatives is a combination $I(Q)$ of non-exact information (interval information) $II(Q)$ on aggregated preference index' values and non-numeric information (ordinal information) $OI(Q)$ on aggregated preference index' values. As a weight-vector may be ambiguously determined by a combination of these two types of information, modifier "non-complete" may be added to the name of the joint information, which is represented in the form of a system $I(Q)$ of equalities and inequalities for aggregated preference index' values for different objects: $I(Q)=\{Q(q(r);w)=Q(q(s);w);Q(q(u);w)>Q(q(v);w);A_i<=Q(q(i);w)<=B_i;\ldots\}$ (marks r, s, u, v, i take values from set $\{1,2,\ldots,k\}$).

Referred above types of direct and indirect uncertain information on weight-coefficients may combine into one *joint NNN-information*. This joint non-numeric, non-exact (inexact), and non-complete (incomplete) information on weight-coefficients and on aggregated preference index' values for different alternatives is a combination $I=\{I(w),I(Q)\}$ of NNN-information $I(Q)$ on aggregated preference index' values and NNN-information $I(w)$ on weight-coefficients. As a weight-vector may be ambiguously determined by a combination of these two types of information, modifier "non-complete" may be added to the name of the joint information, which is represented in the form of two systems ($I(Q)$ and $I(w)$) of equalities and inequalities for weight-coefficients and for aggregated preference index' values for different alternatives. Further, an obtained NNN-information I is using in DSS APIS for reducing down to the limit a set of all possible weight-vectors, i.e. for reducing to the limit uncertainty of weight-vectors and of correspondent aggregated preference estimations [9,12,17,22].

In DSS ASPIS weights $w_1,\ldots,w_m$ are represented with a finite precision. Namely, it is fixed that measurement of weight-coefficients is accurate to within a step $h=1/n$, where n is a positive integer number. In this case an infinite set of all possible weight-vectors may be approximated by a finite set $W(m,n)=\{w(t)=(w_1(t)\ldots,w_m(t)),t=1,\ldots,N(m,n)\}$ of *all possible weight-vectors* with discrete components (a component $w_j(t)$ of weight-vector $w(t)$ takes discrete values $0, 1/n, 2/n, \ldots ,(n-1)/n, 1$). Here $N(m,n)=(n+m-1)!/[n!(m-1)!]$ is a number of all possible weight-vectors with discrete components, which are measuring by a discrete scale with a step $h=1/n$.

A joint NNN-information I may help to reduce a set $W(m,n)$ of all possible weight-vectors to a set $W(m,n;I)=\{w(t)=(w_1(t)\ldots,w_m(t)),t=1,\ldots,N(m,n;I)\}$ of all *admissible* (from the point of view of joint NNN-information I on weight-coefficients and/or on aggregated preference index' values) *weight-vectors* with discrete components. Here $N(m,n;I)$ is a number of all admissible weight-vectors ($N(m,n;I)<=N(m,n)$).

It is rather natural to use as a mean estimation of weight-coefficient w_j an average $Mw_j(I)=[w_j(1)+\ldots+w_j(N(m,n;I))]/N(m,n;I)$ of all admissible (from the point of view of joint NNN-information I) values of the weight-coefficient. The mean $Mw_j(I)$ is such measure of significance of single index q_j, that takes into account the whole joint NNN-information I. So, a vector $(Mw_1(I),\ldots,Mw_m(I))$ of the mean estimations may be treated as a required *numerical image of NNN-information* I. Standard deviation $Sw_j(I)=\{[\{w_j(1)-w_j(I)\}^2+\ldots+\{w_j(N(m,n;I))-w_j(I)\}^2]\}^{1/2}/N(m,n;I)$ may be used as a measure of precision for estimation $Mw_j(I)$ of significance of single index q_j. Also, relative part $Pw(r,s;I)=N(\{t:w_r(t)>w_s(t)\})/N(m,n;I)$ of all admissible weight-vectors $w(t)$ for which inequality $w_r(t)>w_s(t)$ takes place may be used as a *measure of reliability* of r-th single index significance' dominance over analogous parameter of s-th single index.

