A multi-objective approach to the optimal selection of assets for the design of an optical sensor network

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Abstract

This paper presents results of a research work on a decision support problem investigating the allocation of operating time of passive optical sensors (telescopes) associated with participation in the operation of a wide-area observation network. The problem is formulated as a multi-objective optimisation task with constraints extended by a modified Pareto front solution selection method. The main feature of the presented algorithm is the representation of decision variables in the form of binary numbers with limited precision, which allows selection between sensor modes. Two experiments are presented in this paper. First, all the sensors expected to participate in the network were subject to optimisation. Second, involved the use of expert knowledge to establish the core of the network under construction based on the selected resources. Consequently, these resources have been omitted during the optimisation process in this experiment. Our results show that some sensors are strongly preferred by the algorithm. We also note a certain level of equivalence of selected sensors with respect to the criteria considered. Therefore, our conclusion is that the selection of sensors to construct the target network requires human intervention and consideration of criteria not included in the formal definition of the task. The approach adopted in this work provides an effective support in the decision-making process. It allows elimination of decisions that have no rational basis in the adopted criteria.

1. INTRODUCTION

In recent decades, there has been a significant transformation in the field of astronomical observations. Significance of data obtained from a single sensor has been greatly improved by incorporating observations from multiple sensors working simultaneously [1]. This paradigm shift, is crucial for the existence of the space surveillance and tracking (SST) systems. It underlines the fact that the synergy between observations from different sensors is of great importance for understanding the processes affecting the motion of objects orbiting Earth, including artificial satellites [2]. With the increased importance of these multidimensional data sets, there has also been an increased need to effectively manage and utilize them [3].

The main objective of modern SST sensor networks is not only to supply the necessary data, but also to provide the required redundancy while taking into account the economic aspects of operational activities. This requires a thoughtful — optimized — approach to network architecture that balances technical soundness with financial prudence. Today's network architectures must therefore take into account both the complexity of data acquisition, processing, and transmission and the realities of budget constraints. These requirements are not exclusively imposed in the SST domain. They are typical for decentralized sensor networks used, for example, for environmental monitoring [4].

The problem of designing the architecture of a sensor network concerns more than just the structure of the network. Also, it involves aspects of data fusion techniques, real-time processing, and, increasingly, economical issues as these interact strongly with one another [5]. This is a direct result of the characteristics of the process dynamics, where the quality of the information obtained from the system depends on the distribution and characteristics of sensors providing the data as well as the algorithms processing them [6].

It is a natural phenomenon that the increase in the amount of innovations in data provision is crucial for extracting information about the process [7]. In the scope of the geographically distributed sensor network systems this is done using data processing (fusion) algorithms [8, 9]. One of the primary tools used in this regard is the Kalman filter well recognized for its extensive applications in various fields of science and industry [10]. Equipped with efficient algorithms and computing power one can provide real-time processing capabilities. However, this is reflected in the cost of investment and maintenance of the resulting system. Hence, it is essential to give special attention to the design of such systems with particular focus on methods that allow to make an optimal choice according to the indicators adopted for the project [11].

This is also the case for the SST sensor networks [12]. The inherent uncertainty related to the available information on the natural dynamics of the process under consideration — the characteristics of motion of space objects in Earth's orbits — imposes certain requirements or preferences for the distribution of sensors as well as their type and mode of operation. This allows one to look at the problem of SST network design as an optimization problem characterized by a number of evaluation criteria and constraints.

Taking into account constraints, i.e. limitations set by the sensor operators along with the economic and technical indicators on the operational capacity of the equipment, the report illustrates a set of possible solutions and the related consequences.

The study is intended to assist the decision-making process related to optimized selection of sensors declaring an interest in participating in the operation of SST sensor network. The proposed method allows one to consider multiple selection of both objectives and constraints. The latter include not only limitations set by the sensor operators and network managers but also the economic and technical indicators on the operational capacity of the equipment. In contrast to other approaches, this work focuses on tools and algorithms to support decision-making in an optimized manner. To this end, it uses multi-objective optimization framework to formulate decision problem. The goal is to provide an overview of feasible trade-off decision that, in general, span between the quality of the supplied data, redundancy, and the operational cost of the infrastructure. The solution of the problem is being sought by applying evolutionary optimization strategy based on multi-objective genetic algorithms [13, 14, 15, 16]. Moreover, decision support is enhanced by a pre-selection mechanism among the Pareto optimal population of solutions. For this purpose, the gray relational coefficient (GRC) was used [17].

The contribution of the article is as follows.

- A multi-objective optimization approach to SST network design is introduced. It allows independent consideration of multiple assessment criteria. The approach systematically organizes possible choices of network architectures using the Pareto optimality concept.
- The developed decision support mechanism is intended to help decision makers manage both economic and performance factors in a sustainable manner. The algorithm allows the incorporation of external computing engines to evaluate the performance of network elements (sensors). In the case under consideration, an expert-based assessment was used.
- A method for selecting a limited, representative number of solutions from the Pareto front was proposed to simplify the decision-making process. The method is based on the GRC index. A beneficial feature of this approach is its ability to produce samples without using arbitrary preferences. For this purpose, the method employs data normalization based on utopia points.
- The presented mechanism enables to take into account factors related to ownership of the components and individual economic goals expressed through declared availability to participate in the creation of the network.

The reminder of this paper is organized in the following manner. Section 2 introduces the formulation of the network design problem using a multi-objective optimization framework. In Section 3 methods and algorithms proposed to deliver decision support tool are presented. A practical use case of the proposed method is presented in Section 4. In particular, the conditions of the experiment, tools and algorithm configurations are presented, and the results are discussed. Section 5 summarizes the paper.

2. PROBLEM FORMULATION

Let ω_{S} denote an individual passive optical sensor (telescope) submitted by its owner as a candidate to participate in a world-wide sensor network (WSN). Only a carefully selected sensor group (Ω_{WSN}) of all submitted sensor candidates (Ω_{WSNC}) is to be selected for operations, thus $\omega_{\mathrm{S}} \in \Omega_{\mathrm{WSN}} \subseteq \Omega_{\mathrm{WSNC}}$.

Given each sensor is identified by a unique name (ω_{SN}) and, with no loss to the generality of the formulation, can operate in either surveillance or tracking mode ($\omega_{\mathrm{ST}} \in \Omega_{\mathrm{T}} \stackrel{\text{def}}{=} \{\text{‘S’}, \text{‘T’}\}$), its further characterization is provided by considering the n-tuple:

$$\omega_{\mathrm{S}} \stackrel{\text{def}}{=} (\omega_{\mathrm{SN}}, \omega_{\mathrm{ST}}, \omega_{\mathrm{SP}}, \omega_{\mathrm{SD}}, \omega_{\mathrm{SDM}}, \omega_{\mathrm{SC}}, \omega_{\mathrm{SVLA}}), \tag{1}$$

where: $\omega_{\mathrm{SP}} \in \Omega_{\mathrm{P}}$ denotes an indicator that determines the sensor performance, ω_{SD} recommended working time of the sensor, ω_{SDM} is the maximum (specified by the owner or operator) declared working time of the sensor, ω_{SC} determines the cost per hour of working time, $\omega_{\mathrm{SVLA}} \in \Omega_{\mathrm{VLA}}$ signifies sensor localization with accuracy to geographic region — very-large area (VLA), considering:

$$\Omega_{\mathrm{VLA}} \stackrel{\text{def}}{=} \{\text{‘Europe’}, \text{‘Asia’}, \text{‘South Africa’}, \text{‘North America’}, \text{‘South America’}, \text{‘Australia’}\}. \tag{2}$$

Therefore, given the aforementioned setup, a natural manipulated variable ($\boldsymbol{x}_{\mathrm{FTE}}$) in the task is identified as a list specifying the recommended working time to be assuaged to selected sensors candidates considered to participate in the SST sensor network. Hence:

$$\boldsymbol{x}_{\mathrm{FTE}} \stackrel{\text{def}}{=} \left[\omega_{\mathrm{SD}1}, \omega_{\mathrm{SD}2}, \ldots, \omega_{\mathrm{SD}n_{\mathrm{SN}}}\right]^T, \tag{3}$$

where $(\cdot)^T$ denotes a transposition of element $(\cdot)$ and n_{SN} is the total number of all sensors included in Ω_{WSNC}, operating in single mode with respect to Ω_{T}.

