K-best Night Vision Devices by Multi-Criteria Mixed-Integer Optimization Modeling

Daniela I. Borissova, Ivan C. Mustakerov

Abstract—The paper describes an approach for defining of k-best night vision devices based on multi-criteria mixed-integer optimization modeling. The parameters of night vision devices are considered as criteria that have to be optimized. Using different user preferences for the relative importance between parameters different choice of k-best devices can be defined. An ideal device with all of its parameters at their optimum is used to determine how far the particular device from the ideal one is. A procedure for evaluation of deviation between ideal solution and k-best solutions is presented. The applicability of the proposed approach is numerically illustrated using real night vision devices data. The proposed approach contributes to quality of decisions about choice of night vision devices by making the decision making process more certain, rational and efficient.

Keywords—K-best devices, mixed-integer model, multi-criteria problem, night vision devices.

I. INTRODUCTION

THE night vision devices (NVDs) offer significant benefits for night time performed tasks over unaided vision. They allow viewing in night time during numerous applications as military, security, rescue actions, navigation, hidden-object detection, wildlife observation, hunting, tourism, entertainment, etc. [1]-[4]. As a result of technological developments there exist a constantly growing number of different NVDs types and models with different parameters values. The existing wide variety of NVDs puts the problem of proper selection of most appropriate device conforming to given user requirements.

The performance evaluation and optimal selection of engineering systems have multi-level and multi-factor features. This defines essential difficulties that can be approached by multiple criteria decision-making methods [5]. Most decision making problems deals with multiple objectives which cannot be optimized simultaneously due to the inherent incommensurability and conflict between these objectives. Making a trade-offs between these objectives becomes a major subject to get the best compromise solution. A variety of methodologies for solving multiple objective decision-making problems have been proposed [6]-[15]. There are no better or worse techniques, but some techniques better suit to particular decision problems than others do [6]. The advantage of these

methods is that they can account for different impacts. The most popular multiple criteria decision-making methods include such models as scoring models [7], analytic hierarchy process (AHP) [8], analytic network process (ANP) [9], ELECTRE [10], PROMETHEE [11] utility models [12], TOPSIS [13], and axiomatic design [14]. The preference structure of PROMETHEE is based on pairwise comparisons. In this case the deviation between the evaluations of two alternatives on a particular criterion is considered. The AHP/ANP is fundamentally a process of laying out a structure of all the essential factors that influence the outcome of a decision. Numerical pairwise comparison judgments are then elicited to express people's understanding of the importance or likely influence of these elements on the final outcome [15]. The ELECTRE is a comprehensive evaluation approach that tries to rank a number of alternatives, each one of which is described in terms of a number of criteria. The main idea of ELECTRE approach is usage of proper utilization called "outranking relations" [10]. A variant of the ELECTRE approach is the TOPSIS method. It is based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution.

In contrast to these methods where pairwise comparisons and deviation between the evaluations of two alternatives on a particular criterion is considered, the proposed approach defines k-best devices as a solution of a single multi-criteria optimization task. The basic idea is to reduce a given set of alternatives to k-best accordingly the user point of view and taking into account given relations and restrictions. The proposed optimization model allows definition of k-best solution instead determination of a single Pareto-optimal solution.

The aim of current paper is to propose an approach to assist the user by selection of k-best devices in accordance to the importance of NVDs performance parameters. The obtained subset of k-best devices can be a basis for more rational and efficient decision-making. A procedure for evaluation of deviation between ideal solution and each of k-best devices is presented.

II. PROBLEM DESCRIPTION

When choosing a NVD the user acts as a decision-maker (DM) and should consider all the relevant costs and benefits of the options for the set of devices to choose from. The preferred device should be that which comes close to the decision maker's objectives, which may often conflict. The performance of the NVDs depends on many parameters where

D. I. Borissova is with the Institute of Information and Communication Technology at the Bulgarian Academy of Sciences, Sofia – 1113, Bulgaria (phone: 3952 9792055; e-mail: dborissova@iit.bas.bg).
I. C. Mustakerov is with the Institute of Information and Communication Technology at the Bulgarian Academy of Sciences, Sofia – 1113, Bulgaria (phone: 3952 9793241; e-mail: mustakerov@iit.bas.bg).