After the above-stated *principle of uncertain information on weight-coefficients transformation into numerical estimations of these coefficients* is accepted, analogous transformation may be used for construction of aggregated preference estimations for alternative.

Values of an aggregated preference index $Q(q;w)$ for alternative $A(i)$ are elements of set $Q(i;m,n)=\{Q(q(i);w(t)),w(t)=(w_1(t),\dots,w_m(t)),t=1,\dots,N(m,n)\}$ of *all possible values of aggregated preference index* for alternative $A(i)$ ($i = 1,\dots,k$). In other words, the aggregated preference index $Q(q;w)$ for alternative $A(i)$ passes through the set $Q(i;m,n)$ when weight-vector $w(t)$ varies over set $W(m,n)$ of all possible weight-vectors (values $Q(q(r);w(t))$ and $Q(q(s);w(t))$ of aggregated preference index may be equal for some alternatives $A(r)$, $A(s)$).

Correspondingly, admissible values of an aggregated preference index $Q(q;w)$ for alternative $A(i)$ form set $Q(i;m,n;I)=\{Q(q(i);w(t)),w(t)=(w_1(t)\dots,w_m(t)),t=1,\dots,N(m,n;I)\}$ of all *admissible* (from the point of view of joint NNN-information I on weight-coefficients and/or on aggregated preference index' values) values of the aggregated preference index for alternative $A(i)$ ($i=1,\dots,k$). In other words, when a joint NNN-information I is taken into account, the aggregated preference index $Q(q;w)$ for alternative $A(i)$ passes through the set $Q(i;m,n;I)$ when weight-vector $w(t)$ varies over set $W(m,n;I)$ of all admissible weight-vectors (values $Q(q(r);w(t))$ and $Q(q(s);w(t))$ of aggregated preference index $Q(q;w)$ may be equal for some alternatives $A(r)$, $A(s)$). Here $N(m,n;I)$ is a number of all admissible values of aggregated preference index ($N(m,n;I)<=N(m,n)$).

It is rather natural to use as a mean estimation of preference of alternative $A(i)$ an average $MQ(q(i);I)=[Q(q(i);w(1))+\dots+Q(q(i);w(N(m,n;I))]/N(m,n;I)$ of all admissible (from the point of view of joint NNN-information I) values of aggregated index for alternative $A(i)$. The mean $MQ(q(i);I)$ is such measure of preference of alternative $A(i)$, that takes into account the whole joint NNN-information I. As a measure of precision for average estimation $MQ(q(i);I)$ standard deviation $SQ(q(i);I)=\{[\{Q(q(i);w(1))-Q(q(i);I)\}^2+\dots+\{Q(q(i);w(N(m,n;I))-Q(q(i);I)\}^2]/N(m,n;I)\}^{1/2}$ may be used. Also, relative part $PQ(r,s;I)=N(\{t:Q(q(r);w(t))>Q(q(s);w(t))\})/N(m,n;I)$ of all admissible weight-vectors $w(t)$ for which inequality $Q(q(r);w(t))>Q(q(s);w(t))$ takes place may be used as a measure of *reliability of dominance* of alternative $A(r)$ preference' degree over preference' degree of alternative $A(s)$.

