Mission-driven Sensor Management based on Expected-Utility and Prospect Objectives

Teun H. de Groot, Oleg A. Krasnov and Alexander G. Yarovoy
Microwave Sensing, Signals and Systems
Delft University of Technology, Netherlands
{T.H.deGroot, O.A.Krasnov, A.Yarovoy}@tudelft.nl

***Abstract*—A set of mission-driven objective functions, which can be used for sensor management, is proposed. While an optimization algorithm maximizes the output of objective functions, the definition of such a function is a challenge in itself. Objectives in sensor research are usually based on sensing characteristics (e.g. estimation error, information measure), but they do not necessary describe mission goals. To improve this, we present two types of objective functions based on expected-utility and prospect. Their generality are demonstrated and their properties are compared in two case studies where the end-user has the goal to protect and/or capture physical objects using effectors that are supported by radar sensors and video cameras. A benefit is that the objectives are linked to relevant operational parameters, that are understandable for end-users, and the objectives can be fine-tuned according to end-user's preferences. Because the mission-driven objectives define on a high level what should be achieved in the end, they actually allow to utilize the employed sensors at their full potential.**

I. Introduction

A modern trend in sensor development is that the flexibility of sensors' capabilities increase. More adaptive sensors should result in sustainable added value in cases where the operational conditions are changing significantly over time. However, this benefit is only realized and maximized when sensors are optimally managed. When an end-user has to manage the system, there are too many choices to consider and they are usually defined in terms that are too strongly focused on technical aspects. Furthermore, possible changes can happen too fast for an end-user to react to. Thus, when modern sensor systems are required to operate at their full potential, an automatic resource allocator is necessary to support end-users.

There are mainly two challenges within the domain of sensor management. Firstly, the translation of the end-user needs into a mathematically formulated objective function. Such a function can be called the *utility* or the *satisfaction* of the end-user. Secondly, to find the optimal system configuration and settings that maximize the objective function's output value. This optimization problem is usually NP-hard or non-convex and different algorithms exist to find an approximate solution [1], [2]. Usually, the focus of resource allocation research is on the second challenge, but in this paper we focus on the challenge of optimality definition.

The optimality definition is related to a basic resource allocation dilemma: there are more than one task that need to be executed, but the available resources are limited. As result, not every task can be executed with the highest possible performance and a trade-off has to be made. For instance, if two targets need to be tracked, but there are insufficient resources to track them both with the lowest possible track-loss probability, then the critical question is: should the system drop one target track or should the provided tracking performance be reduced? Formally, the best answer is provided by maximizing the value of an objective function. It is clear that such a control decision can have immense operational consequences, and therefore, the selection of the correct function is crucial.

This research was conducted as part of the Sensor Technology Applied in Reconfigurable Systems (STARS) project funded by the Dutch Government.

A. Literature Survey

There exist several approaches for defining the objectives for sensor management. In this paper we discuss them briefly, but a more detailed review can be found in [3], [4].

The information theoretic approach [5], [6] tries to minimize an entropy parameter and maximize the information gain. However, intrinsic information value does not necessarily equal to a system's usefulness from a mission point of view (also argued by [7], [8]). Information is unnecessary - and maybe even distractive - if it cannot be used in the current mission.

Risk analysis approaches for sensor management [9], [10], [11] have the advantage that "risk" is a term used by end-users. Therefore, risk can be potentially better linked to operational parameters that are actually relevant for end-users. However, different implementations exist (i.e. different understanding of risk/cost) and it seems to be a challenge to define gains, losses and threats in a consistent manner.

An energy-aware approach [12], [13] aims to maximize the system lifetime (e.g. network of battery-powered sensors). However, this is achieved by not sensing at all, thus this objective is usually combined with another requirement (e.g. area coverage). In the end, the required energy is just one of the aspects in perspective of mission success.

Task-driven approaches [7], [14], [15] mostly create a single additive-utility function that aggregates multiple task parameters such as task priorities and task-utilities/qualities together. Eventually, such an approach does not solve the problem of utility definition, but translates it into new problems, namely, the definition of priorities and qualities. Tasks need to be executed to achieve mission success, but solely task execution in itself does not provide mission success.

B. Presented approach

In this paper, we develop an objective function from the perspective of the mission. Thus, the sensor system's usefulness should not depend on what kind of resources are used, how they configured or which tasks are executed, but on mission success. After studying the above discussed sensor management literature, we concluded that the risk analysis is currently the best solution that could satisfy this demand. However, we improve the solution in two steps:

1) Solely link the utility to objects of interest that can be lost or gained by the end-user during missions;
2) Modify the trade-off mechanism with prospect theory [16] in such a way that it matches human reasoning.

Thus, first an *expected-utility* objective function is developed that solely depends on mission goals. However, an expected-utility solution may suffer from poor preferences among the goals. With the second step, an expected-utility objective is changed to a *prospect* objective. With a prospect objective the optimization trade-offs are made in a similar way as humans would make during critical decisions under uncertainty. This paper illustrates the usage of the expected-utility and prospect objective functions in two types of missions that include critical trade-offs. By doing this, the mission-driven concept is clarified, its generality is illustrated and the differences between expected-utility and prospect is investigated.

The structure of this paper is as follows. In Section II we discuss two examples of missions for which we need to define an objective function that take into account the end-user needs. The expected-utility objective is presented in Section III and the prospect objective in Section IV. To evaluate the developed objective functions, Section V presents models of sensors and other components that are required to calculate an expected mission result. The sensors are controlled by maximizing the objective function's output and we evaluate and compare the selected control decisions. The benefits of the proposed functions are explained in Section VI.

