Multicriteria Choice of Night Vision Devices Considering the Impact of Their Performance Parameters

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Abstract
The problem of technical devices evaluation and choosing is not easy decision making process. The technological development and the availability of many different technical solutions with different performance parameters specify complex combinatorial choice problems. The night vision devices (NVD) have become quite popular recently and are an example of complex technical choice with conflicting performance parameters. The paper describes important NVD parameters that should be considered and a multicriteria optimization approach for smart NVD choice. The proposed approach uses popular weighted sum method to comply with different user preferences by defining relative weights among NVD parameters considered as objective functions. The practical applicability of the proposed approach has been demonstrated by some case study examples of choosing night vision goggles satisfying different user preferences. Real set of devices offered on Internet are used to formulate and solve optimization tasks reflecting user's preferences. The proposed multicriteria choice approach can be used for all types of night vision devices and other technical devices also to make a smart choice corresponding to decision-makers preferences and restrictions.

Keywords: *night vision devices choice, multicriteria optimization, weighted sum method, case study examples.*

1. Introduction

The problem of the technical device evaluation and choosing based on mathematical quantative analysis could be a complex combinatorial problem. The technological development and the availability of many design variants and different technical solutions with different performance parameters define sets of devices to choose from. Due to the combinatorial nature of the available choices all of them have to be evaluated and selected by complex decision-making processes. One of the possible ways to solve that kind of problems could be the using of proper optimization methods. The choosing of night vision devices (NVD) is an example for such complex selection problem.

The night vision devices are used to enhance visual capability during low light level (night) activities as security, hunting, wildlife observation, boating, law enforcement, etc. Night vision devices use two different technologies – light enhancement or thermal imaging. The NVD using light enhancement technology are more popular and come in many different types with different parameters. They intensify available ambient illumination making it possible to see in the dark despite insufficient light for normal vision [4]. The NVD are basically composed of optical system (objective) which projects an image onto the photocathode of an image intensifier tube (IIT) which in its turn produces a light intensified image that is viewed through another optical system (ocular). All of these modules including the needed for IIT electrical power supply are mounted in some mechanic construction as a complete (and usually portable) device. Depending on the optical magnification and application area there are different types of night vision devices – night vision goggles, night vision binoculars and monoculars, night vision digital cameras (still or video), night vision sights, etc. The device parameters –

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resolution, field of view, brightness gain, distortion, eyepiece dioptric adjustment, objective focus range, mechanical adjustments, weight, center of gravity, working range, price, etc., influence NVD performance [25, 26]

2. Night vision devices parameters and their impact on the performance

The performance of the NVD depends on many device parameters. The goal of the current paper is to propose a mathematical quantative approach to the problem of choosing proper device considering the user preferences about the NVD performance. The paper focuses on the device parameters and their importance from the user point of view. The device parameters values shown in the datasheets could be used as objective basis for comparison when trying to make a proper choice. The NVD parameters discussed bellow affect on the NVD performance and most of them should be considered when making a reasonable choice.

2.1. Depth perception and stereopsis

The depth perception and stereopsis could be treated as two sides of an important NVD parameter depending on the NVD type i.e. monocular, biocular or binocular construction [17]. Depth perception is the ability to estimate absolute distances between an object and the observer or the relative distances between two objects, i.e. how far to the left or right the object is and whether the different objects are in front or behind each other [15]. Stereopsis goes with binocular perception and is the result of the two retinae viewing slightly different images of the same object [21, 27]. Only night vision binoculars constructed as two independent optoelectronic channels add the advantage of depth perception and stereopsis imaging and should be preferred to the monocular and biocular constructions when depth perception and stereopsis are expected [11, 12].

2.2. Field of view

The field of view (FOV) is NVD parameter defining the amount of visual information provided via the device. In principle, the larger the FOV is the more information is available. It determines the width or spatial angle of the outside scene that can be viewed measured horizontally and vertically. In terms of impact on the NVD performance, FOV can be considered to be as important as another NVD parameter described bellow – NVD resolution [14]. The binocular NVD type provides an effect of increasing the field of view by a partial display overlap [2, 20].