So, the **main goal of APIS Project is obtained** – all alternatives $A(1),\dots,A(k)$ of the decision-making get correspondent average aggregated preference estimations $MQ(q(1);I),\dots,MQ(q(k);I)$. Also, measures of these average estimations' precision (standard deviations) $SQ(q(1);I),\dots,SQ(q(k);I)$ are calculated. Thus, alternatives $A(1),\dots,A(k)$ may be *ranked* by degrees $MQ(q(1);I),\dots,MQ(q(k);I)$ of their preference for the decision maker. Reliability of such ranking may be estimated for a pair of alternatives $A(r)$, $A(s)$ by calculated reliability dominance estimation $PQ(r,s;I)$, $r,s=1,2,\dots,k$. It must be noted especially, that all above mentioned estimations ($MQ(q(i)$, $SQ(q(i);I)$, $PQ(r,s;I)$) take into account non-numerical (ordinal), imprecise (interval) and incomplete information I, which is accessible to the decision-maker. These estimations are visualizing by a diagram which shows a pictorial rendition of final ranking of the alternatives by their degrees of preference (by values of the aggregated preference index) [5].

7 CASE STUDY

The shortest way to understand how Decision Support System (DSS) APIS works is the well known "case study approach". Here a simple illustrative case study of cars usability estimation by a consumer is proposed.

Suppose, that a consumer is estimating quality "usability" (convenience, utility for his personal needs) of nine cars listed below (these cars are taken from category "Small Cars" with price up to $ 15 000).

List of cars under estimation

1.Ford Fiesta

2.Hyundai Getz

3.Honda Jazz

4.Toyota Echo

5.VW Polo Club

6.Daihatsu Charade

7.Suzuki Ignis

8.Daihatsu YRV

9.Peugeot 206

The consumer takes into account next five initial characteristics (attributes) which are relevant (in his opinion) to a car's usability estimation. Any relevant characteristic may be treated as a single criterion for a car's usability estimation. These characteristics (attributes, criteria) are listed below with a short comment.

List of car's relevant characteristics (attributes)

1."Price": Consideration is given to ongoing drive-away pricing.

2."Expenses": Current expenses (operational expenditures), i.e. fuel consumption, servicing and repair costs over three years, including insurance.

3."Safety": All safety features, including the car's pedestrian safety performance and its dynamic safety features such as anti locking brake and stability control systems; the car's theft prevention features.

4."Comfort": Interior design, and the position, layout, access and operation of all controls and facilities; noise, vibration and harshness levels of the car's engine and transmission; all seats shaping and support. "Comfort" is the human aspect of usability and determines how occupants interface with the machine.

5."Performance": Acceleration and passing performance in combination with every-day driveability; the car's stability, precision and control in cornering manoeuvres; steering sensitivity, response, and road feedback; braking performance, stability, control/regulation, and pedal feel.

The relevant characteristics of the cars under estimation were scored by top cars experts in the framework of the program "Australia's Best Cars" (ABC-2004). Every score varies from the "worst" gradation "well below average" (numerical value is equal to one) to the "best" gradation "well above average" (numerical value is equal to five). The scores are represented in the following table (these numeric data are taken from ABC web site).

Scores of the cars characteristics (particular criteria)

Car's name	1.Price	2.Expenses	3.Safety	4.Comfort	5.Performance
1.Ford Fiesta	4,0	3,5	3,5	3,7	4,3
2.Hyundai Getz	4,0	4,0	3,0	3,7	3,3
3.Honda Jazz	2,0	3,0	3,0	4,0	4,3
4.Toyota Echo	4,0	4,0	3,0	3,0	3,0
5.VW Polo Club	2,0	3,0	4,5	3,7	3,3
6.Daihatsu Charade	5,0	4,5	2,5	1,3	1,7
7.Suzuki Ignis	4,0	4,0	2,5	2,3	2,0
8.Daihatsu YRV	3,0	4,0	2,5	2,0	2,3
9.Peugeot 206 XR	2,0	3,5	3,0	2,3	3,3

So, the consumer has five single scores of different aspects of cars' usability. How can he obtain an aggregated score of a car's usability from the abovementioned data? For such single "aggregated estimation" ("aggregated index", "overall estimation", "universal indicator", etc.) constructing from a set of single estimations just the DSS APIS may be proposed.