II. Two Example Mission Tasks

Two different tasks are introduced to illustrate the general applicability of the objective functions. For the first task the end-user has something to lose, and for the second task the opposite - something to gain. Mission goals do not depend on the available resources or their quality, and therefore, they are not discussed in this section.

A. First Task: Protect high-value assets

Assume that intelligence information has been received by the end-user: a threatening object is expected to damage a high-value asset. For example, the expected threat is caused by a small air plane which is able to approach and damage a nuclear plant. As a result, the end-user has the mission to protect the defined assets against any threatening object.

B. Second Task: Capture high-value assets

Let us assume that the end-user receives an order to search for and capture important assets. For instance, criminals have just robbed a bank and are trying to flee the country. The end-user has to find and chase these criminals before they escape. The task is successful when at the end of the mission (e.g. before the criminals leave the country) the assets are captured.

III. Expected-Utility Objective

Mission success is defined by linking it to the possession of assets and their utility at the end of the mission:

$$U(t_e) = \sum_{z=1}^{Z} u_z(t_e) \tag{1}$$

where $u_z(t_e)$ is the utility of having asset z at moment t_e which is equal to the end of the mission and Z is the number of assets of interest. The mission is accomplished when this utility function is maximized (i.e. all assets are undamaged and in the possession of the end-user).

However, only the utility $U(t)$ at this current moment t, and the ones in the past, can be calculated. The utility $U(t_e)$ that pertains to the future cannot be calculated, because future events are not certain. Because $U(t_e)$ cannot be calculated, it cannot be controlled. To partly overcome this problem, the expected-utility function [17], [18] can be used to calculate controllable values at any moment t:

$$U_E(t_e, t) = \sum_{z=1}^{Z} u_z(t_e, t) P(S_z, t_e, t) \tag{2}$$

where t is the current moment during the mission, $u_z(t_e, t)$ is the utility of having asset z at moment t_e calculated at moment t and $P(S_z, t_e, t)$ is the probability that asset z is secured (i.e. protected or captured, $S_z = 1$) at moment t_e calculated at moment t. The expected-utility can be altered with the use of sensors as demonstrated in Section V, and then, the actual utility within the future is *expected* to be altered.

A. Variants of Expected-Utility

There is no need to define u_z, which can be challenging, if there is only one asset of interest during the mission (e.g. [19]). In that case, the summation and u_z can be omitted:

$$U_E(t_e, t) = P(S_{z=1}, t_e, t) \tag{3}$$

For simplicity, variables t and t_e are omitted from the equations in the rest of this paper.

Expected-utility could be related to risk analysis. If risk R is estimated as expected loss, and utilities u_z are defined in a consistent manner, then U_E is linearly related to risk:

$$R = \sum_{z=1}^{Z} u_z P(L_z) = \sum_{z=1}^{Z} u_z \left(1 - P(S_z)\right) = \sum_{z=1}^{Z} (u_z) - U_E \tag{4}$$

where $P(L_z)$ is the probability that asset z is lost. Thus, when the expected-utility is maximized, then the risk is minimized.

B. Rationality of Expected-Utility

Although it can be assumed that the expected-utility is a rational model for making decisions, it is not correct for all decision problems. For example, in the St. Petersburg paradox [20]. In this paradox a single player can pay a fee to enter a game where there is a pot with one euro and every round a fair coin is tossed. If a head appears, the amount of money in the pot is doubled. If the tail appears, the game ends and the player receives the pot's contents. With probability 0.5 the player wins 1 euro, with probability 0.25 the player wins 2 euro, etc. Thus, the expected-utility $U_E = 0.5 + 0.5 + 0.5 + \ldots$ of this game is infinite. Therefore, according to the expected-utility model, it is rational to pay any fee (e.g. one milliard euro) to enter the game. Nevertheless, no rational person is willing to pay (much) to participate. This game shows that a criterion only based on the expected-utility could take a decision that no rational person would be willing to take.

To emphasize, the above described problem of expected-utility is not related to the incorrect assessment of the probabilities. It is the case that a fair coin in the St. Petersburg paradox has a fifty-fifty chance that a head or tail appears. A game that investigates (in)correct assessment of probabilities is, for example, the Monty Hall Problem [21]. In any case, the estimation of the probabilities for outcomes, that requires accurate sensor system, environment and events modeling, is not the core of this paper.

Another clarification, the expected-utility functions (and objective functions in general) have been used in the past for two purposes. They can be used as a normative theory or as a descriptive theory [22]. A normative theory aims to model how individual beliefs and preferences *should* be structured if the individual is assumed to be rational. Opposite to this, a descriptive theory tries to represent beliefs of decision makers as they actually are *done* in reality. In the end, this paper investigates how an objective function should be constructed (i.e. normative). Because we cannot justify non-rational behavior, any existing non-rational behavior should be eliminated by modifying the objective definition. In order to do this, we have to investigate how rational decisions are currently made (i.e. descriptive).

IV. Prospect Objective

Prospect theory was introduced in a paper [16] that presents several cases in which human preferences systematically violate the axioms of expected-utility theory. The theory of prospect can be regarded as a correction to the expected-utility theory, and it assigns values to gain and loss rather than to final assets and it replaces probabilities by decision weights:

$$U_P = \sum_{z=1}^{Z} v\left(u_z\right) w\left(P(S_z)\right) \tag{5}$$

where functions $v(.)$ and $w(.)$ translate the utilities into the subjective values and the probabilities into the weights. This model assumes that decision-makers select options with the highest *prospect* instead of the highest expected-utility.