World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:7, No:10, 2013

the most essential are:

- *working range* (*R*) of NVD depends on ambient light illumination, atmospheric transmittance, contrast between target and background, target area, diameter of the inlet pupil, objective focal length, objective transmittance, image intensifier tube (IIT) luminous sensitivity, IIT limiting resolution, IIT photocathode limiting light flow and signal-to-noise ratio;
- *field of view* (*FOV*) is parameter defining the amount of visual information provided via the device. In principle, the larger the *FOV* is the more information is available;
- *objective focus range* (*FR*) define the minimum focusing range of near objects;
- *battery life* (*BL*) determine the operational time duration of devices accordingly used battery types and capacity and the current of image intensifier tube;
- *weight* – currently the most of NVDs are portable devices and the weight is an important parameter that should be minimized.
- *price* – a parameter that depends on used NVDs modules that is always worth to consider when making some choice decision.

The most essential NVDs parameter taken into account when choosing a particular night vision device is its working range. A distinguish feature of working range is its dependency not only on the device modules parameters, but also on the external surveillance conditions as *ambient light illumination, atmospheric transmittance, contrast between target and background*, and not at last on the *target area*. In practice, it is unlikely that some device will perform best against all objectives and parameters to be clearly preferred. Each one will demonstrate different advantages and disadvantages. Describing the balance between objectives, and identifying the preferred option is a complex problem. The choice is usually done intuitively based on the decision-maker experience. The choice of a NVD adjusted to the user requirements is an example of complex combinatorial problem characterized by the presence of many conflicting preferences (criteria) about the NVDs parameters values. For example, choosing of the NVD using the latest technological solutions reflects on higher prices to pay. It is reasonable to look for the "user best" device among the offered NVDs, i.e. whose parameters values are best accordingly to the user point of view.

There are considerable advantages in making an explicit decision-aiding framework ensuring that all concerns are identified and addressed and the reasons behind a particular choice are made clear. The advantages of such a structured approach are particularly apparent where there are many alternative devices with numerous different parameters values. Moreover, often user is interesting in more than one alternative to make his final selection. To define k-best alternatives conforming to the given user preferences toward NVDs parameters a proper mathematical model is developed.

III. Multi-Criteria Model Formulation of k-Best NVDs Problem

The purpose of multi-criteria problem is to support users in exploring solutions that correspond best to their preferences, i.e. multi-criteria approach fits to the situations in which users are not able to define a single goal function. On the other hand, mixed-integer optimization provides a powerful framework for mathematically modeling of many optimization problems that involve discrete and continuous variables. Therefore, the NVDs performance could be modeled as multi-criteria mixed-integer optimization problem for determining of k-best selection of devices taking into account NVDs parameters (working range, field of view, battery life, focus range, weight and price) and external surveillance conditions as follows:

$$\begin{aligned} & maximize\{R, FOV, BL\} \\ & minimize\{FR, Weight, Price\} \end{aligned} \tag{1}$$

subject to

$$R = \sum_{i=1}^{n} x_i \sqrt{0.07 E \tau_a C A_t^* \frac{D_{in}^i f_{ob}^i \tau_{ob}^i \delta^i S^i}{\Phi_{\min}^i M^i}} \tag{2}$$