As some sensors may declare their participation as either sensors operating in tracking or surveillance mode, which is important due to the operational limitations discussed in the following paragraphs, an additional variable, to select operating mode, is introduced:

$$\boldsymbol{x}_{\mathrm{T}} \stackrel{\text{def}}{=} \left[\omega_{\mathrm{ST}1}, \omega_{\mathrm{ST}2}, \ldots, \omega_{\mathrm{ST}n_{\mathrm{ST}}}\right]^T, \tag{4}$$

where n_{ST} denotes the total number of all sensors included in Ω_{WSNC}, capable of operating, interchangeably, in both considered modes provided by Ω_{T}.

Finally, a vector of decision variables is defied as:

$$\boldsymbol{x} \stackrel{\text{def}}{=} \left[\boldsymbol{x}_{\mathrm{FTE}}^T, \boldsymbol{x}_{\mathrm{T}}^T\right]^T. \tag{5}$$

The sensor's contribution to the SST sensor network is not arbitrary and is subject to constraints (C). These, include the network designers' (stakeholders') architectural and economical preferences and the participants' desired involvement, are quantified in the following manner.

C_1: The preferred by network designers declared percentage of each sensor operating time should remain within predefined bounds, in reference to the maximum operating time, if the sensor is selected, hence:

$$\Omega_{\mathrm{C1}} \stackrel{\text{def}}{=} \{\omega_{\mathrm{S}} : 0.2 \leq \omega_{\mathrm{SD}} \leq 1 \vee \omega_{\mathrm{SD}} = 0\}. \tag{6}$$

C_2: The percentage of contributed time declared for sensors located in Europe operating in survey mode should not exceed an allowable cap value of 1 full-time equivalent (FTE), which yields:

$$\Omega_{\mathrm{C2}} \stackrel{\text{def}}{=} \left\{\omega_{\mathrm{S}} : \sum \omega_{\mathrm{SD}} \leq 1 \wedge \omega_{\mathrm{ST}} = \text{‘S’} \wedge \omega_{\mathrm{SVLA}} = \text{‘Europe’}\right\}. \tag{7}$$

C_3: The percentage of contributed time declared for all sensors included in WSN operating in survey mode should not exceed an allowable cap value of 2 FTE, thus:

$$\Omega_{\mathrm{C3}} \stackrel{\text{def}}{=} \left\{\omega_{\mathrm{S}} : \sum \omega_{\mathrm{S\,D}} \leq 2 \wedge \omega_{\mathrm{S\,T}} = \text{‘S’}\right\}. \tag{8}$$

C_4: The percentage of contributed time declared for sensors located in Europe operating in tracking mode should not exceed an allowable cap value of 1 FTE, hence:

$$\Omega_{\mathrm{C4}} \stackrel{\text{def}}{=} \left\{\omega_{\mathrm{S}} : \sum \omega_{\mathrm{S\,D}} \leq 1 \wedge \omega_{\mathrm{S\,T}} = \text{‘T’} \wedge \omega_{\mathrm{S\,VLA}} = \text{‘Europe’}\right\} \tag{9}$$

C_5: The percentage of contributed time declared for all sensors included in WSN operating in tracking mode should not exceed an allowable cap value of 2 FTE, therefore:

$$\Omega_{\mathrm{C5}} \stackrel{\text{def}}{=} \left\{\omega_{\mathrm{S}} : \sum \omega_{\mathrm{S\,D}} \leq 2 \wedge \omega_{\mathrm{S\,T}} = \text{‘T’}\right\}. \tag{10}$$

C_6: The recommended percentage for contributed time should not exceed the maximum specified by the sensor owner (operator) for each individual instrument, which reads:

$$\Omega_{\mathrm{C6}} \stackrel{\text{def}}{=} \{\omega_{\mathrm{S}} : \omega_{\mathrm{S\,D}} \leq \omega_{\mathrm{S\,DM}}\}. \tag{11}$$

Given C_i, $\forall i \in \overline{1,6}$, the feasible problem set yields:

$$\Omega_{\mathrm{FPS}} \stackrel{\text{def}}{=} \bigcap_{i \in \overline{1,6}} \Omega_{\mathrm{C}i}, \tag{12}$$

where $\bigcap$ denotes a set intersection and $\overline{(\cdot),(\cdot\cdot)}$ signifies an interval in the set of integers between $(\cdot)$ and $(\cdot\cdot)$.

The assessment of the selection of sensors and their involvement in the operation of the SST network under design is carried out by adopting the following criteria.

O_1: The *total number of sensors* contributing to the WSN under design.

O_2: The sensor *performance index* is based on the operational evaluation of the sensor.

O_3: The *network distribution* over anticipated VLAs.

O_4: A yearly *operational cost* normalized using average market prizes.

Considering H to denote the Heaviside function the assessment criteria (O_1 – O_4) are quantified as follows:

$$O_1: \qquad J_1(\omega_{\mathrm{S}}) \stackrel{\text{def}}{=} \sum_{\omega_{\mathrm{S}} \in \Omega_{\mathrm{SN}}} H(\omega_{\mathrm{S\,D}}), \tag{13}$$

$$O_2: \qquad J_2(\omega_{\mathrm{S}}) \stackrel{\text{def}}{=} \frac{\sum\limits_{\omega_{\mathrm{S}} \in \Omega_{\mathrm{SN}}} (\omega_{\mathrm{S\,D}}\, \omega_{\mathrm{S\,P}})}{\sum\limits_{\omega_{\mathrm{S}} \in \Omega_{\mathrm{SN}}} \omega_{\mathrm{S\,D}}}, \tag{14}$$

$$O_3: \qquad J_3(\omega_{\mathrm{S}}) \stackrel{\text{def}}{=} \frac{1}{n_{\mathrm{VLA}}} \sum_{i \in \Omega_{\mathrm{VLS}}} \sqrt{\sum_{\omega_{\mathrm{S}(i)} \in \Omega_{\mathrm{SN}}} \omega_{\mathrm{S\,(i)}}}, \tag{15}$$

$$O_4: \qquad J_4(\omega_{\mathrm{S}}) \stackrel{\text{def}}{=} \sum_{\omega_{\mathrm{S}} \in \Omega_{\mathrm{SN}}} \omega_{\mathrm{S\,D}}\, \omega_{\mathrm{S\,C}}, \tag{16}$$

where n_{VLA} denotes the total number of geographical areas listed in the (2).