The cars under estimation are exemplifying more general notion "***objects*** under estimation", which is used in the DSS. In the case number k of objects is equal to nine ($k = 9$). As the user wants to estimate quality "usability" for the most usable car selection, he (she) can treat these cars (objects) as decision alternatives. In this case the user plays role of a Decision Maker (DM).

The cars' characteristics may be treated as single criteria for objects' quality estimation. So, the DM has five relevant (in relation to his needs) cars' characteristics, these characteristics being measured in conditional "scores", which are usually ascribed to objects by experts. The characteristics determine corresponding single criteria of cars' usability and are exemplifying more general notion "***attributes*** of objects", which is used in the DSS. In our cases number $\boldsymbol{m}$ of attributes is equal to five ($\boldsymbol{m = 5}$).

Then the user inserts objects attributes values. Any column of the inserted table of attributes values is connected with a corresponding attribute, and any row of the table consists of a corresponding object's attributes values. In the case these values are equal to the scores given by top cars experts in the framework of the program "Australia's Best Cars" (ABC-2004). Every score varies from the "worst" gradation "well below average" (numerical value is equal to one) to the "best" gradation "well above average" (numerical value is equal to five).

In working window "Single Preference Indices Manager" a user sets rules for single indices construction. A single index is a function (power function, in this version of the DSS) of a corresponding attribute and provides the attribute's values normalization. The normalization reduces arbitrary variation interval of the attribute to standard variation interval [0,1] of the single index. Suppose that the user (the consumer of the cars) selects the simplest linear increasing functions to normalize the cars attributes values, and sets variation intervals for the attributes from their minimal to their maximal values.

On the base of the rules for single indices construction DSS APIS calculates a table of particular indices values with the standard variation interval [0,1]. Every row of this table may be treated as a multi-criteria estimation of a corresponding object (alternative).

Now, the user may state his opinion on comparative significance of different single indices for final estimation of the objects quality (alternatives preference). This step is the most subtle and delicate operation in the chain of aggregated preference indices construction. **The main advantage of the DSS just consists in the ability to work with non-numeric (namely, ordinal), non-exact (interval), and non-complete information (*nnn-information*)** on *weight-coefficients* ("weights") $\boldsymbol{w(1),\ldots,w(m)}$, these weights being estimations of corresponding single indices significance.

Suppose that the user sets an ordinal information only in the form of the next chain of equalities and inequalities for the corresponding weight-coefficients $\boldsymbol{w(1),\ldots,w(5)}$ of cars particular indices: $\boldsymbol{w(5) = w(4) > w(3) > w(1) > w(2)}$, where $\boldsymbol{w(1) = w(Price); w(2) = w(Expenses); w(3) = w(Safety); w(4) = w(Comfort); w(5) = w(Performance)}$. Additionally the interval information is fixed in the form of inequality $\boldsymbol{w(2) >= 0{,}10}$.

The nnn-information for particular indices significance for final estimation of cars usability being fixed and the step $\boldsymbol{h=1/n=1/100}$ of the weight-coefficients measuring being set, the user passes to the next subtle and delicate operation. Namely, the DM must state his/her opinion on comparative "degree of quality" of the objects under estimation, this degree of quality being treated as a numeric value $\boldsymbol{Q(Object\ j)}$ of an a index $\boldsymbol{Q}$ for a corresponding object with name "***Object j***".

The value $\boldsymbol{Q(Object\ j)=0}$ ($\boldsymbol{Q(Object\ j)=1}$) of an aggregated preference index $\boldsymbol{Q}$ is the "worst" ("best") estimation of the object's preferability from the point of view of the general criterion $\boldsymbol{Q}$. The important advantage of DSS APIS consists in the ability to work with non-numeric (namely, ordinal), non-exact (interval), and non-complete information (*nnn-information*) on objects' degrees of quality. Suppose that the user has ordinal information about general estimations of the cars quality (usability, in the case): Ford Fiesta is more preferable for him/her then Honda Jazz. Number $\boldsymbol{N}$ of all possible weight-vectors is determined by a previously fixed step $\boldsymbol{h=1/n=1/100}$ of weight-coefficients measuring and is equal to $\boldsymbol{N = 4\ 598\ 126}$.