2.3. Resolution

The resolution is an essential NVD evaluating parameter. The resolution by definition is the ability of distinguishing between close objects, i.e. the detail or fidelity of the image. The quality of the optics and the IIT technology define the NVD resolution. The resolution is, perhaps, the most important parameter in determining the image quality of any NVD system [11].

2.4. Signal-to-noise ratio

Signal to noise ratio (SNR) plays a key role in night vision performance. An image intensifier tube's SNR determines the low-light resolution capability and measures the light signal reaching the eye, divided by the perceived noise as seen by the eye. The higher the SNR is the better is the ability of the IIT to resolve objects under low illumination conditions [18, 24].

2.5. Luminance gain

The parameter luminance gain (also called brightness gain) is the number of times an image intensifier tube amplifies the light input. It could be measured as IIT gain or as system gain.

The IIT gain is reduced by the system's lenses and is affected by the quality of the optics and/or any filters, so the system gain is a more important parameter to the user [15, 22].

2.6. IIT photocathode's sensitivity

By definition the sensitivity or photoresponse is the ability of the photocathode material to produce an electrical response when subjected to light photons. The different IIT production technologies result in so called IIT "generations" with different photocathode's sensitivity. For example, the Generation 2 IIT are sensitive to light from about 400 nm to about 900 nm whereas the more sensitive 3rd Generation tubes are sensitive from about 600 nm to a little over 900 nm. The Gen 3 tubes are about 4 to 5 times more sensitive to night sky illumination than the Gen 2 tubes but they also cost significantly more [26]. The higher the photocathode's sensitivity value is the better is the ability to produce a visible image under darker conditions.

2.7. Distortion

Distortion can be defined as any difference in the apparent geometry of the outside scene as viewed on or through the display. Sources of distortion in the display image include the image source and display optics. Three types of distortion are most significant to the night vision devices: geometric, "S" and sheer [11, 22]. The ideal design will project the image from the display to the viewer without altering the shape of the image. Because all distortions reduce the image quality the better NVD would have low distortions.

2.8. Mechanical adjustments

All night vision devices have some mechanical construction and as they include optical systems their mechanic should provide some typical for the optical systems adjustments.

2.8.1. Objective focus range

The objective lens focus range is independent of the eyepiece (ocular) focus. Focusing of the near objects or far objects is possible by the objective focus adjustment. Usually different NVD models provide adjustments for near objects from 0.20 m to 1 m and to infinity for far objects.

2.8.2. Eyepiece (ocular) dioptric adjustment

The eyepiece focus adjusts the spherical lens power to compensate for the user's refractive error (hyperopia or myopia) to get proper accommodation. Usually NVD provide different adjustments range between –6 and +6 dpt [26].

2.8.3. Interpupillary adjustment

Interpupillary distance is the distance between the centers of the viewer pupils. It determines the stereo separation of the two images which are combined in the brain to produce stereo perception. Mean interpupillary distance is important in the design of stereoscopic display devices and the production of stereoscopic content [13]. The interpupillary adjustment of the centers of a binocular's exit pupils is needed to adjust to the different users' eyes interpupillary distance.

2.9. Exit pupil

The exit pupil is the image of the stop of the optical system. When the eye pupil is fully within the exit pupil of the NVD then the entire FOV is observed; if the eye pupil is only partially in the exit pupil then the observer will still see the entire FOV but it will be reduced in brightness. From a visual capability standpoint it is important for the exit pupil to be as large as possible to ensure the eye pupil will remain within it to permit viewing through the NVD [11, 20].

2.10. Eye relief

The exit pupil is located at a distance called the optical eye relief and is defined as the distance from the last optical element to the exit pupil [11]. As with so many other NVD parameters, larger eye relief usually means larger and heavier optics but allows the use of eyeglasses.

2.11. Optical lens system

The night vision devices have optical systems and the optical lenses characteristics also affect the NVD performance. The *f-number* is a measure of the size and light-collecting ability of the lens system [16]. The *f-number* of a lens is given by the ratio of the focal length of the lens to the aperture (the opening through which light passes). A lens with a large aperture has a small *f-number* and therefore lets more light to pass through than a smaller diameter lens. The pay off is that aberrations become increasingly noticeable as the *f-number* decreases [19].