The pursued solution is to determine the percentage of sensor working time involved in the operation of the SST network under design allowing maximization of the criteria O_1 – O_3 while minimizing O_4. Solving a mixed task combining min and max operators in a direct way is not practical. Therefore, for implementation purposes, without any loss to the problem under consideration, a vector of objectives is assumed to be defined as:

$$\boldsymbol{J}\left(\omega_{\mathrm{S}}\right) \stackrel{\mathrm{def}}{=} \left[-J_1(\omega_{\mathrm{S}}),\, -J_2(\omega_{\mathrm{S}}),\, -J_3(\omega_{\mathrm{S}}),\, J_4(\omega_{\mathrm{S}})\right]^T. \tag{17}$$

Taking (5), (12) and (17) enables one to pose the problem of SST network design as a multi-objective optimization task with constraints, which yields:

$$\Omega_J^* = \min_{\boldsymbol{x}} \boldsymbol{J}\left(\omega_{\mathrm{S}}\left(\boldsymbol{x}\right)\right), \quad \text{subject to: } \omega_{\mathrm{S}}\left(\boldsymbol{x}\right) \in \Omega_{\mathrm{FPS}} \subseteq \Omega_{\mathrm{SN}}, \tag{18}$$

where $\omega_{\mathrm{S}}\left(\boldsymbol{x}\right)$ emphasizes the dependency of sensors considered on the operating mode and percentage of their contribution — operational time involvement (5) — in the activities of for WSN under design.

In addition, taking the argument set of the above multi-criteria optimization task as Ω_{x}^*, the following holds:

$$\Omega_J^* = \boldsymbol{J}\left(\Omega_{\mathrm{x}}^*\right). \tag{19}$$

In addition, Ω_{x}^* is a set of proposed solutions for the SST network design task which indicates the percentage of sensor operating time, optimized with respect to the adopted criteria O_1 – O_4.

The scope of further considerations is specified by adopting the following set of assumptions.

Assumption 1 *It is assumed that the set of Ω_{J}^* is ordered in the Pareto sense.*

By the virtue of Assumption 1, the set of proposed solutions (Ω_{J}^*) to a problem consists of elements having such a characteristic that any change in the selection of a solution that improves a certain assessment criterion cannot take place without deteriorating another (the inverse is also true).

Assumption 2 *It is assumed that the sensor's performance index ω_{SP} is determined on a discrete rating scale from* 1 *to* 6*, thus:*

$$\Omega_{\mathrm{P}} \stackrel{def}{=} \overline{1,6}. \tag{20}$$

Assumption 3 *It is assumed that the sensor performance index takes into account the characteristics of the object, the quality of the generated data, reliability and response to disturbances affecting its operation.*

Assumption 3 enables decoupling of the design method presented in the paper from the method of evaluating the performance of sensors. This means that it is possible to use any method of evaluation of sensor performance as long as it allows the result to be obtained as a single value.

3. METHODS AND TOOLS

Given the nature of the task (18) and the order in the solution space imposed by the Assumption 1 for the purpose of finding the numerical solution of the task, the NSGA-III algorithm [15] was employed. The subsequent steps of the algorithm are described in the following paragraphs of Subsection 3.1. The details regarding constraint handling are provided in Subsection 3.2. A pre-selection mechanism devoted to restrict the number of solutions to a limited number of representative elements is given in Subsection 3.3.

3.1 Evolutionary algorithm

First, an initial population of decision variables ($\boldsymbol{x}$) is randomly drawn as vectors of floating point numbers with limited precision with the assumption of a uniform distribution between 0 and 100 ($\boldsymbol{x}_{\mathrm{FTE}}$) and binary values ($\boldsymbol{x}_{\mathrm{T}}$). At this point the (initial) population may consist of individuals both meeting and exceeding the constraints. Second, the initial population is evaluated based on the adopted criteria O_1 – O_4. Taking the elementary stopping criterion as the maximum number of generations, as long as it remains unsatisfied, the algorithm proceeds with the evolutionary process.

During the evolution process, the successive steps of the algorithm use the mechanisms of natural selection, crossover, mutation, and two dedicated operators to take into account the characteristics of the problem. The natural selection is implemented using *tournament selection* [18]. In case of crossover operator two independent mechanisms are used. First to handle floating point numbers. Second to provide support for binary valued part of $\boldsymbol{x}$. In the former case a *simulated binary bounded* crossover operator is applied. In the latter case a *two point* operator is used. A similar distinction was applied to the selection of mutation operators. For floating-point encoded part of $\boldsymbol{x}$ the *polynomial bounded* mutation operator is invoked. In case of a binary encoded part of $\boldsymbol{x}$ a simple *flip bit* mechanism is used. The two additional operators used are designed to adapt the numerical conditions of the population to the characteristics of the task being solved. The task of the first additional operator is to attract an independent individual of the population closer to the constraints on the FTE. The second proposed operator guards the numerical precision adopted in the calculation by making adjustments to the genes (values in $\boldsymbol{x}_{\mathrm{FTE}}$) of individuals accordingly.

The workflow of the algorithm is presented in Fig. 1.

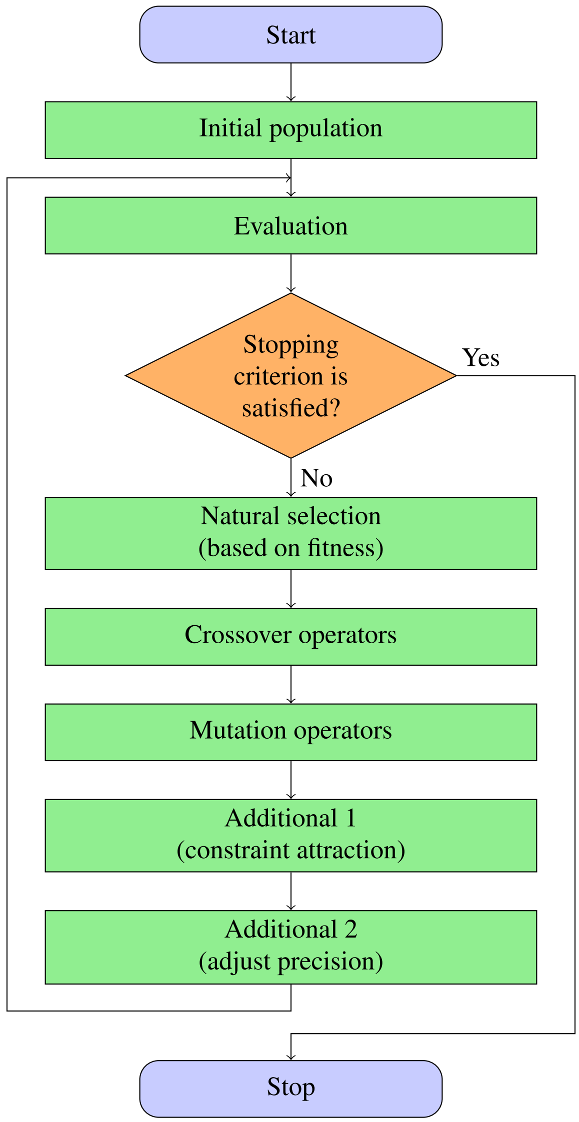

Figure 1: NSGA-III based algorithm workflow

3.2 Constraint handling

Among the mechanisms typically used to account for the constraints of the optimization task in the evolutionary process is the penalty function method [19]. In this study, this method was used for $C_1 - C_6$. Thus, the implementation of the constraints consisted of adding a penalty to all objective functions ($O_1 - O_4$), according to the relationships shown below.