$$FOV = \sum_{i=1}^{n} FOV_i x_i \tag{3}$$

$$BL = \sum_{i=1}^{n} BL_i x_i \tag{4}$$

$$FR = \sum_{i=1}^{n} FR_i x_i \tag{5}$$

$$Weight = \sum_{i=1}^{n} Weight_i x_i \tag{6}$$

$$Price = \sum_{i=1}^{n} Price_i x_i \tag{7}$$

$$\sum_{i=1}^{n} x_i = k, \ x_i \in [0, 1] \tag{8}$$

$$1 < k < n \tag{9}$$

where *R* is the NVD working range [16], *E* – ambient light illumination in *lx*, τ_a – atmospheric transmittance, *C* – contrast, A_t^* – reduced target area in m^2 [16], D_{in} – diameter of the inlet pupil in *m*, f_{ob} – objective focal length in *mm*, τ_{ob} – objective transmittance, *S* – IIT luminous sensitivity in *A/lm*, δ – IIT limiting resolution in *lp/mm*, $\Phi_{min.}$ – IIT photocathode limiting light flow in *lm*, *M* – IIT signal-to-noise ratio; FOV – field of view, FR – objective focus range, BL – battery life (operational time duration of NVD), weight and price of NVD,

World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:7, No:10, 2013

x_i are binary integer variables corresponding to each device, k is integer decision variable determining the number of k-best solutions, and n is the number of devices to choose from.

The k-best solutions/alternatives are modeled by means of the decision variables x_i. The relation (9) of the decision variables is generalization of the classical optimization problem of finding a single solution. It contains as a special case the single-choice case for $k = 1$.

In relative ratio method for the multiple attributes decision making problems, a compromise solution/alternative is determined based on the concept that the chosen alternative should be as close to the ideal solution as possible [17]. The selection process is based on evaluation of the alternatives with respect to the set of relevant criteria.

The problem of evaluation of alternatives in terms of their distance to the ideal solution can be seen as a "second-order" decision problem. After determining of k-best devices, if the user is interested to evaluate each of the chosen devices, the relative estimation between ideal device and devices from the k-best set can be performed by following the procedure:

1) determine the objective function value for an ideal device with all of its parameters at their optimal values;
2) determine the objective function values for each device within the k-best set;
3) determine the relative estimation for each device of k-best set compared to the ideal device.

IV. NUMERICAL RESULTS AND DISCUSSION

To illustrate the applicability of the proposed approach real parameters data for ten night vision goggles are used as input data shown in Table I.

TABLE I
NIGHT VISION DEVICES PARAMETERS

No	NVDs type	δ, lp/mm	f_{ob}, mm	τ_{ob}	M	S, A/lm	FOV, degree	Battery life, hours	Min. focus range, cm	Weight, gr	Price, $
1	Night Optics D-2MV, Gen 1+	40	26	0.78	12	0.00024	40	40	25	482	650
2	Rigel 3250, Gen 1+	30	35	0.78	12	0.00022	30	30	25	430	699
3	ATN Cougar 2, Gen 2	32-40	35	0.78	16	0.00031	30	10-20	100	500	3071
4	ATN Cougar CGTI, Gen 2+	45-54	35	0.78	15	0.00035	30	10-20	100	500	3696
5	ATN Night Cougar-3, Gen 3	64	35	0.78	20	0.00087	30	10-20	100	500	4884
6	ATN Night Cougar-4, Gen 4	64-72	35	0.80	25	0.00115	30	10-20	100	500	9932
7	ATN PS23-2, Gen 2	36-45	24	0.80	13	0.00070	40	60	25	700	3550
8	ATN PS23-CGT, Gen. 2+	45-54	24	0.80	17	0.00110	40	60	25	700	4195
9	ATN PS23-3, Gen 3	55-72	24	0.80	22	0.00160	40	35	25	700	5895
10	ATN PS23-4, Gen 4	64-72	24	0.80	24	0.00190	40	35	25	700	12995

Note: The values in Table I are taken from Internet resources [18]-[27]

To solve the formulated multi-criteria problem (1)-(9), the following normalization [28], [29] scheme is used:

$$P_j^* = \frac{P_j - P_{j_{min}}}{P_{j_{max}} - P_{j_{min}}} \quad \text{for maximizing criteria} \quad (10)$$

$$N_k^* = \frac{N_{k_{max}} - N_k}{N_{k_{max}} - N_{k_{min}}} \quad \text{for minimizing criteria} \quad (11)$$

Distinguish feature of this normalization scheme is providing the values for parameters between 0 and 1 based on the maximal and minimal objective values of each parameter. This normalization not only transforms data to have comparable values but also transforms the problem to a maximizing problem.