2.12. Weight

The NVD are mainly portable devices and their weight is a very important parameter to consider. In general, the NVD weight depends on the NVD type – monocular, biocular or binocular because of the fact that optoelectronic channels number of modules (number of the objectives, IITs and oculars) and their weights affect the overall device weight. For head-mounted devices (the majority of the devices) the center of gravity is at some distance from the support point and the bigger weight means bigger rotating moment and bigger neck load [20].

2.13. Battery lifetime duration

As it was pointed out the NVD are mainly portable devices using image intensifier tube. The IIT itself needs some electrical power supply to operate and usually it is battery power supply. Depending on the used battery types (3V coin type or two 1.5V standard AA types) and their capacity, the NVD operational time duration, i.e. battery lifetime duration is different and should be considered also when NVD performance is evaluated.

2.14. Dimensions

The NVD overall dimensions depend on the NVD type (monocular, binocular or binocular) and by the dimensions of the used optoelectronic channel modules (objective, IIT and ocular). The NVD length, the NVD center of gravity and the NVD weight define a rotating moment provoking weariness and discomfort during the long time usage. In most cases this rotating moment can not be avoided but decreasing of the discomfort by decreasing of the NVD dimensions helps to avoid degrading NVD performance [20].

2.15. Working range

Last but not least an important NVD performance parameter is the working range. Whilst there are many different NVD parameters and external conditions that affect the NVD working range it is important to know some data for working ranges to evaluate the NVD performance. There exist different types working ranges – detection, orientation, recognition or identification but one of them is enough to compare different NVD models of the same type (goggles vs. goggles, binoculars vs. binoculars, etc.) [3, 23].

Some generalized typical data for the detection range of NVD with different IIT technological generations are shown in the Table 1 [4]:

Table 1: Typical NVD detection range using different IIT generations

NVD generation	Gen 2	Super Gen 2	Gen 3 OMNI I, II	Gen 3 OMNI III	Gen 3 OMNI IV	GEN IV
Detection Range (m)	170	270	240	290	360	430

There exist a few investigations how the NVD parameters influence on the NVD performance. A comparative evaluation of the parameters influence on the panoramic night vision goggles (PNVGII) performance used in air force is conducted by the U.S. Army Aeromedical research laboratory. The results show that the relative importance of the NVD parameters depend on the application area and the NVD parameters impact on the device performance could not be avoided [1, 17].

3. The NVD choice problem and multicriteria approach

As a result of a technological development there exist a constantly growing number of different NVD types and models with different parameters values. The user preferences should be dominant for the importance of the NVD parameters and their values. Most of the offered NVD have specifications datasheets with information about the NVD essential parameters values and that information can be used to make an intelligent choice. Some flexible objective approach based on a quantative evaluation is needed to make a choice considering the NVD parameters importance and values accordingly to the different user's preferences.

When choosing the NVD the user acts as a decision-maker and should consider all the relevant costs and benefits of the options for the set of devices to choose from and to adequately address all of his/her preferences. The preferred device should be that which comes close to the decision maker's objectives, which may often conflict. In practice, it is unlikely that some device will perform best against all objectives and can 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 NVD 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 NVD, 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.

The multicriteria techniques model a decision maker'preferences to express in an explicit manner a choice between options involving a number of often conflicting objectives. Through the aggregation of disparate information onto a common index of utility they aim to provide a rational basis for classifying choices. They give the option to identify the preferences and trade-offs between the benefits and disbenefits of all alternatives. The problem of NVD choice by flexible adjusting to the user preferences could be formulated as multicriteria optimization problem if the parameters of the different NVD are considered as objective functions. In other words, the choosing of a proper NVD means choosing of a device with parameters values as close to the user expected values as possible. Some of the NVD parameters values reflect in better NVD performance when increasing, while the other – when decreasing. The generalized multicriteria optimization problem definition can be formulated as:

$$\begin{aligned} &\text{maximize } \mathrm{P(x)} = (\mathrm{P_1(x), P_2(x), \ldots,\ P_j(x)})^{\mathrm{T}}, \\ &\text{minimize } \mathrm{N(x)} = (\mathrm{N_1(x), N_2(x), \ldots, N_k(x)})^{\mathrm{T}}, \end{aligned} \tag{1}$$

subject to

$$\mathrm{P_j(x)} = \sum_{i=1}^{I} P_{ij} x_i\ ,\ j = 1,2,\ldots,\mathrm{J}, \tag{2}$$