In the case of C_1, the penalty function was used in the quadratic form given by:

$$h_1 \overset{\text{def}}{=} \sum h_{1\,i}, \tag{21}$$

where:

$$h_{1\,i}(\boldsymbol{x}) = \begin{cases} 0 & \text{, if } \omega_{\text{S}} \in \Omega_{\text{C1}} \\ 5+3(1-100*(0.1-\omega_{\text{Si}})^2) & \text{, otherwise} \end{cases}. \tag{22}$$

In contrast, the C_2 - C_6 constraints used a linear penalty function, following:

$$C_2: \qquad h_2(\boldsymbol{x}) = \begin{cases} 0 & \text{, if } \omega_{\text{S}} \in \Omega_{\text{C2}} \\ 0.5+\sum \omega_{\text{S D}}-1 & \text{, otherwise} \end{cases}, \tag{23}$$

$$C_3: \qquad h_3(\boldsymbol{x}) = \begin{cases} 0 & \text{, if } \omega_{\text{S}} \in \Omega_{\text{C3}} \\ 0.5+\sum \omega_{\text{S D}}-2 & \text{, otherwise} \end{cases}, \tag{24}$$

$$C_4: \qquad h_4(\boldsymbol{x}) = \begin{cases} 0 & \text{, if } \omega_{\text{S}} \in \Omega_{\text{C4}} \\ 0.5+\sum \omega_{\text{S D}}-1 & \text{, otherwise} \end{cases}, \tag{25}$$

$$C_5: \qquad h_5(\boldsymbol{x}) = \begin{cases} 0 & \text{, if } \omega_{\text{S}} \in \Omega_{\text{C5}} \\ 0.5+\sum \omega_{\text{S D}} \leq 2 & \text{, otherwise} \end{cases}, \tag{26}$$

$$C_6: \qquad h_6 \overset{\text{def}}{=} \sum h_{6\,i}, \tag{27}$$

where:

$$h_{6\,i}(\boldsymbol{x}) = \begin{cases} 0 & \text{, if } \omega_{\text{S}} \in \Omega_{\text{C6}}, \\ 1+\omega_{\text{S D}}-\omega_{\text{S DM}}, & \text{, otherwise} \end{cases}. \tag{28}$$

In the case of constraints $C_2 - C_6$, the (classical) penalty function in its quadratic form is abandoned in favor of linear functions. This treatment was intended to strengthen the mechanism against exceeding the constraints in the case of minima located close to the constraints.

3.3 Solution pre-selection

Typically, the evolutionary algorithm generates a diverse set of Pareto optimal solutions. This makes the task of decision-making laborious due to the large number of available options. To simplify the selection process (decision-making) a pre-selection method based on the GRC is implemented. Further insight into this approach is provided in the subsequent paragraph.

Subsequent steps of the proposed selection method are as follows:

Step 1: Select only scenarios for which the number of sensors is maximum.

$$\Omega^*_{J\text{r}1} \overset{\text{def}}{=} \left\{ \omega_{\text{S}} \in \Omega^*_J : J_1(\omega_{\text{S}}) = \max_{\omega \in \Omega^*_J} J_1(\omega) \right\}. \tag{29}$$

Step 2: Restrict the selection to 10% of scenarios, with the best performance index:

$$\Omega^*_{J\text{r}2} \overset{\text{def}}{=} \left\{ \omega_{\text{S}\,i} \in \Omega^*_{J\text{r}1} : \forall_{i \in 1..(N_{\Omega^*_{J\text{r}1}}-1)} J_2(\omega_{\text{S}\,i}) > J_2(\omega_{\text{S}\,i+1}), i < 0.05 N_{\Omega^*_{J\text{r}1}} \right\}. \tag{30}$$

Step 3: Span the results over cost (16) and network distribution (15) objectives.

Step 4: Select Pareto optimal solution with respect to the objective functions selected, in Step 3:

$$\Omega^*_{Jr3} \overset{\text{def}}{=} \arg\min_{\boldsymbol{x}} \left[-J_3, J_4\right](\omega_{\text{S}}), \quad \text{subject to: } \omega_{\text{S}} \in \Omega^*_{Jr2}. \tag{31}$$

Step 5: Use GRC [17, 20] to select final set of results candidates (network architectures) for final decision-making.

The application of the above procedure makes it possible to significantly reduce the population of solutions to those representative, reflecting the strategic objectives adopted in the decision-making process.

4. RESULTS

This section sequentially presents the preparation of the experiment (Subsection 4.1), the configuration of the method used to solve the decision support task (Subsection 4.2), and the results obtained along with a discussion (Subsection 4.3).

4.1 Experiment setup

The algorithm input data — considered sensor candidates — is given in Table 1. There is a direct relation of the data in Table 1 with the problem characteristics (Section 2), in terms of sensor name ($\omega_{\mathrm{S\,N}}$), operational mode ($\omega_{\mathrm{S\,T}}$), sensor performance ($\omega_{\mathrm{S\,P}}$), maximum FTE ($\omega_{\mathrm{S\,DM}}$), cost per hour ($\omega_{\mathrm{S\,C}}$), and location ($\omega_{\mathrm{S\,VLA}}$). The last column is used to calculate the objective — yearly operational cost (O_4).

Table 1: Sensor candidates (Ω_{WSNC})

Name ($\omega_{\mathrm{S\,N}}$) [-]	Operation mode ($\omega_{\mathrm{S\,T}}$) (S/T)	Sensor performance ($\omega_{\mathrm{S\,P}}$) (1–6)	Maximum working time ($\omega_{\mathrm{S\,DM}}$) [% of FTE]	Normalized cost ($\omega_{\mathrm{S\,C}}$) [1/h]	VLA ($\omega_{\mathrm{S\,VLA}}$) [-]	Night time on-site [h/y]
A	(S)urvey	3	66%	1,005	Europe	3557
B	(S)urvey	4	50%	0,992	Europe	3351
C	Both (S/T)	5	50%	1,005	Europe	3556
D	(S)urvey	3	50%	1,003	Europe	3198
E	Both (S/T)	6	35%	1,005	Europe	3186
F	(S)urvey	6	15%	0,991	Europe	3664
G	Both (S/T)	6	20%	1,004	Europe	3447
H	(S)urvey	6	50%	1,020	North America	3634
I	(S)urvey	6	40%	0,991	Southern Africa	3653
J	Both (S/T)	6	60%	1,005	Southern Africa	3717
K	Both (S/T)	6	80%	0,976	Australia	3662

4.2 Methods and tools

The NSGA-III based algorithm presented in Section 3 has been implemented using Python 3.10. For numerical calculations, the precision of floating-point decision variables was assumed to be equal to 5. This is in line with 5% points granularity in terms of working time contribution ($\omega_{\mathrm{S\,D}}$) composing the $\boldsymbol{x}_{\mathrm{FTE}}$ part of the decision vector $\boldsymbol{x}$. In turn, the parameters characterizing the algorithm's workflow are listed in the Table 2.

Table 2: Evolutionary algorithm configuration parameters

no.	Value	Description
1	700	total number of generations
2	0.1	probability of using one of crossover operators (*simulated binary bounded* or *two point*)
3	0.8	probability of using one of the mutation operators (*polynomial bounded* or *flip bit*)
4	0.05	probability of using a dedicated mutation operator
5	10	total number of algorithm runs

4.3 Results and discussion

By applying the presented method (Section 3) to the WSN design problem (18), a 4-dimensional set of non-dominated — Pareto-optimal — solutions was obtained using the presented input data (Table 1). A projection of the solution set onto a 3-dimensional subspace, ignoring the cost (O_4) is presented in Fig. 2.