The widely used approach for solving multi-objective optimization problems is to transform a multiple objective (vector) problem into single-objective (scalar) problems. Among decision methods, weighted-sum aggregation of preferences is by far the most common, as it is a direct specification of importance weights. The weighted sum method transforms multiple objectives into an aggregated scalar objective function by multiplying each objective function by a weighting coefficient and summing up all contributors to look for the Pareto solution [30]. The transformed scalar optimization problem determining the k-best solution is defined as follows:

maximize $\{w_1 R*(x) + w_2 FOV*(x) + w_3 BL*(x) +$
$w_4 FR*(x) + w_5 Weight*(x) + w_6 Price*(x)\}$ (12)

subject to

$$\sum_{i=1}^{10} x_i = k, \; x_i \in [0, 1] \quad (13)$$

$$\sum_{i=1} w_i = 1, \; 0 \leq w_i \leq 1 \quad (14)$$

where w_i, $i = (1, 2, \dots, 6)$ are weighting coefficients for each of the normalized objective functions.

The proposed model defines k-best Pareto optimal solutions considering the importance of each criteria expressed by DM preferences. The applicability of the proposed approach is demonstrated by four different sets of weighting coefficients reflecting four different DM preferences about importance of criteria shown in Table II.

World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:7, No:10, 2013

TABLE II
WEIGHTING COEFFICIENTS

DM preferences	Weighting coefficients					
	w_1	w_2	w_3	w_4	w_5	w_6
DM-1	0.17	0.17	0.16	0.16	0.17	0.17
DM-2	0.30	0.03	0.04	0.03	0.30	0.30
DM-3	0.20	0.20	0.10	0.10	0.20	0.20
DM-4	0.30	0.00	0.00	0.10	0.30	0.30

First set of weighting coefficients (DM-1) expresses equivalent importance toward all criteria – *detection range, field of view, battery life, focus range, price* and *weight*. The second set (DM-2) simulate the DM preferences emphasizing on *working range, weight* and *price*; the corresponding set for DM-3 reflect the preferences on *working range, field of view, weight* and *price* and DM-4 expresses DM preferences about *working range, focus range, weight* and *price*. The solutions of task (12) – (14) for different sets of weighting coefficients considering all 10 devices of Table I for k=3 and k=5 best devices selections are illustrated in Fig. 1.
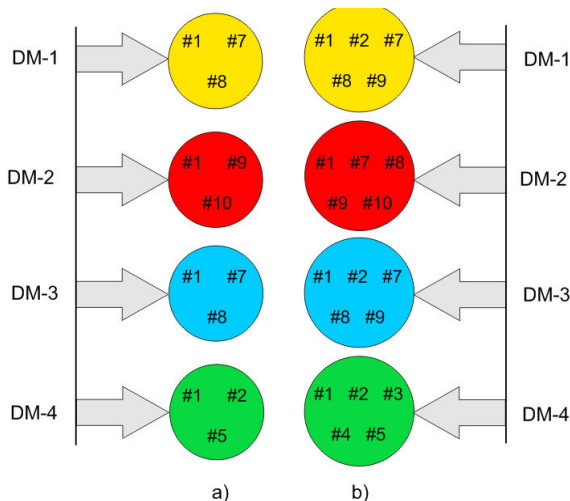

Fig. 1 K-best NVDs selections for different DM preferences:
a) for k = 3; b) for k = 5

These groups of devices satisfy DM preferences expressed by defined weighted coefficients sets in Table III. These k-best selections of devices could be the base from which the user can make final choice decision. From the formal point of view, every Pareto-optimal solution is equally acceptable as the solution to the multi-objective optimization problem. In practice, only one solution has to be chosen as final decision and this is realized by involvement of decision maker. A procedure is proposed for helping the DM in taking of his final decision, for defining how far each of these k-best devices is from the "ideal" device:

Step 1: Definition of an "ideal" device with "ideal" parameters i.e. device whose parameters values have their optimal (maximal/minimal) values. Having in mind the normalization scheme, the objective function value of (12) – (14) for the "ideal" device is equal to 1.