After calculation the user may see a number $\boldsymbol{N(I)}$ of all admissible (from the point of view of a previously introduced nnn-information $\boldsymbol{I}$ on weight-coefficients and aggregated indices) weight-vectors. Additionally, an amount $\boldsymbol{Inf(I)}$ (measured in the binary units – *bits*) of the information $\boldsymbol{I}$ is calculated. In the case under investigation the number $\boldsymbol{N(I)}$ of all admissible (from the point of view of a previously introduced by the user nnn-information $\boldsymbol{I}$ on weight-coefficients and aggregated indices) weight-vectors is equal to $\boldsymbol{N(I) = 151}$, the amount $\boldsymbol{Inf(I)}$ of the corresponding nnn-information being equal to $\boldsymbol{Inf(I) = 14{,}89}$ bits.

Using this input information DSS APIS visualizes a diagram of the single preference indices ordering by their significance, i.e. by corresponding weight-coefficients average values. Namely, on the diagram we can see red and blue intercepts of a straight line; an abscissa of a midpoint of a red interval shows an average estimation of a correspondent weight-coefficient, while the interval's length is equal to the doubled standard deviation of the weight-coefficient. An abscissa of a blue interval's right end shows the reliability for dominance relation between neighboring weight-coefficients.

In the case one can see that the Decision Maker (the user, the cars customer) rates highly comfort and performance of a car (w(Comfort) = w(Performance) 0,26), but doesn't afraid of high current expenses on car (see Fig.1).

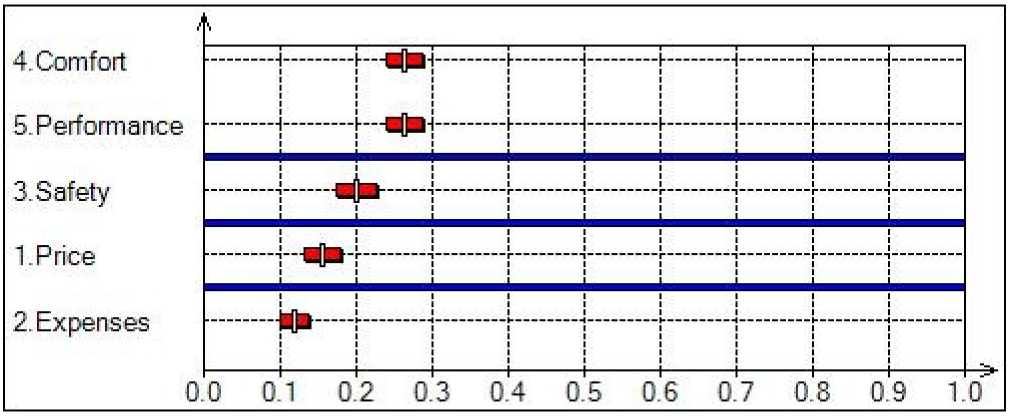

Figure 1. Weight-coefficients estimations visualization

DSS APIS simultaneously calculates and visualizes (see Fig.2) the main result of the Project – a diagram of the objects (alternatives) ordering by estimated degrees (values of the corresponding aggregated index ***Q***) of quality under evaluation. Namely, on the diagram we can see red and blue intercepts of a straight line; an abscissa of a midpoint of a red interval shows an average estimation of a correspondent object, while the interval's length is equal to the doubled standard deviation of the constructed aggregated preference index; an abscissa of a blue interval's right end shows the reliability for dominance relation between neighboring aggregated estimations.