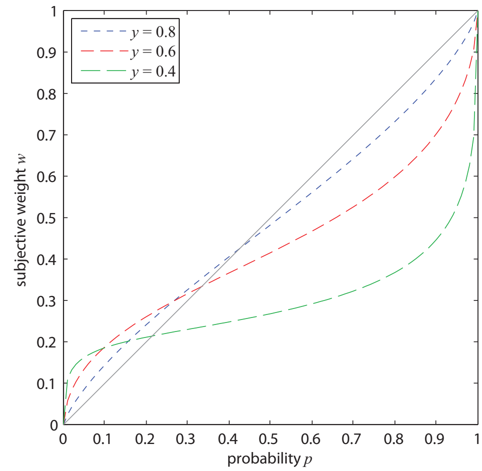

Fig. 1. Probability weighting based on prospect theory.

A. Probabilities, Certainties and Weights

Humans usually assess probabilities non-linearly [16]:

> "People underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty. This [...] certainty effect, contributes to risk aversion in choices involving sure gains and to risk seeking in choices involving sure losses."

For example, assume that there are two options:

- Option A: A chance of 80% to win 4,000 euro,
- Option B: A chance of 100% to win 3,000 euro.

If this opportunity only arises once (i.e. "one shot"), then there is, in principle, no really wrong answer. Of course, the satisfaction of 4,000 euro is higher than 3,000 euro, but these outcomes are related to probabilities (choice A is uncertain). If this opportunity is given many times (e.g. > 100), selecting every time A is optimal, because this will probably result in the highest outcome. However, option B can become more preferred when the opportunity is only offered once. In fact, in an experiment [16] with 95 persons, 80% chose option B.

According to the prospect theory, the reasons for this preference is that people prefer to minimize uncertainty. A person who chooses option B rather wants to have certainly 3,000 euro than, possibly, nothing. The prospect theory models this behavior by translating the probabilities into weights. This translation function can be modeled as follows [23]:

$$w(p) = \frac{p^y}{(p^y + (1-p)^y)^{1/y}} \tag{6}$$

where $w(p)$ is the weight for probability p and y captures the tendency to overweight low-probability outcomes. A few example curves are shown in Fig. 1. Except for low probabilities, decision weights are generally lower than the corresponding probabilities. Products such as insurance and gambling are probably attractive due to over-weighting low probabilities.

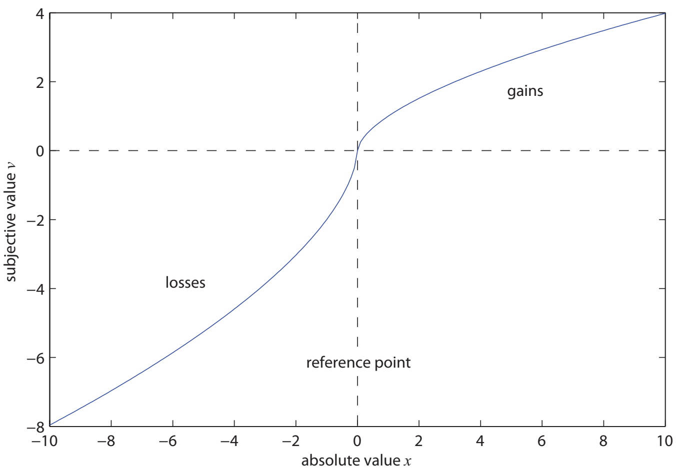

Fig. 2. Subjective value based on prospect theory.

B. Gains and Losses

Prospect theory also transforms the absolute values of the assets into relative values. This is summarized in [16] as:

> "The value function is (i) defined on deviations from the reference point; (ii) generally concave for gains and commonly convex for losses; (iii) steeper for losses than for gains."

This can be modeled as follows [23]:

$$v(x) = \begin{cases} x^{\alpha} & \text{if} x \geq 0 \\ -\lambda(-x)^{\beta} & \text{if} x < 0 \end{cases} \quad (7)$$

where $v(x)$ is the subjective value of "absolute" outcome x, λ is the loss aversion, and α and β are the diminishing sensitivity in gain and loss, respectively. Thus, if $\lambda > 1$, then losses hurt more than gains feel good, and therefore, the value depends on the current situation of the person, the so-called reference point (e.g. status quo). Fig. 2 shows as example a curve for the case $\lambda = 2$ and $\alpha = \beta = 0.6$.

Loss aversion can result in risk avoidance. Risk-averse people choose, for example, to put their money into a bank account rather than into a stock. Although the stock has a higher expected return, it also involves a chance of losing. Risk-seekers prefer higher risks to hopefully gain more.

C. Criticism

Prospect theory has become a well-known theory and it has also received criticism. For example in [24]:

> "Decision making involves the critical tasks of defining the situation, editing the choice problem, and then evaluating options under dynamic and interactive conditions of present and future uncertainties. [...] it is difficult to distinguish empirically between a prospect theory explanation and an expected-utility [...] explanation."

The situation in the above description is similar to the one in the missions of Section II. Besides the probability weighting, also the problem of the reference point is identified [24]:

> "Dynamic situations are particularly likely to induce variations in the way people select reference points because of the absence of a stable status quo that might serve as an obvious focal point."

We also experienced the challenge of defining the reference point and in the next section we will elaborate on that.