Step 2: Calculation of the objective function value for each

of the selected k-best devices.

Step 3: Subtract calculated value of objective function for each k-best device from objective function value of "ideal" device and determine in percentage the relative distance of devices from "ideal" one.

The results of execution of the described procedure for each of selected k-best devices are shown in Tables III-VI.

TABLE III
RELATIVE DISTANCES FOR DM-1 K-BEST DEVICES

5-best devices selection	Objective function value	Relative distance in %
#1	0.629	37.02
#2	0.457	54.27
#7	0.584	41.56
#8	0.589	41.01
#9	0.494	50.60

TABLE IV
RELATIVE DISTANCES FOR DM-2 K-BEST DEVICES

5-best devices selection	Objective function value	Relative distance in %
#1	0.4545	54.55
#7	0.3300	67.00
#8	0.3538	64.62
#9	0.3567	64.33
#10	0.3541	64.59

TABLE V
RELATIVE DISTANCES FOR DM-3 K-BEST DEVICES

5-best devices selection	Objective function value	Relative distance in %
#1	0.6037	39.63
#2	0.4204	57.96
#7	0.5110	48.90
#8	0.5175	48.25
#9	0.4539	54.61

TABLE VI
RELATIVE DISTANCES FOR DM-4 K-BEST DEVICES

5-best devices selection	Objective function value	Relative distance in %
#1	0.4723	52.77
#2	0.5306	46.94
#3	0.3116	68.84
#4	0.3550	64.50
#5	0.3578	64.22

Imposing the DM-1 preferences, where all NVDs parameters are considered as of equal importance, the results show that the device #1 has a minimal deviation from the ideal solution followed by devices #8, #7 and #2. In case of DM-2 preferences minimal deviation from the ideal solution also has device #1 followed by devices #9, #10, #8 and #7. For DM-3 preferences the order of devices is #1, #8, #7, #9 and #2 and for DM-4 set of weightings the devices are ranked as #2, #1, #5, #4 and #3.

The relative distances for determined k-best devices for different sets of weighting coefficients (different DM preferences) comparing the alternatives in terms of their rank acceptability are shown on Fig. 2.
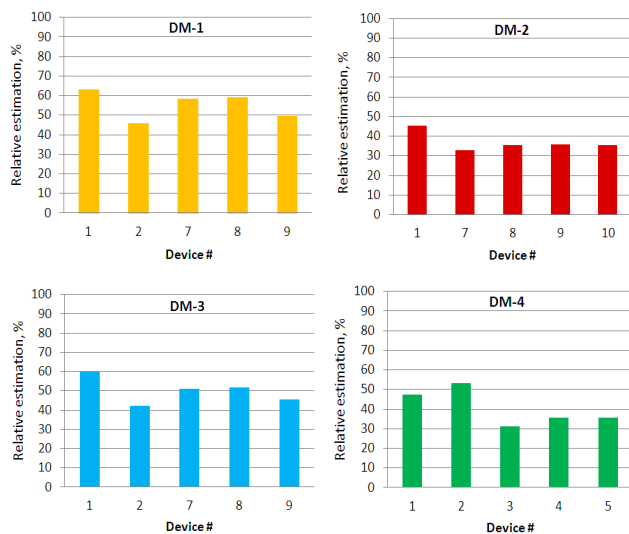
World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:7, No:10, 2013

Fig. 2 Relative estimations of K-best NVDs for different DM preferences

As it is seen from Fig. 2, the proximity of devices to the "ideal" depends on given DM preferences. Some of the devices in particular k-best selections are close to the "ideal" then others and could be considered as a good reasonable choice. For example, in DM-1 selection of devices 1, 7, 8, the device #1 is closest to the "ideal" and devices #7 and #8 have almost same deviation from the "ideal". The same is valid for DM-3 k-best selections. Using the information of relative estimations for NVDs k-best selections to analyze the results, the DM could make the final choice in more informed and reasonable way.