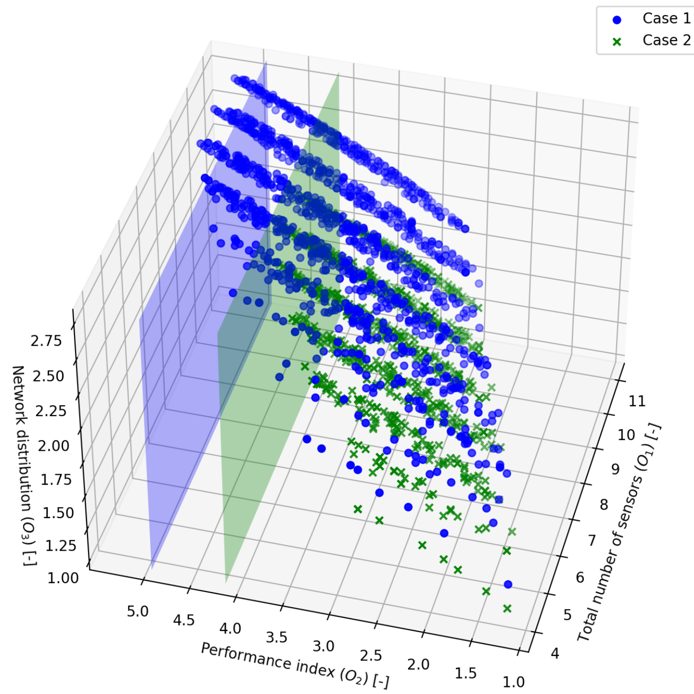

Figure 2: Pareto front projection on O_1 –O_3 subspace

Due to the discrete nature of the first objective function (O_1), it was decided to divide the non-dominated solutions into series with respect to the number of sensors. As a consequence, this enables to represent subsets of the front in a 3-dimensional space. In Figs. 3 and 4, the subsets, generated for the maximum number of 11 and subsequently 10 sensors considered, are shown, respectively.

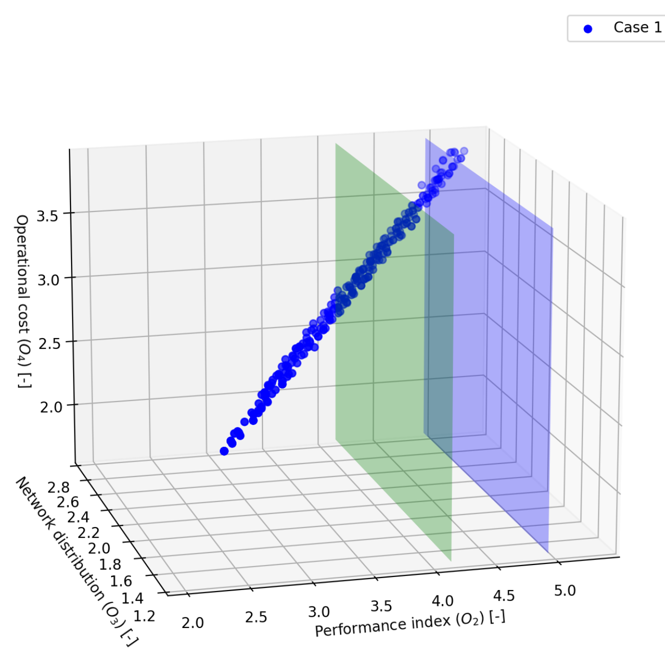

Figure 3: Pareto front projection on O_1 –O_3 subspace considering 11 sensors

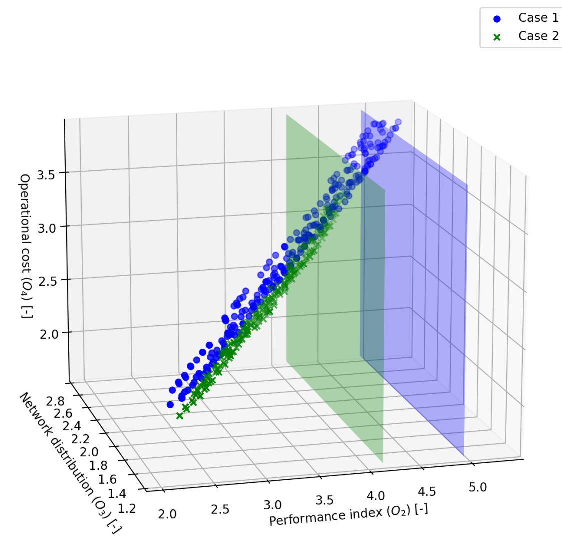

Figure 4: Pareto front projection on O_1 –O_3 subspace considering 10 sensors

Analyzing the set of non-dominated solutions, it can be seen that for the assumed number of sensors, the points are arranged along a certain straight line intersecting the objectives subspace. The situation can be analyzed in the context of O_3 relative to O_2 at the selected values of O_1 and O_4. From this viewpoint, one can observe the existence of solutions for which the preservation of a high value of the quality index (O_2) does not force significant changes (deterioration) in the parameter of distribution across the VLA (O_3). In the case of network system operating costs (O_4), the situation is different. A change in the network performance index (O_2) and network distribution (O_3) force a change — an increase — in costs (O_4). Hence flows the conclusion that an increase in the quality of network operation is associated with a higher cost of maintenance, as one would actually expect.

By comparing Case 1 and Case 2 (Figs. 2 – 4) it is possible to see how the possibility of adding an additional "K" sensor influences the design of the network. It is observed that adding a sensor enables one to design a network with a larger number of sensors. Apparently, it also allows to increase both the network dispersion (O_3) and its quality (O_2), which is directly related to the sensor parameters (e.g., VLA and quality).

According to the adopted method of limiting the set of solutions to the decision problem (Section 3.3), a set of representative proposals for WSN architecture was generated. The population of results thus restricted has the characteristic that the higher the value of the GRC, the closer the solution is to the utopian point in the solution space of task (18) — see Fig. 5.

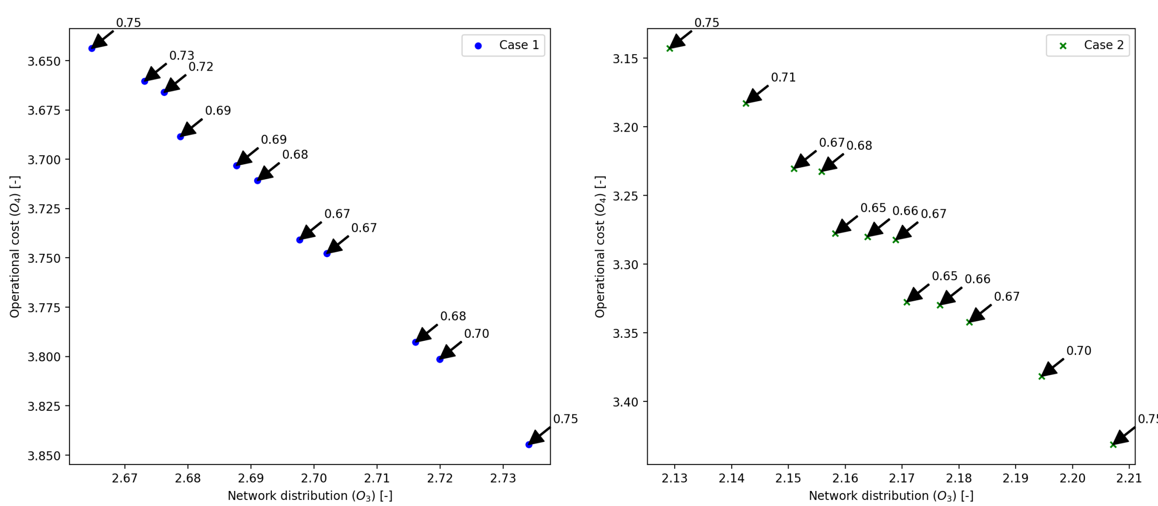

Figure 5: Reduced Pareto front with GRC coefficient

The selected 10 network architectures having the highest GRC for both Case 1 and Case 2 are shown as Tables 3 and 4.