V. Case Studies for Sensor Resource Allocation

To achieve the mission goals, resources are deployed that need to be controlled. The main problem described in this paper is that the actual utility after the mission cannot be controlled directly. Therefore, two objective functions are proposed that can be used to maximize the expectation or prospect of the result. This section investigates the difference between these two objectives. A developed simulator [25] is used to deploy sensors, execute sensing tasks and participate in the missions as formulated in Section II.

A. Surface-based radar to defend two assets

Suppose that two assets need to be protected and a (monostatic) radar station is available that can find and identify threatening objects and support effectors to intercept threats with sensing data. The end-user may expect multiple threatening objects for the same asset, but let us assume that there is only one threat for every asset. In that case, the probability that asset z is secured at the end of the mission is given by:

$$P(S_z) = 1 - P(E_z)(1 - P(S_z|E_z)) \quad (8)$$

where $P(E_z)$ is the probability that the threatening object attacks, and succeeds (from the opponent perspective) without any intervention, and $P(S_z|E_z)$ is the probability that the system intercepts such threat. The probability that a threatening object is intercepted depends on which trajectory is taken (for simplicity the set of such trajectories is countable and limited):

$$P(S_z|E_z) = \sum_{n=1}^{N_z} P(S_z|X_{zn})P(X_{zn}|E_z) \quad (9)$$

where $P(S_z|X_{zn})$ is the probability that the object is intercepted by the system if it takes path n, $P(X_{zn}|E_z)$ is the probability that the object takes path n if asset z is attacked, and N_z is the number of trajectories that a hostile object can take towards asset z. Let us assume that the threatening object takes a straight path to the asset with an uniformly distributed probability of its attack angle. The probability that an object is intercepted by the system is given by:

$$P(S_z|X_{zn}) = P(S_z|C_{zn}, D_{zn}, X_{zn}) \\ P(C_{zn}|D_{zn}, X_{zn})P(D_{zn}|X_{zn}) \quad (10)$$

where $P(S_z|C_{zn}, D_{zn}, X_{zn})$ is the probability that the threatening object is intercepted in time after it has been identified as a threat in time, $P(C_{zn}|D_{zn}, X_{zn})$ is the probability that the detected threatening object is identified in time as an threat, $P(D_{zn}|X_{zn})$ is the probability that the threatening object is detected in time if it takes path n.

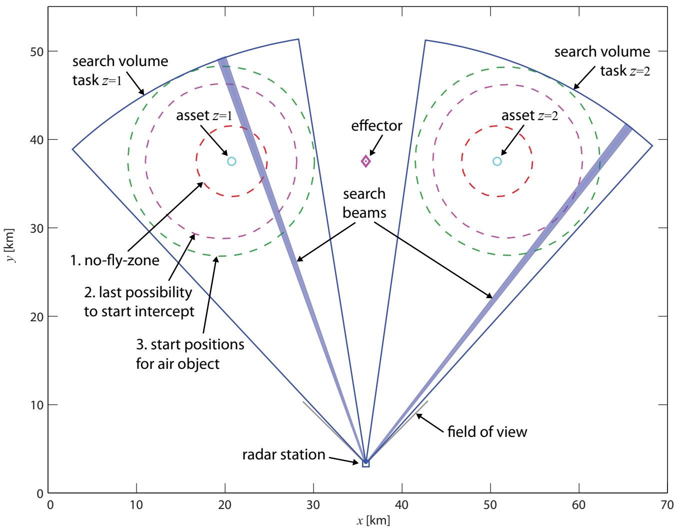

Fig. 3. Radar station executing two search tasks and covering two assets.

Let us assume that $P(E_z) = 1$, $P(C_{zn}|D_{zn}, X_{zn}) = 1$, $P(S_z|C_{zn}, D_{zn}, X_{zn}) = 1$, and that only $P(D_{zn}|X_{zn})$ is adaptable with the radar by spending resources on the search task. A search task is generated for each asset. The resulting search volumes for the radar is shown in Fig. 3. All boundaries around both assets are based on the characteristics of the threatening objects and available effectors. The second boundary specifies the target range at which the effector should start its interception in such a way that the first boundary is not reached by a hostile target. The third boundary specifies the positions at which the objects can start its attack. Based on these boundaries, the radar search volumes are specified in which the radar can spend resources on searching objects.

Estimating the radar performance as a function of allocated resources requires a model. The basis of many radar models is formed by the radar equation [26], [27]:

$$SNR_R = \frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3 R^4 N L} \tag{11}$$

where SNR_R is received signal-to-noise-ratio for radar, P_t is transmit power, G is antenna gain, λ is wavelength, σ is radar cross section, R is target range, N is noise power, and L is system losses.

The radar detection probability P_R is a function of SNR_R, number of processed pulses n_p and false alarm rate P_{fa} [27]. As a result, P_R can be improved by increasing n_p, which increases the integration time. However, adapting n_p also influences the dwell time. The dwell time for a low pulse repetition frequency radar is given by:

$$DT_z = n_p \left(\frac{2R_z}{c} + \tau \right) \tag{12}$$

where R_z is the search range for asset z, c is the wave propagation speed, and τ is the pulse duration. A search volume specifies the range and azimuth width and will influence the revisit time for the radar to scan a volume completely:

$$RT_z = \frac{1}{a_z} \left\lceil \frac{\theta_z}{\theta_r} \right\rceil DT_z \tag{13}$$

where a_z is the amount of allocated resources (within range [0,1]) to asset z, θ_z is the angular size of the search sector around asset z, θ_r is the radar beam-width in azimuth, and operator $\lceil . \rceil$ is ceiling the input to the nearest higher integer.