Increasing the number of devices and their diversity will increase the variety of choices but will also increase the tasks sizes and their computational complexity. Despite the fact that mixed integer nonlinear problems are difficult to solve (NP-complete), the formulated optimization problem and its numerical results show quite acceptable solution times. The branch and bound algorithms implemented in LINGO solver [31] proved to be quite effective for those kinds of sparse restrictions matrixes that are typical for the formulated optimization problems. Further investigations with large scale problems are needed to define the computational complexity of the proposed approach.

V. CONCLUSION

The multi-criteria optimization approach is the most natural way to support users in exploring solutions that correspond best to their preferences when multiple criteria should be optimized simultaneously. The described NVD choice problem concerns devices optimal selection when a given number of alternatives have to be selected from a finite set of alternatives with different parameters. The proposed approach is based on solving of mixed integer nonlinear optimization task. In contrast to the multi-criteria decision making where the solution is single Pareto optimal choice from all of the feasible alternatives, the proposed approach defines k-best alternatives as a result of single run of the optimization task.

Four different scenarios for DM preferences are numerically tested to demonstrate the applicability of the proposed approach: 1) equivalent importance toward all defined device criteria; 2) emphasizing on *working range, weight* and *price*; 3) interesting in *working range, field of view, weight* and *price* 4) emphasizing on *working range, focus range, weight* and *price*.

The problem of comparing the alternatives in terms of their rank is considered as a "second-order" decision problem. After determining the k-best solutions, they are arranged using the relative estimation between "ideal" device and devices from particular k-best selection. A proper procedure is proposed for this goal.

The described approach for k-best choice by multi-criteria mixed-integer optimization modeling is suitable for other real-life problems to support users in exploring solutions that correspond best to their preferences. Using such an approach would contribute to improving the quality of decisions by making the decision-making process more comprehensible, efficient and rational.

REFERENCES

[1] J. G. Winkel, L. Faber. Civil use of night vision goggles within the National Airspace System, In: Proc. *SPIE*, no 4361, pp. 159-163, 2001
[2] N.S. Martinelli, R. Seoane. Automotive night vision system. In: Proc. *SPIE Thermosense XXI*; Dennis H. LeMieux, John R. Snell, Jr.; Eds., vol. 3700, pp. 343-346, 1999.
[3] Aviation Research Report B2004/0152. Night vision goggles in civil helicopter operations. Australian Transport Safety Bureau, ISBN 1877071943, 2005.
[4] Y. Tsz-Ho, Moon,Y-S., J. Chen, H-K. Fung, H-F. Ko, R. Wang. An intelligent night vision system for automobiles. In: *Conference on Machine Vision Applications*, May 20-22, Yokohama, Japan, 2009
[5] M. Dagdeviren, S. Yavuz, N. Kilinc. "Weapon selection using the AHP and TOPSIS methods under fuzzy environment", *Expert Systems with Applications*, vol. 36, pp. 8143-8151, 2009.
[6] I. Mergias, K. Moustakas, A. Papadopoulos, M. Loizidou, "Multi-criteria decision aid approach for the selection of the best compromise management scheme for ELVs: The case of Cyprus", *Journal of Hazardous Materials*, vol. 147, pp. 706-717, 2007.
[7] C. A. Nelson, "A scoring model for flexible manufacturing system project selection", *European Journal of Operational Research*, vol. 24, pp. 346-359, 1986.
[8] M. S. Garcia-Cascales, M. T. Lamata. "Selection of a cleaning system for engine maintenance based on the analytic hierarchy process", *Computers & Industrial Engineering*, vol. 56, pp. 1442-1451, 2009.
[9] W.-W. Wu, Y.-T. Lee. "Selecting knowledge management strategies by using the analytic network process", *Expert Systems with Applications*, vol. 32, pp. 841-847, 2007.
[10] X. Wang, E. Triantaphyllou. "Ranking irregularities when evaluating alternatives by using some ELECTRE methods", *Omega*, vol. 36, pp. 45-63, 2008.
[11] M. Behzadian, R. B. Kazemzadeh, A. Albadvi, M. Aghdasi. "PROMETHEE: A comprehensive literature review on methodologies and applications", *European Journal of Operational Research*, vol. 200, pp. 198-215, 2010.
[12] N. Kalouptsidis, K. Koutroumbas, V. Psaraki. "Classification methods for random utility models with i.i.d. disturbances under the most