Table 3: Top 10 GRC network architecture candidates in Case 1

Sensor name	Desired sensor contribution (mode)									
A	20%(T)	20%(T)	25%(T)	20%(T)	20%(T)	25%(T)	25%(T)	20%(T)	20%(T)	20%(T)
B	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)
C	20%(S)	20%(S)	55%(S)	60%(S)	60%(S)	60%(S)	60%(S)	45%(S)	55%(S)	55%(S)
D	25%(T)	45%(T)	20%(S)	20%(S)	20%(S)	35%(S)	35%(S)	35%(S)	35%(S)	35%(S)
E	35%(S)	20%(S)	20%(S)	20%(S)	20%(S)	20%(T)	20%(S)	20%(S)	20%(T)	20%(S)
F	15%(T)	15%(T)	20%(S)	20%(S)	20%(T)	20%(S)	20%(T)	20%(S)	20%(S)	20%(T)
G	20%(T)	20%(S)	80%(S)	80%(S)	80%(S)	80%(S)	80%(S)	80%(S)	80%(S)	80%(S)
H	50%(T)	50%(T)	15%(T)	15%(T)	15%(T)	15%(T)	15%(T)	15%(T)	15%(T)	15%(T)
I	40%(T)	40%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)
J	45%(S)	60%(S)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)
K	80%(S)	80%(S)	25%(T)	25%(T)	25%(T)	20%(T)	20%(T)	30%(T)	20%(T)	20%(T)
FTE tracking Europe [-]	1.00	1.00	0.85	0.80	1.00	1.00	1.00	0.85	0.95	0.95
FTE survey Europe [-]	0.55	0.60	0.60	0.60	0.40	0.55	0.55	0.75	0.55	0.55
FTE tracking [-]	1.90	1.90	1.75	1.70	1.90	1.90	1.90	1.75	1.85	1.85
FTE survey [-]	1.80	2.00	1.95	2.00	1.80	1.95	1.95	2.00	1.90	1.90
O_1 [-]	11	11	11	11	11	11	11	11	11	11
O_2 [-]	4.96	5.11	4.94	4.96	4.96	5.20	5.20	5.00	5.08	5.08
O_3 [-]	2.66	2.73	2.67	2.68	2.68	2.72	2.72	2.68	2.69	2.69
O_4 [-]	3.64	3.84	3.66	3.67	3.67	3.80	3.80	3.69	3.70	3.70
GRC	0.75	0.75	0.73	0.72	0.72	0.70	0.70	0.69	0.69	0.69

Table 4: Top 10 GRC network architecture candidates in Case 2

Sensor name	Desired sensor contribution (mode)									
A	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)
B	35%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)	20%(T)
C	20%(S)	45%(S)	60%(S)	60%(S)	60%(S)	55%(S)	60%(S)	60%(S)	55%(S)	55%(S)
D	25%(T)	45%(T)	35%(S)	35%(S)	35%(S)	35%(S)	25%(S)	35%(S)	35%(S)	35%(S)
E	35%(S)	35%(S)	20%(S)	40%(S)	25%(S)	30%(S)	45%(S)	30%(S)	40%(S)	35%(S)
F	15%(T)	15%(T)	20%(S)	20%(S)	20%(S)	20%(S)	20%(S)	20%(S)	20%(S)	20%(S)
G	20%(S)	20%(S)	15%(T)	15%(T)	15%(T)	15%(T)	15%(T)	15%(T)	15%(T)	15%(T)
H	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)	50%(T)
I	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)	40%(T)
J	60%(S)	60%(S)	45%(T)	45%(T)	45%(T)	45%(T)	45%(T)	45%(T)	45%(T)	45%(T)
FTE tracking Europe [-]	0.95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
FTE survey Europe [-]	0.75	1.00	0.75	0.95	0.80	0.85	0.90	0.85	0.95	0.90
FTE tracking [-]	1.85	1.90	1.90	1.90	1.90	1.90	1.90	1.90	1.90	1.90
FTE survey [-]	1.35	1.60	1.35	1.55	1.40	1.40	1.50	1.45	1.50	1.45
O_1 [-]	10	10	10	10	10	10	10	10	10	10
O_2 [-]	4.14	4.33	4.14	4.29	4.18	4.14	4.18	4.21	4.21	4.18
O_3 [-]	2.13	2.21	2.14	2.19	2.16	2.15	2.18	2.17	2.18	2.16
O_4 [-]	3.14	3.43	3.18	3.38	3.23	3.23	3.34	3.28	3.33	3.28
GRC	0.75	0.75	0.71	0.70	0.68	0.67	0.67	0.67	0.66	0.66

The following Figs. 6 – 9 illustrate the network architectures for the two highest GRC values for both Case 1 and Case 2. The maps shown illustrate the use of tracking and survey sensors in various VLAs. In addition, in the lower left corner there is a summary describing the allocation of resources between the sensors in the network.

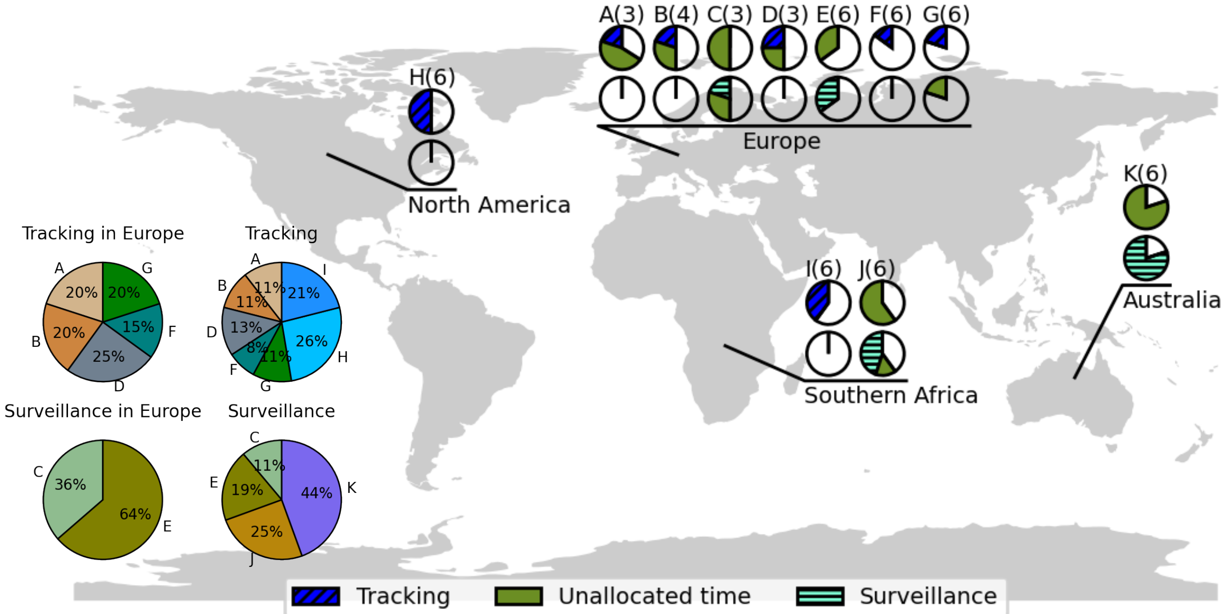

Figure 6: Sensor network architecture (Case 1, GRC= 0.75, column 1)