The available time AT_z for the sensor to detect the threat in time for asset z is calculated based on the expected speed of the threatening object and the distance between the second and third boundary. When the radar can scan the search volume M times during AT_z, then the probability that an object is detected in time is given by:

$$P(D_{zn}|X_{zn}, M) = \sum_{g=G}^{M} \binom{M}{g} (P_{zn})^g (1 - P_{zn})^{M-g} \tag{14}$$

where integer G is the number of required detections for a confirmed track, P_{zn} is the detection probability for scenario n within search volume z. The object range R_{zn} and number of pulses n_p, which are both used to calculate P_{zn}, are based on the object trajectory n towards asset z and predefined radar settings. However, on average a sensor can revisit a position also non-integer times, and then, the performance is:

$$\begin{aligned} P(D_{zn}|X_{zn}) = (1-\gamma)\, P\left(D_{zn}|X_{zn}, \left\lfloor \frac{AT_z}{RT_z} \right\rfloor\right) \\ + \gamma P\left(D_{zn}|X_{zn}, \left\lceil \frac{AT_z}{RT_z} \right\rceil\right) \end{aligned} \tag{15}$$

$$\gamma = \frac{AT_z}{RT_z} - \left\lfloor \frac{AT_z}{RT_z} \right\rfloor \tag{16}$$

where RT_z is the radar revisit time within the search volume around asset z, and $\lfloor . \rfloor$ is flooring the input to the nearest lower integer. To conclude, above model can estimate probability $P(D_{zn}|X_{zn})$, which influences probability $P(S_z)$, and thus, the expected-utility U_E and prospect U_P can be adapted.

B. Air-based camera to find fugitives and threats

Within the second mission a video camera is mounted on an airplane. The airplane is flying a predefined path and the camera can be used to search surface and air objects. The resulting situation is given in Fig. 4. A mission is considered in which one asset needs to be defended and another asset that needs to be captured. The ranges around the assets for the escape task are based on the characteristics of the escaping object and effectors. This mission is not limited to only pursuit tasks, because this results in the same allocation dilemma as in a mission with only defense tasks, which is already discussed in the previous section.

Equations (8), (9) and (10) also hold for the pursuit task, because (i) the object first has to escape, (ii) can also take various routes, and (iii) also has to be detected, identified

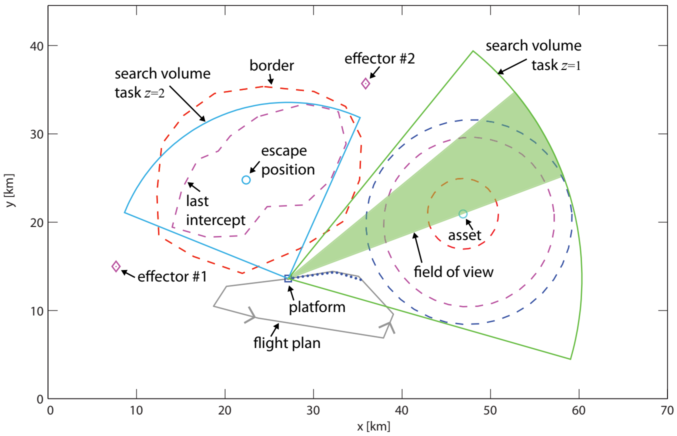

Fig. 4. Camera scanning two areas for defense and pursuit tasks.

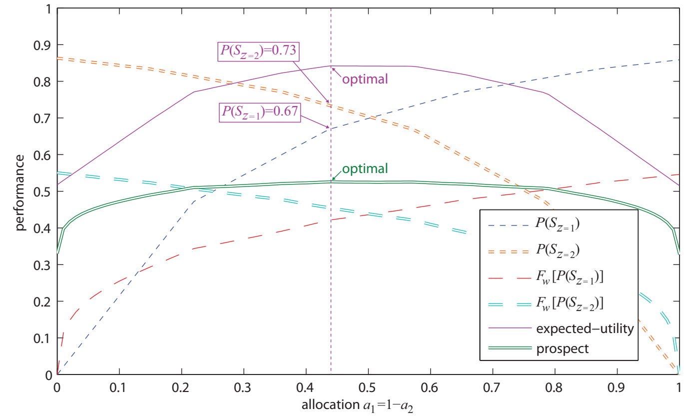

Fig. 5. Optimal allocation during defense with $u_1 = u_2 = 0.6$.

and intercepted by the sensor. As in the previous case, only $P(D_{zn}|X_{zn})$ can be altered by the sensor.

The signal to noise ratio for an electro-optical device is given by [28]:

$$SNR_E = \frac{I_t}{N_E R^2} \tag{17}$$

where SNR_E is the camera received signal-to-noise ratio, I_t is the target intensity within the camera bandwidth and field of view, and N_E is a noise equivalent for the camera. Note that the camera is a passive device and that the radiated energy I_t is beyond the control of the sensor. The optical detection probability is estimated with the use of detection theory [29], [30] and also depends on maximum false alarm rate.