World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:7, No:10, 2013

probable alternative rule", *European Journal of Operational Research*, vol. 176, pp. 1778-1794, 2007.

[13] M. Behzadian, S. K. Otaghsara, M. Yazdani, J. Ignatius. "A state-of the-art survey of TOPSIS applications", *Expert Systems with Applications*, vol. 39, pp. 13051-13069, 2012.

[14] O. Kulak, S. Cebi, C. Kahraman. "Applications of axiomatic design principles: A literature review", *Expert Systems with Applications*, vol. 37, pp. 6705-6717, 2010.

[15] T. L. Saaty. Making and validating complex decisions with the AHP/ANP. *Journal of Systems Science and Systems Engineering*, vol. 14, pp. 1-36, 2005.

[16] D. Borissova, I. Mustakerov. "A working distance formula for night vision devices quality preliminary information", *Cybernetics and Information Technologies*, vol. 6, pp. 85-92, 2006.

[17] D-F Li. Relative ratio method for multiple attribute decision making problems, *International Journal of Information Technology & Decision Making*, vol.08, pp. 289-311, 2009.

[18] D-2MV Night Vision Goggle, http://www.nightoptics.com/includes/tech_specs/TS_NO-D-2MV.pdf

[19] Rigel 3250 Compact Night Vision Goggles, http://www.opticsplanet.com/ri32conivigo.html

[20] ATN Night Cougar 2, http://www.atncorp.com/atn-nightcougar-2-archived-product

[21] ATN Night Cougar CGT, http://www.atncorp.com/atn-nightcougar-cgt-archived-product

[22] ATN Night Cougar 3, http://www.atncorp.com/atn-nightcougar-3-archived-product

[23] ATN Night Cougar 4, http://www.atncorp.com/atn-nightcougar-4-archived-product

[24] ATN PS23-2, http://www.atncorp.com/atn-ps23-2-archived-product

[25] ATN PS23-CGT, http://www.atncorp.com/atn-ps23-cgt-archived-product

[26] ATN PS23-3, http://www.atncorp.com/atn-ps23-3-archived-product

[27] ATN PS23-4, http://www.atncorp.com/atn-ps23-4-archived-product

[28] T. Marler. A study of multi-objective optimization methods for engineering applications, PhD Thesis, pages 351, 2005.

[29] A.Osyczka. Multicriterion optimization in engineering with fortran programs, John Wilev and sons, New York, 1984.

[30] Kim, I.Y., O.L. de Weck, "Adaptive weighted-sum method for bi-objective optimization: Pareto front generation", *Structural and multidisciplinary optimization*, vol. 29, No 2, pp. 149-158, 2005.

[31] Lindo Systems ver. 12, http://www.lindo.com

Dr. Daniela I. Borissova is Associated Professor at the Institute of Information and Communication Technologies – BAS, Acad. G. Bonchev St., Bl. 2, Sofia 1113, Bulgaria; e-mail: dborissova@iit.bas.bg.

Major fields of scientific research: decision support systems, modeling and optimization, night vision devices, software systems for information processing, Web-based applications.

Dr. Ivan C. Mustakerov is Associated Professor at the Institute of Information and Communication Technologies – BAS, Acad. G. Bonchev St., Bl. 2, Sofia 1113, Bulgaria; e-mail: mustakerov@iit.bas.bg.

Major fields of scientific research: operations research, engineering systems modeling and design, software systems for information processing.