In the case of the cars quality ("usability") estimation, the cars ordering by decreasing degrees of this quality (i.e., by values of the constructed aggregated preference index ***Q***) is shown on the diagram. The consumer may see, for example, that the "best" (the "worst") car for his needs (previously formulated and correspondingly formalized in the DSS terms) is *Ford Fiesta* (*Daihatsu YRV*) with general index of quality "usability" value being approximately equal to ***Q(Ford Fiesta) = 0,74*** (***Q(Daihatsu Charade) = 0,26***) . Also, one can see that the ordering of *Daihatsu Charade* and *Daihatsu YRV* by their average estimations of quality "usability" is not too reliable: probability of *Daihatsu Charade* domination over *Daihatsu YRV* is approximately equal 0,65 (not far from ½) (see Fig. 2).

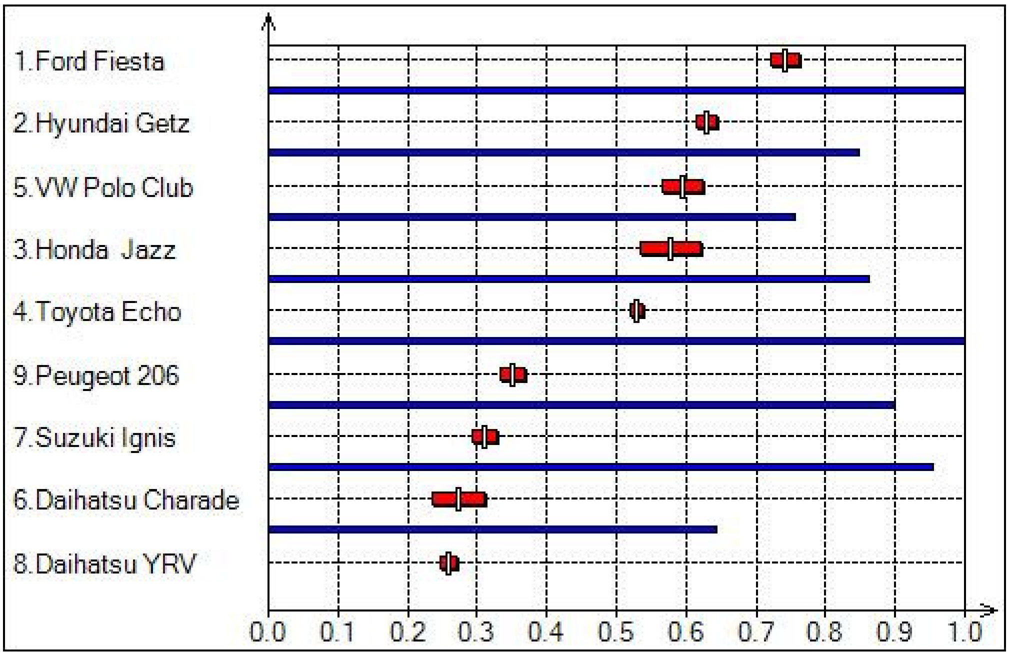

Figure 2. Aggregated preference indices visualization

So, the needed aggregated preference indices are constructed, and all 9 alternatives (objects – cars) are ranged by decreasing of the level of quality under estimation – namely, quality of "usability", which is scored from the point of view of the fixed Decision Maker.

The above outlined case study is one from a great amount of aggregated indices method application under deficiency of information. In any list of complex problems which may be decided by the developed AIM next topics must be mentioned: financial performance of commercial banks estimation [19]; energy systems assessment with sustainability indicators [1]; assessment of clean air technologies [2,6]; complex economical systems evaluation [10]; environmental and sustainability's indices construction [7,11,20,21]; complex biological systems scoring [16], and so on.

8 CONCLUSION

The idea of this paper is to show applicability of state-of-the-art ideas being developed in high technologies field to everyday needs. In spite of complex mathematic basis the usage of these technologies is available to PC or smartphone real user. The above technology adoption for wide user will allow to significantly reduce decision time for various problems as well as to decrease financial losses by restricting possibility of a wrong decision making. As a further research guideline is supposed a significant extension of services set for solving a major class of everyday tasks and problems.

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