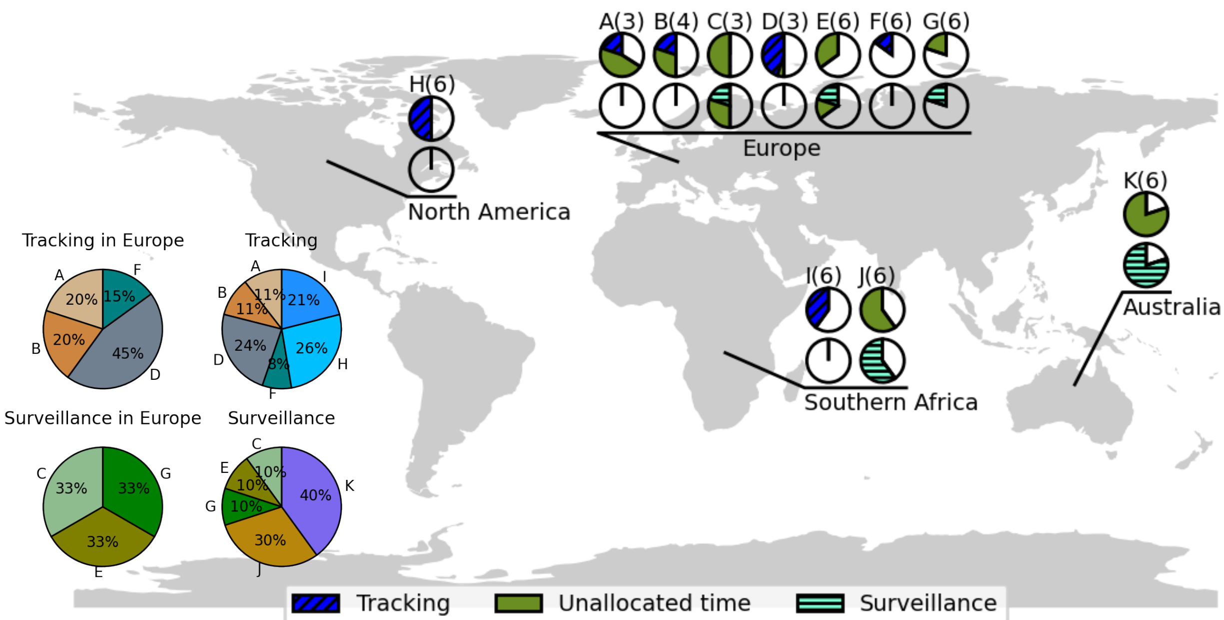

Figure 7: Sensor network architecture (Case 1, GRC= 0.75, column 2)

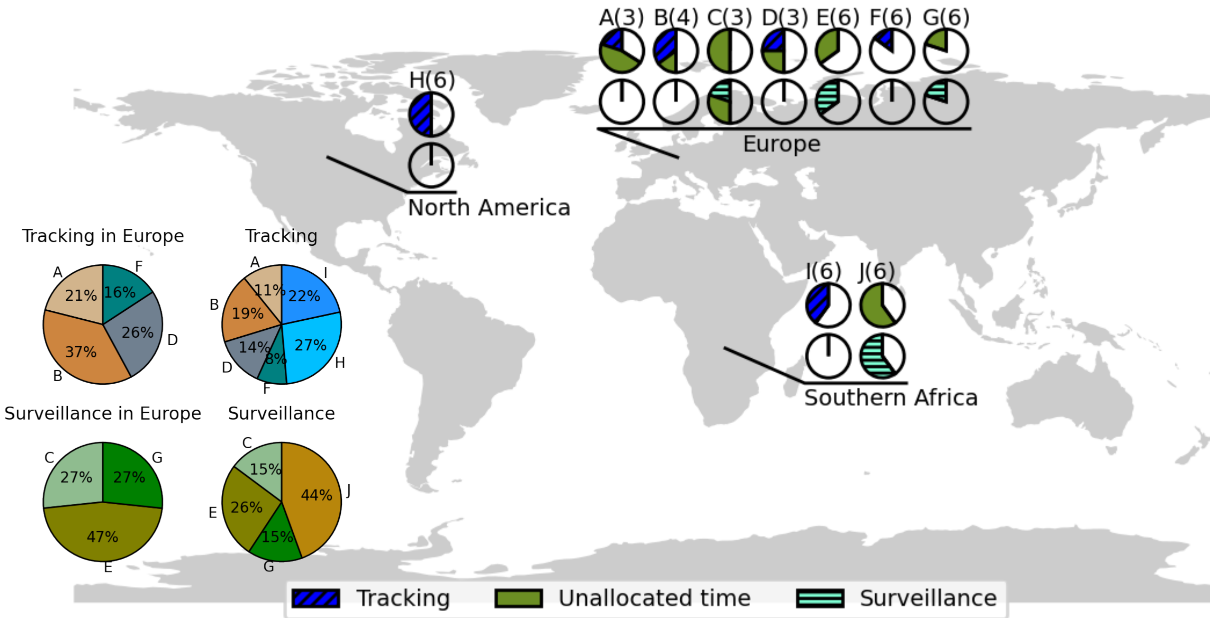

Figure 8: Sensor network architecture (Case 2, GRC= 0.75, column 1)