The required time for the camera to revisit each position in the search volume depends on the optical angle of view [31]:

$$\alpha = 2 \arctan \frac{d}{2f} \tag{18}$$

where d represents the size of the film and f the effective focal length. The magnification (zoom)factor m can be taken into account with $f = F(1+m)$ where F is the stated focal length of the lens. If a reference configuration 0 and non-wide-angle lenses is considered, the angle of view is given by:

$$\alpha = \frac{1+m_0}{1+m}\alpha_0 \tag{19}$$

where α_0 and m_0 are the reference angle of view and magnification factor, respectively. The magnification factor m is controlled according to the required range that is needed to execute the search task. Based on the angle of view and the time it is required to capture a picture CT_z, the time to scan a whole search angle RT_z for asset z is estimated by:

$$RT_z = \frac{1}{a_z}\left\lceil \frac{\theta_z}{\alpha_z} \right\rceil CT_z \tag{20}$$

where α_z is the angle of view for search around asset z. Equations (14), (15) and (16) are reused to estimate $P(D_{zn}|X_{zn})$.

C. Evaluation of decision-making procedure

The two objective functions take differently into account the uncertainties of the mission result. Thus, the "optimal" control decision may (only if $Z > 1$) depend on if expected-utility or prospect is maximized. During both missions there are two tasks and one resource, and the discussion is simplified by spending all resources and solely optimizing allocation a_1. Allocation a_2 is then a function of a_1: $a_2 = 1 - a_1$. Therefore, the allocation options are limited to one dimension, which allows us to plot all allocation solutions in each figure.

First, utilities $u_1 = u_2 = 0.6$ are equal for the defense mission, the probabilities within the prospect model are transformed using (6), and the values are not yet transformed using (7). The resulting curves as a function of allocation a_1 are given in Fig. 5. Also the selection of the optimal allocation and the resulting performances $P(S_z)$ are given in Fig. 5. Because the analyzed situation is almost symmetric and all involved functions are monotonic, the expected-utility and prospect objectives suggest the same solution.

Different optimal solutions are suggested for non-equal utility values $u_1 = 0.8$ and $u_2 = 0.4$ as shown in Fig. 6. The use of (6) results in more prospect when more resources are spent to task one: the uncertainty of securing asset one is reduced at the cost of asset two protection. This is caused by the uncertainty effect: it is better to save one asset and lose the other, than potentially to lose both. This can be considered as a valid argument for drifting from the expected-utility solution.

Next, the second mission with the camera is considered. The utilities u_1 and u_2 are equalized, (7) is used to transform the utilities, but the probabilities are not yet transformed. Because the first asset can be lost, and losing hurts more than gaining, the task that protects asset one is made more important than the task two that aims to capture the fugitive. In fact, as Fig. 7 shows, the prospect objective is maximized when task two is dropped. The performance can be negative, because losing an asset is now represented by a negative value.

Fig. 8 shows another optimal decision when the probabilities are transformed with (6). Task two (i.e. capture fugitive) is not completely dropped anymore and both tasks are still executed, but task one receives still more resources than if the expected-utility model was used. This difference is caused

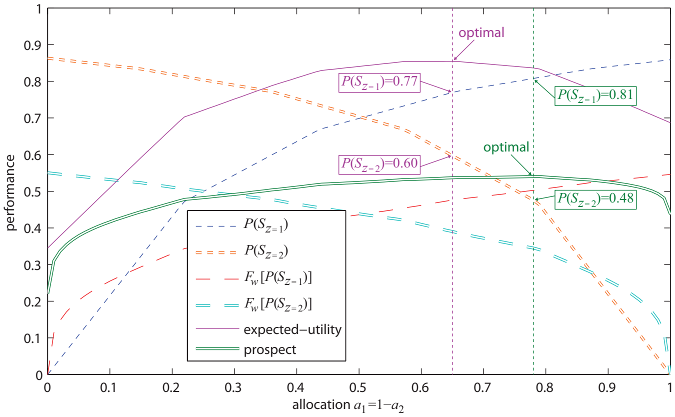

Fig. 6. Optimal allocation during defense with $u_1 = 0.8$ and $u_2 = 0.4$.

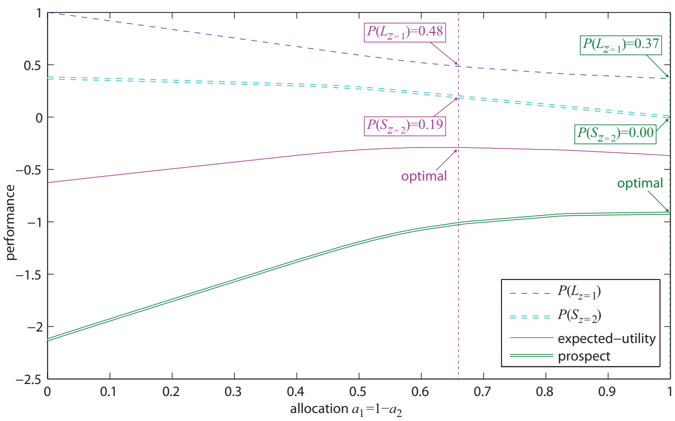

Fig. 7. Optimal allocation during defense and pursuit mission without (6).

by the shape of the weight function (6). The weights in the prospect model remain low, because the camera is not able to provide enough performance (i.e. max 63%). Note, the derivative of (6) is in this region low and any performance improvement is assessed in a pessimistic manner.