$$\mathrm{N_k(x)} = \sum_{i=1}^{I} N_{ik} x_i\ ,\ k = 1,2,\ldots,\mathrm{K}, \tag{3}$$

$$\sum_{i=1}^{I} x_i = 1,\ x_i \in [0,\ 1] \qquad (4),$$

where $P_1(x)$, $P_2(x)$, …, $P_J(x)$ are the J objective functions expressing the NVD parameters that should be maximized i.e. bigger values increase NVD performance; $N_1(x)$, $N_2(x)$, …, $N_K(x)$ are the K objective functions of the NVD parameters that should be minimized i.e. lower values increase NVD performance; P_{ij} and N_{ik} represents the j-th respectively k-th parameters values of the i-th device and are known constants; x = (x_1, x_2, …, x_I) are binary integer variables corresponding to the indexes $i = 1, 2, \ldots, I$, of each particular NVD considered to be a candidate for the "user best" NVD as a result of multicriteria optimal choice.

There should be pointed out that such formulation of the multicriteria optimization problem is a formulation of linear integer combinatorial choice problem. The result of its solution is a choice of one particular NVD from a defined set of NVD with predetermined and known parameters values. The above formulation has no additional restrictions on the parameters values and all choices of a particular NVD are feasible. The Pareto optimal choice depends on the decision-maker preferences.

The applicability of the proposed multicriteria NVD choice approach is demonstrated by case study numerical examples.

4. Case study examples for night vision goggles choice by multicriteria optimization approach

The night vision goggles (NVG) are the most widely used device type both for military and civil applications. To illustrate the proposed approach applicability some practically proven parameters with values data for real binoculars type NVG are collected from the Internet published offers (see Table 2). Other parameters as described in section 2 could be considered also but the shown in Table 2 NVG parameters are adequate for a case study example.

Table 2: NVG parameters data

No	NVG	Resolution, Lp/mm	FOV, deg	Battery life, hours	Detection range, m	Minimum focus range, cm	Length, (Dimensions) mm	Weight, gr	Price, $
	User criteria	P1	P2	P3	P4	N1	N2	N3	N4
1	ATN Cougar Gen 1	40	30	15 (10-20)	150	100	137 (137x125x50)	800	629
2	NZT-22 Gen 1	40	36	15	120	25	180 (180x120x170)	740	1350
3	MV-221G Gen. 2+	32	40	40	125	25	114 (114x114x64)	482	2699
4	ATN Night Cougar-2 Gen 2+	36 (32-40)	30	15 (10-20)	150	100	137 (137x125x50)	800	2695
5	ПН-9К Gen. 2+	34 (30-38)	36	10	180	25	127 (127x105x50)	750	4943
6	ATN Night Cougar-CGT Gen 2+	50 (45-54)	30	15 (10-20)	250	100	137 (137x125x50)	800	3696
7	ATN Night Cougar-HPT Gen 2+	59 (54-64)	30	15 (10-20)	300	100	137 (137x125x50)	800	4519
8	Dipol 221H Gen 2+	59	40	30	300	25	117 (117x112x58)	650	6052
9	ATN Night Cougar-3 Gen 3	64	30	15 (10-20)	300	100	137 (137x125x50)	800	4889
10	ATN Night Cougar-3A Gen 3	68 (64-72)	30	10-20 (15)	325	100	137 (137x125x50)	800	5629
11	ATN Night Cougar-4 Gen 4	68 (64-72)	30	15 (10-20)	325	100	137 (137x125x50)	800	9299
12	ATN PS-23 Gen 2+	41 (36-45)	40	35	200	25	151 (151x85x120)	700	2420
13	ATN PS-23 Gen CGT	50 (45-54)	40	35	200	25	151 (151x85x120)	700	3995
14	ATN PS-23 Gen 3	64	40	35	300	25	151 (151x85x120)	700	5685
15	ATN PS-23 Gen 4	72	40	35	350	25	151 (151x85x120)	700	11149

Considering the NVG parameters from Table 2 as users' criteria for a preferable choice a multicriteria optimization problem can be formulated:

$$\begin{aligned}&\text{maximize } P(x) = (P_1(x), P_2(x), P_3(x), P_4(x),)^T,\\&\text{minimize } N(x) = (N_1(x), N_2(x), N_3(x), N_4(x))^T,\end{aligned} \tag{5}$$

subject to

$$P_j(x) = \sum_{i=1}^{15} P_{ij} x_i \text{ , } j = 1, 2, 3, 4, \tag{6}$$

$$N_k(x) = \sum_{i=1}^{15} N_{ik} x_i \text{ , } k = 1, 2, 3, 4, \tag{7}$$

$$\sum_{i=1}^{15} x_i = 1, \; x_i \in [0, 1], \tag{8}$$

where $P_1(x)$, $P_2(x)$, $P_3(x)$, $P_4(x)$ are the NVG resolution, field of view, battery lifetime duration and working range which values should be chosen as big as possible; P_{i1}, P_{i2}, P_{i3}, P_{i4}, are resolution, field of view, battery lifetime duration and working range values of the *i*-th device from table 2; $N_1(x)$, $N_2(x)$, $N_3(x)$, $N_4(x)$ are the NVG objective focus range, length, weight and price which values should be chosen as low as possible; N_{i1}, N_{i2}, N_{i3}, N_{i4}, are objective focus range, length, weight and price values of the *i*-th device from table 2; x = (x_1, x_2, …, x_{15}) are binary integer variables corresponding to each of the fifteen NVG shown in Table 2.

The widely used approach for solving multiobjective 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 [5].

The NVG parameters in task formulation (5)-(8) are quite different by nature and values and could not be aggregated as comparable objectives. Thus the normalization is needed for objectives of different units to be comparable criteria and their weights correctly to represent their relative importance [6, 7]. The following normalization scheme is chosen

$$P_j^* = \frac{P_j - P_{j\min}}{P_{j\max} - P_{j\min}} \text{ for maximizing objectives,} \tag{9}$$

$$N_k^* = \frac{N_{k\max} - N_k}{N_{k\max} - N_{k\min}} \text{ for minimizing objectives.} \tag{10}$$

It supplies parameters values between 0 and 1 based on the maximal and minimal objective values of the parameters [6, 8]. The *max* and *min* values for each of the objectives (criteria) and their differences are shown in Table 3.

Table 3: Objectives min and max values and their differences

Value \ Criteria	P1	P2	P3	P4	N1	N2	N3	N4
max	72	40	40	350	100	180	800	11149
min	32	30	10	120	25	114	482	629
(*max–min*)	40	10	30	230	75	66	318	10520

The normalization not only transforms data to have comparable values but also transforms the problem to a maximizing problem [8]. The *weighted sum* method requires multiplying each of the normalized objective functions by some weighting coefficients and summarizing them into a single objective function. So, the following optimization choice problem is defined:

$$\text{maximize } (w_1P_1^*(x) + w_2P_2^*(x) + w_3P_3^*(x) + w_4P_4^*(x) + \\ + w_5N_1^*(x) + w_6N_2^*(x) + w_7N_3^*(x) + w_8N_4^*(x)), \tag{11}$$

subject to

$$P_j^*(x) = \sum_{i=1}^{15} P_{ji}^* x_i, \quad j = 1, 2, 3, 4, \tag{12}$$

$$N_k^*(x) = \sum_{i=1}^{15} N_{ki}^* x_i, \; k = 1, 2, 3, 4, \tag{13}$$

$$\sum_{i=1}^{15} x_i = 1, \; x_i \in [0, 1], \tag{14}$$

$$\sum_{i=1} w_i = 1, \; 0 \le w_i \le 1, \tag{15}$$

where w_i=(1, 2,…, 8) are weighting coefficients for each of the objective functions. If $\sum_{i=1}^{8} w_i = 1$ and $0 \le w_i \le 1$, the weighted objectives sum is said to be a convex combination of objectives [9]. The solution of the transformed single objective optimization problem determines one particular Pareto optimal point. When weights are changed the *weighted sum* method defines different single objective optimization problem with different Pareto solutions points.