In the last mission, the end-user does not only have something to lose, but also to gain. This is a significant difference from a mission perspective, but the expected-utility objective

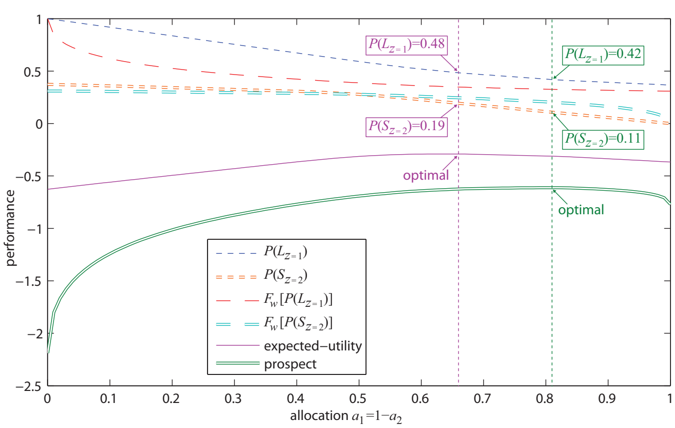

Fig. 8. Optimal allocation during defense and pursuit mission with (6).

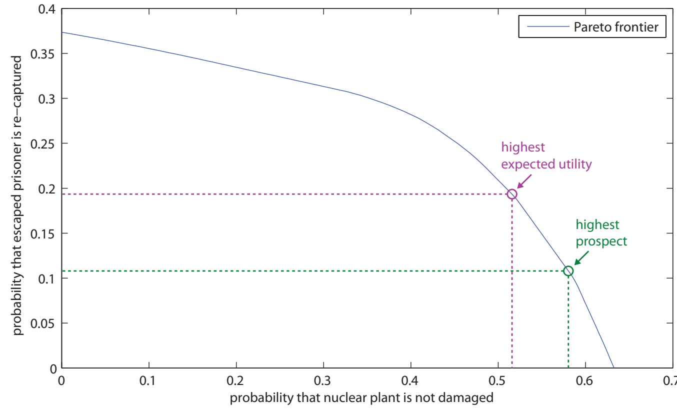

Fig. 9. Possible interface between resource allocation and end-user.

cannot make this distinction. The prospect objective can, and prefers to defend instead of pursue, because the losing hurts more than gains feel good. However, it could be argued that it is difficult to apply this approach with a reference-point. For example, assume that the fugitive is an ex-prisoner. If the reference point has to be set before the fugitive escaped, the end-user has something to lose when he does not re-capture the prisoner. When the reference point has to be set after the escape happen, the end-user has something to gain by capturing the fugitive. Thus, even in this simple case, it is hard to apply (7).

D. End-user interface

This paper argues that one should not blindly rely on an expected-utility solution in all cases, but it does not argue that the prospect objective is always better. Both the objective functions have their (dis)advantages, and it is still hard to decide which one is the most "optimal" or the most "rational" one. This is because decisions have to be made in circumstances with many uncertainties. To overcome the discussed problems, it is possible to make an interface for end-users that was actually requested in [32]:

> "A system supporting rational decision making must be designed to cope with these problems. [...] What is required is a presentation of the situation that allows decision makers to see their options, get support in processing their questions, and critique of proposed decisions."

To achieve this, multiple objective functions can be simultaneously employed, for example, based on risk-avoiding, risk-neutral and risk-seeking strategies. Each function will produce its own "optimal" solution that can be presented to the end-user. Potentially a whole range of options can be provided and represented by a so-called Pareto frontier [33], [34]. All these options for the camera case can be presented as in Fig. 9.

The Pareto frontier can support end-users in selecting which exact allocation is preferred considering two objectives. The benefit of using multiple objective functions and/or the Pareto frontier is that end-users get a good overview of optimal options and possible outcomes, hides all unnecessary technical details, useless multi-dimensional aspects and provides a limited set of optimal solutions in operational terms.

VI. Conclusion

A mission-driven approach to derive objective functions, that can be used to optimally control (network of) sensor resources, is presented. The two proposed objectives functions are created by linking the mission objective to assets instead of solely considering sensor characteristics. In this way, the optimization is related to operational aspects that are meaningful to the end-user. We also exploited the knowledge of prospect theory, which was originally used to model processes of human decision-making, to better match human reasoning during sensor optimization. Note that the difference between expected-utility and prospect is only revealed when the number of assets is larger than unity. In the mean time, we clarified the mission-driven concept and illustrated the generality of the proposed solution. In the end, the differences between the objectives are investigated by applying these functions to different sensor types and missions. Additionally we discussed a possible interface between resource allocation and end-users.

The proposed mission-driven resource-independent objective functions can be used in many scenarios to make decisions in an optimal manner. For instance, they can also be used to select a flight plan for the camera platform or to optimally select the radar waveform parameters. The proposed objective functions are also not limited to stand-alone sensors. The only difference with sensor networks is that the resulting performance estimation in the network case is more exhaustive to compute and that the degrees of freedom increased. In any case, the end-user mission goals can be effectively included into the system optimization, increasing reliability and trust for many mission-critical, high-risk applications.

Acknowledgment

The authors thank prof. P. van Genderen (Delft University of Technology), and dr. L. Kester (TNO Research Organization) for numerous fruitful discussions.

References

[1] H. Rowaihy, S. Eswaran, M. Johnson, D. Verma, A. Bar-Noy, T. Brown, and T. La Porta, "A survey of sensor selection schemes in wireless sensor networks," in *Defense and Security Symposium*. International Society for Optics and Photonics, 2007, pp. 65 621A–65 621A.

[2] D. Datta, C. M. Fonseca, and K. Deb, "A multi-objective evolutionary algorithm to exploit the similarities of resource allocation problems," *Journal of Scheduling*, vol. 11, no. 6, pp. 405–419, 2008.