Using of the *weighted sum* method is based on the decision-maker's composite measure of importance across all the device parameters values i.e. all criteria are weighted according to how important each is regarded in relation to the others. The weights represent a preference set for a particular DM and probably they will change with the different decision makers. For the goal of numerical experimentation some practical preferences of four imaginary users are chosen:

- User 1 has equal preferences for all NVG parameters.
- User 2 puts more weight on the price and weight then the other NVG parameters.
- User 3 is interested in better NVG resolution but stresses much more on the NVG detection range and is less interested in the price and other parameters.
- User 4 looks is equally keen on better NVG resolution, detection range and lower weight and price and is not interested at all in other parameters.

The corresponding sets of weight coefficients are shown in Table 4.

Table 4: Sets of weight coefficients

	w_1 *(Resolution)*	w_2 *(FOV)*	w_3 *(Bat. life)*	w_4 *(Det. range)*	w_5 *(Focus range)*	w_6 *(Lenght)*	w_7 *(NVG Weight)*	w_8 *(NVG Price)*
Set 1	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
Set 2	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.20
Set 3	0.20	0.10	0.10	0.30	0.05	0.10	0.10	0.05
Set 4	0.25	0.0	0.0	0.25	0.0	0.0	0.25	0.25

Two types of optimization tasks are defined for "unrestricted" and "restricted" optimization choices. "Unrestricted" optimization choice tasks implement different sets of weight coefficients. When those tasks are extended by additional restrictions for some parameters values the "restricted" optimal choice is performed.

4.1. Numerical examples for "unrestricted" NVG choice

Four numerical examples are presented in this section to demonstrate the applicability of the proposed multicriteria NVG choice approach. All optimizations were performed using the *weighted sum* method and the Lingo software [10] on PC under Windows XP OS. The four numerical examples corresponding to the sets of weight coefficients from Table 4 are formulated. Each table row defines particular optimization task – Task 1 (for set 1), Task 2 (for set 2), Task 3 (for set 3) and Task 4 (for set 4) following the model:

$$\text{maximize } \Big(w_1\sum_{i=1}^{15}\left(\frac{P_{i1}-32}{40}\right)x_i + w_2\sum_{i=1}^{15}\left(\frac{P_{i2}-30}{10}\right)x_i + w_3\sum_{i=1}^{15}\left(\frac{P_{i3}-10}{30}\right)x_i + w_4\sum_{i=1}^{15}\left(\frac{P_{i4}-120}{230}\right)x_i + $$
$$+ w_5\sum_{i=1}^{15}\left(\frac{100-N_{i1}}{75}\right)x_i + w_6\sum_{i=1}^{15}\left(\frac{180-N_{i2}}{66}\right)x_i + w_7\sum_{i=1}^{15}\left(\frac{800-N_{i3}}{318}\right)x_i + w_8\sum_{i=1}^{15}\left(\frac{11149-N_{i4}}{10520}\right)x_i\Big) \quad (16)$$

subject to

$$\sum_{i=1}^{15} x_i = 1,\ x_i \in [0, 1], \quad (17)$$

$$\sum_{i=1} w_i = 1,\ 0 \le w_i \le 1, \quad (18)$$

where P_{i1}, P_{i2}, P_{i3}, P_{i4}, are resolution, field of view, battery lifetime duration and working range values of the i-th device from table 2; N_{i1}, N_{i2}, N_{i3}, N_{i4}, are objective focus range, length, weight and price values of the i-th device from table 2 and w_1, w_2, w_3, w_4, w_5, w_6, w_7 and w_8 are weight coefficients with values from corresponding row of Table 4. The task solutions define Pareto optimal choices shown in Table 5.

Table 5: Pareto optimal "unrestricted" choices for different sets of weight coefficients

Tasks/ Weight coefficients	**Resolution lp/mm**	**FOV, deg**	**Battery life, hours**	**Detection range, m**	**Min. focus range, cm**	**Length, mm**	**Weight gr**	**Price, $**	**Chosen NVG from Table 2**
Task 1	59	40	30	300	25	117	650	6052	**No 8.** Dipol 221H Gen 2+
Set 1	*0.125*	*0.125*	*0.125*	*0.125*	*0.125*	*0.125*	*0.125*	*0.125*	
Task 2	32	40	40	125	25	114	482	2699	**No 3.** MV-221G Gen 2+
Set 2	*0.1*	*0.1*	*0.1*	*0.1*	*0.1*	*0.1*	*0.2*	*0.2*	
Task 3	72	40	35	350	25	151	700	11149	**No 15.** ATN PS-23 Gen 4
Set 3	*0.20*	*0.10*	*0.10*	*0.30*	*0.05*	*0.10*	*0.10*	*0.05*	
Task 4	64	40	35	300	25	151	700	5685	**No 14.** ATN PS-23 Gen 3
Set 4	*0.25*	*0.0*	*0.0*	*0.25*	*0.0*	*0.0*	*0.25*	*0.25*	