[3] T. de Groot, O. Krasnov, and A. Yarovoy, "Generic utility definition for mission-driven resource allocation," in *IET International Conference on Radar Systems*, 2012, pp. 1–5.

[4] ——, "Mission-driven management and allocating operational tasks to reconfigurable sensors," *submitted to IEEE Transactions on Aerospace and Electronic Systems*, vol. x, no. x, p. x, 2014.

[5] J. L. Williams, "Information theoretic sensor management," Ph.D. dissertation, Massachusetts Institute of Technology, 2007.

[6] Y. Zhang and Q. Ji, "Efficient sensor selection for active information fusion," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 40, no. 3, pp. 719–728, 2010.

[7] A. Charlish, "Autonomous agents for multi-function radar resource management," Ph.D. dissertation, University College London, 2011.

[8] J. Wintenby, "Resource allocation in airborne surveillance radar," Ph.D. dissertation, Chalmers University of Technology, 2003.

[9] F. Bolderheij, "Mission-driven sensor management - analysis, design, implementation and simulation," Ph.D. dissertation, Delft University of Technology, 2007.

[10] D. Papageorgiou and M. Raykin, "A risk-based approach to sensor resource management," in *Advances in Cooperative Control and Optimization*. Springer, 2007, pp. 129–144.

[11] M. Ditzel, L. Kester, S. van den Broek, and M. van Rijn, "Cross-layer utility-based system optimization," in *International Conference on Information Fusion*, 2013, pp. 507–514.

[12] B. Dieber, C. Micheloni, and B. Rinner, "Resource-aware coverage and task assignment in visual sensor networks," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 21, no. 10, pp. 1424–1437, 2011.

[13] M. Perillo and W. Heinzelman, "Optimal sensor management under energy and reliability constraints," in *IEEE Wireless Communications and Networking*, vol. 3, 2003, pp. 1621–1626.

[14] J. Wintenby and V. Krishnamurthy, "Hierarchical resource management in adaptive airborne surveillance radars," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 42, no. 2, pp. 401–420, 2006.

[15] M. Zink, E. Lyons, D. Westbrook, and J. Kurose, "Closed-loop architecture for distributed collaborative adaptive sensing of the atmosphere: meteorological command and control," *International Journal of Sensor Networks*, vol. 7, no. 1, pp. 4–18, 2010.

[16] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica: Journal of the Econometric Society*, pp. 263–291, 1979.

[17] M. Friedman and L. J. Savage, "The utility analysis of choices involving risk," *Journal of Political Economy*, vol. 56, no. 4, pp. 279–304, 1948.

[18] P. J. Schoemaker, "The expected utility model: Its variants, purposes, evidence and limitations," *Journal of Economic Literature*, pp. 529–563, 1982.

[19] T. de Groot, O. Krasnov, and A. Yarovoy, "Mission-driven system design during runtime for reconfigurable radars and antennas," in *European Radar (EuRAD) Conference*, Oct 2013, pp. 463–466.

[20] N. Bernoulli, "Correspondence of nicolas bernoulli concerning the st petersburg game," *Letter to Pierre Raymond de Montmart*, 1713.

[21] S. Selvin, M. Bloxham, A. Khuri, M. Moore, R. Coleman, G. R. Bryce, J. A. Hagans, T. C. Chalmers, E. Maxwell, and G. N. Smith, "A problem in probability (letters to the editor)," *American Statistician*, vol. 29, no. 1, pp. 67–71, 1975.

[22] T. Bedford and R. Cooke, *Probabilistic risk analysis: foundations and methods*. Cambridge University Press, 2001.

[23] A. Tversky and D. Kahneman, "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and uncertainty*, vol. 5, no. 4, pp. 297–323, 1992.

[24] J. S. Levy, "Prospect theory, rational choice, and international relations," *International Studies Quarterly*, vol. 41, no. 1, pp. 87–112, 1997.

[25] T. de Groot, O. Krasnov, and A. Yarovoy, "Simulator for studying resource allocation in reconfigurable multi-sensor networks," in *European Radar (EuRAD) Conference*, 2012, pp. 326–329.

[26] M. I. Skolnik, *Introduction to radar systems*. McGraw-Hill, New York, 2001.

[27] B. R. Mahafza, *Radar systems analysis and design using MATLAB*. Chapman & Hall, 2013.

[28] F. T. Heilenday, "Principles of air defense and air vehicle penetration," DTIC Document, Tech. Rep., 1988.

[29] H.-C. Zheng, X. Mao, Y.-L. Xue, and L. Jiang, "Evaluation for detection probability of infrared point target under complicated backgrounds," *Journal of Electromagnetic Waves and Applications*, vol. 26, no. 11-12, pp. 1528–1537, 2012.

[30] M. A. Richards, *Fundamentals of Radar Signal Processing*. McGraw-Hill, New York, 2005.

[31] E. McCollough, *Photographic Topography*. Industrial Publishing Company, San Francisco, 1893.

[32] S. Arnborg, J. Brynielsson, H. Artman, and K. Wallenius, "Information awareness in command and control: precision, quality, utility," in *Int. Conference on Information Fusion*, vol. 2, 2000, pp. 25–32.

[33] V. Pareto, *Cours d'economie politique*. Librairie Droz, 1964.

[34] S. Dabia, E.-G. Talbi, T. van Woensel, and T. D. Kok, "Approximating multi-objective scheduling problems," *Computers & Operations Research*, vol. 40, no. 5, pp. 1165–1175, 2013.