The chosen devices satisfy the relative user's importance of different parameters defined by their numerical weights. Four different choices are available as results of optimization tasks solution. If some user is not satisfied with the result of the choice he or she can try another weight coefficients combination. Due to the fact that the choice is done from a known finite discrete set of devices any weights combination satisfying (18) could be used to get a feasible Pareto optimal choice. So, the solved four numerical examples are adequate to demonstrate the applicability of the proposed choice approach by adjusting to the different users' preferences choice strategy.

4.2. Numerical examples of "restricted" NVG choice

To refine more precisely the user preferences a "restricted" choice problem can be formulated. It is possible to add restrictions on some parameter values to comply with tighter DM preferences. The NVG optimal choice problem (16)-(18) can be extended by adding of restrictions for some NVG parameters. For example, price not bigger then some upper limit $Price_{max}$ and/or detection range above some lower limit $Det.Range_{min}$ and/or resolution with lower limit $Resolution_{min}$. Combinations of similar restrictions could define different optimization tasks:

- **Task 1e** - Task 1 with additional restrictions about the NVG resolution and price:

$$\sum_{i=1}^{15} P_{i1} x_i \geq Resolution_{min} = 50, \tag{19}$$

$$\sum_{i=1}^{15} N_{i4} x_i \leq Price_{max} = 5500. \tag{20}$$

- **Task 2e** - Task 2 with additional restriction about the NVG price:

$$\sum_{i=1}^{15} N_{i4} x_i \leq Price_{max} = 2500. \tag{21}$$

- **Task 3e** - Task 3 with additional restrictions about the NVG resolution, detection range and price:

$$\sum_{i=1}^{15} P_{i1} x_i \geq Resolution_{min} = 50, \tag{22}$$

$$\sum_{i=1}^{15} P_{i4} x_i \geq Det.Range_{min} = 220,$$

$$\sum_{i=1}^{15} N_{i4} x_i \leq Price_{max} = 4000. \tag{23}$$

- **Task 4e** - Task 4 with additional restrictions about the NVG detection range and price:

$$\sum_{i=1}^{15} P_{i4} x_i \geq Det.Range_{min} = 200, \tag{24}$$

$$\sum_{i=1}^{15} N_{i4} x_i \leq Price_{max} = 5000. \tag{25}$$

The solutions of the Task 1e, 2e, 3e, 4e defining different NVG choices are shown in Table 6.

Table 6: Pareto optimal "restricted" choices

Tasks/ Weight coefficients	**Resolution lp/mm**	**FOV, deg**	**Battery life, hours**	**Detection range, m**	**Min. focus range, cm**	**Length, mm**	**Weight gr**	**Price, $**	**Chosen NVG from Table2**
Task 1e	50	40	35	200	25	151	700	3995	**No 13.** ATN PS-23 Gen CGT
	Resolution$_{min}$ **50**							*Price$_{max}$* **5500**	
Set 1	*0.125*	*0.125*	*0.125*	*0.125*	*0.125*	*0.125*	*0.125*	*0.125*	
Task 2e	41	40	35	200	25	151	700	2420	**No 12.** ATN PS-23 Gen 2+
								Price$_{max}$ **2500**	
Set 2	*0.1*	*0.1*	*0.1*	*0.1*	*0.1*	*0.1*	*0.2*	*0.2*	
Task 3e	50	30	15	250	100	137	800	3696	**No 6.** ATN Night Cougar-CGT Gen 2+
	Resolution$_{min}$ **50**			*Det.Range$_{min}$* **220**				*Price$_{max}$* **4000**	
Set 3	*0.20*	*0.10*	*0.10*	*0.30*	*0.05*	*0.10*	*0.10*	*0.05*	
Task 4e	64	30	15	300	100	137	800	4889	**No 9.** ATN Night Cougar-3 Gen 3
				Det.Range$_{min}$ **200**				*Price$_{max}$* **5000**	
Set 4	*0.25*	*0.0*	*0.0*	*0.25*	*0.0*	*0.0*	*0.25*	*0.25*	

The "restricted" NVG choice approach allows more precisely refining of the user preferences by adding of restrictions for some NVG parameters. This is illustrated by solutions of Task 1e, 2e, 3e and 4e where different parameters numerical limits result in different devices choices.

4.3. Numerical examples discussion

The solutions of optimizations Tasks 1 – 4, shown in Table 5 illustrate the possibility to choose the devices complying with the different user's preference strategies, expressed via sets of weight coefficients.

The differences between the chosen devices in Table 6 and Table 5 demonstrate the influence of the additional parameters restrictions. Unlike the "unrestricted" choices described in section 4.1 introducing of some parameters restrictions or combinations of restrictions could result to unfeasible optimization tasks. It is evident that if those additional restrictions are unrealistic or their combinations can not be satisfied by any particular device the choice will be impossible. It is the decision maker's expertise that could help to resolve that unfeasibility. Usually the software for optimization tasks solving provides some post optimization analysis that could help to define the unfeasible restrictions which should be changed appropriately.

The formulated integer linear optimization tasks can be solved by means of most of the existing optimization software systems. The described in the paper case study examples are solved by Lingo v.11 [10] software system on PC with Intel processor at 2.6 GHz, 1 GB RAM under Windows XP platform. The solution times were about a second or less but obviously depend on the size of the formulated tasks i.e. on the number of devices and parameters to choose from and on the computational power. The used number of devices and parameters data from Table 2 are chosen as illustrative numerical data for the case study examples but the sizes of the solved examples are close to the practical needs and the solution times could be an acceptable merit for the real applications. Any other number of devices and different parameters can be used appropriately to the particular applications and user requirements. Increasing of the devices number increases the complexity of the combinatorial choice problem and validates the need of quantative multicriteria choice approach using.

5. Conclusion

The paper presents a multicriteria optimization approach for intelligent night vision devices choice. The availability of many night vision devices technological designs with different performance parameters defines a complex combinatorial decision-making choice process. The used multicriteria approach gives flexible options to identify the user's preferences and trade-offs between the benefits and disbenefits of all alternative choices. In this approach, multicriteria optimization tasks are defined and solved by the *weighted sum* method. The *weighted sum* is extensively used method for multicriteria optimization and was chosen as it is simple to understand and easy to implement. Other multicriteria optimization methods could be used and investigated upon the suitability and advisability for night vision devices choice.

The night vision devices parameters are considered as objective functions to be optimized and using of the weight coefficients is a direct reflection of the user's relative importance among them. The real engineering choice problem depends not only on the importance weights, but also on the parameters limits restricted by the user. Two types of optimization tasks are defined for "unrestricted" and "restricted" optimal choices. Unrestricted optimization tasks implement different sets of weight coefficients. The solution of each task gives different device choices satisfying different users' preferences. This type of formulated optimization tasks is always feasible because of the nature of combinatorial choice from finite discrete sets of devices with known parameters values. The "restricted" optimal choice is based on adding of some parameters values restrictions. The corresponding optimizations tasks allow better refining of the users preferences but it is possible to formulate unrealistic parameters restrictions leading to unfeasible choices. The users experience and the tools of post optimization analysis could be used to overcome those unfeasibility problems.

The practical applicability of the introduced NVD choice approach has been demonstrated by a case study examples to chose a night vision goggles satisfying different user preferences from real set of devices offered on Internet. "Unrestricted" NVG choice is demonstrated by solving of four optimization tasks reflecting four different users' preference strategies for the relative importance of NVG parameters. Other four optimization tasks are solved by introducing additional parameters restrictions to get possibly better "restricted" NVG choices.

The proposed multicriteria optimization choice approach can be used for other night vision devices (night vision binoculars, sights, etc.) and also for other types of technical devices considering appropriate performance parameters.

The multicriteria techniques are decision aiding tools that do not replace the role of the decision-maker or its responsibility for the decision taking but they are a good tool to supply reasonable alternatives to make a smart choice.

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