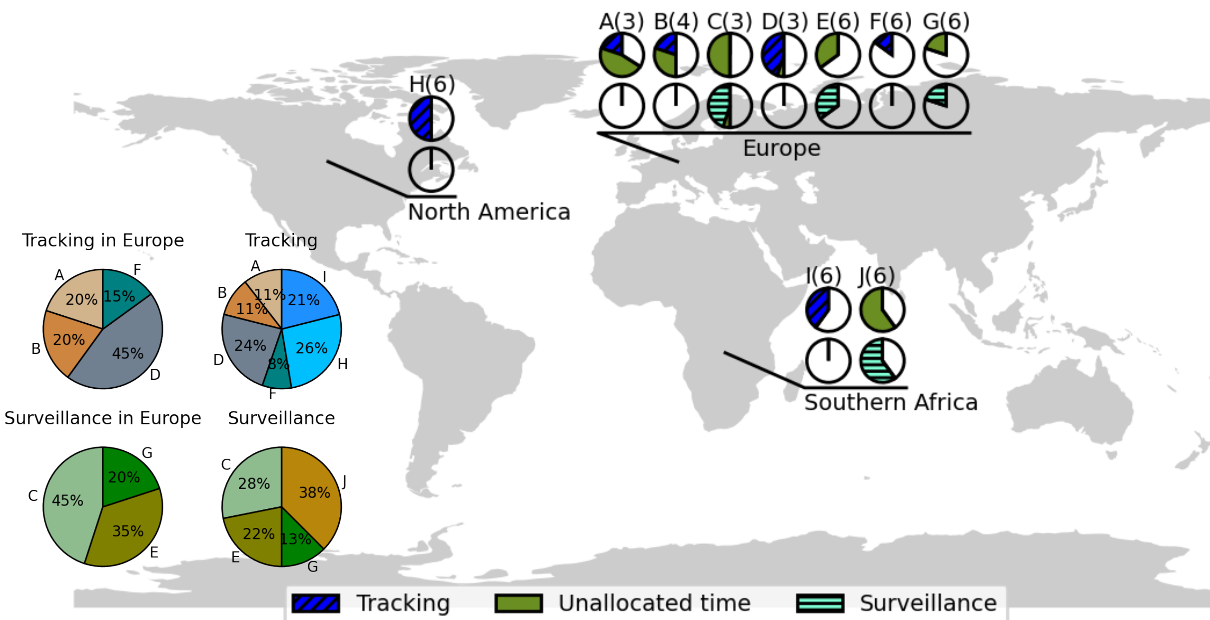

Figure 9: Sensor network architecture (Case 2, GRC= 0.75, column 2)

Analyzing the network architectures designed by the algorithm (Figs. 6 – 9) for both Case 1 and Case 2, certain distinctive features can be observed. In each case, the proposed representative solutions — network architectures — consist not only of different sets of sensors, e.g., Figs. 6 and 8. In fact, even in case of the same sensors being considered it is possible to observe different proposals for their operating modes, as well as contributions in operating times, e.g., Figs. 6 and 7.

The above-mentioned features illustrate that a multi-objective problem can have many combinations of Pareto-equivalent solutions. Moreover, the proposed mechanism for limiting the size of the set of proposed solutions to a certain representative subset preserves the diversity. That is, the proposed solutions are easily distinguishable. This gives the decision-maker freedom of choice, which enables to consider soft requirements — not included in the algorithm code. These can be, for example, conditions of a political nature that are difficult to code.

5. CONCLUSIONS

This paper describes a proposed decision support method for the design of a world-wide SST network. The proposed solutions were generated by solving a multi-objective optimization task with constraints. For this purpose four quality indicators were adopted, as well as constraints of the task resulting from organizational conditions and preferences of sensor operators. In addition, a method was developed to limit the population of possible (Pareto optimal) solutions to a certain small group of representative cases — proposed network architectures. The goal is to ease the network design on a decision-making level.

Further research plans include, among others, the following activities. Focus on solutions dedicated to explore the decision space in the vicinity of constraints. Carrying out the optimization in stages in order to improve the resolution of the Pareto front approximation in the areas indicated by the decision maker.

CRediT authorship contribution statement

Krzysztof Armiński Conceptualization, Methodology, Formal analysis, Software, Investigation, Data Curation, Writing - Original Draft, **Tomasz Zubowicz** Supervision, Conceptualization, Methodology, Formal analysis, Validation, Writing - Original Draft, Writing - Review & Editing, **Stefania Wolf** Resources, Writing - Original Draft, Writing - Review & Editing, **Mikołaj Krużyński** Resources, Writing - Original Draft, **Zygmunt Anioł** Resources, Writing - Original Draft, **Tymoteusz Trocki** Resources, **Edwin Wnuk** Supervision, Conceptualization, Resources, Data Curation, Writing - Review & Editing.

REFERENCES

[1] Simon Haykin and K. J. Ray Liu. *Handbook on Array Processing and Sensor Networks*. John Wiley & Sons, Ltd, 2010.

[2] D.A. Vallado and W.D. McClain. *Fundamentals of Astrodynamics and Applications*. Fundamentals of Astrodynamics and Applications. Microcosm Press, 2001.

[3] Bruno Coelho, Domingos Barbosa, Miguel Bergano, João Pandeirada, Paulo Marques, Alexandre Correia, and José Matias de Freitas. Developing a data fusion concept for radar and optical ground based sst station. *arXiv preprint arXiv:2211.04443*, 2022.

[4] J. Agre and L. Clare. An integrated architecture for cooperative sensing networks. *Computer*, 33(5):106–108, 2000.

[5] Tomasz Zubowicz and Rafał Łangowski. On the problem of optimised allocation of water quality sensors and actuators in dwds. In *2021 25th International Conference on Methods and Models in Automation and Robotics (MMAR)*, pages 150–155, 2021.

[6] Hairong Qi, S.Sitharama Iyengar, and Krishnendu Chakrabarty. Distributed sensor networks—a review of recent research. *Journal of the Franklin Institute*, 338(6):655–668, 2001. Distributed Sensor Networks for Real-time Systems with Adaptive C onfiguration.

[7] H.H. Afshari, S.A. Gadsden, and S. Habibi. Gaussian filters for parameter and state estimation: A general review of theory and recent trends. *Signal Processing*, 135:218–238, 2017.

[8] I.R. Goodman, R.P. Mahler, and H.T. Nguyen. *Mathematics of Data Fusion*. Theory and Decision Library B. Springer Netherlands, 2013.

[9] Bahador Khaleghi, Alaa Khamis, Fakhreddine O. Karray, and Saiedeh N. Razavi. Multisensor data fusion: A review of the state-of-the-art. *Information Fusion*, 14(1):28–44, 2013.

[10] R. E. Kalman and R. S. Bucy. New Results in Linear Filtering and Prediction Theory. *Journal of Basic Engineering*, 83(1):95–108, 03 1961.

[11] S.S. Dhillon and K. Chakrabarty. Sensor placement for effective coverage and surveillance in distributed sensor networks. In *2003 IEEE Wireless Communications and Networking, 2003. WCNC 2003.*, volume 3, pages 1609–1614 vol.3, 2003.

[12] Krzysztof Kamiński, Edwin Wnuk, Justyna Gołębiewska, Mikołaj Krużyński, Monika Kamińska, Michał Żołnowski, Marcin Gędek, and Rafał Borek. Leo cubesats tracking with a network of polish optical sst sensors. In *The Advanced Maui Optical and Space Surveillance Technologies Conference*, page E71, 2018.

[13] Eckart Zitzler, Kalyanmoy Deb, and Lothar Thiele. Comparison of multiobjective evolutionary algorithms: Empirical results. *Evolutionary Computation*, 8(2):173–195, 2000.

[14] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, 2002.

[15] Kalyanmoy Deb and Himanshu Jain. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: Solving problems with box constraints. *IEEE Transactions on Evolutionary Computation*, 18:577–601, 2014.

[16] Tomasz Zubowicz, Krzysztof Armiński, Bartosz Szulczyński, and Jacek Gębicki. Electronic nose algorithm design using classical system identification for odour intensity detection. *MEASUREMENT*, 202:111677–, 2022.

[17] Zhiyuan Wang and Gade Pandu Rangaiah. Application and analysis of methods for selecting an optimal solution from the pareto-optimal front obtained by multiobjective optimization. *Industrial & Engineering Chemistry Research*, 56(2):560–574, 2017.

[18] Brad L Miller, David E Goldberg, et al. Genetic algorithms, tournament selection, and the effects of noise. *Complex systems*, 9(3):193–212, 1995.

[19] Mitsuo Gen and Runwei Cheng. A survey of penalty techniques in genetic algorithms. In *Proceedings of IEEE International Conference on Evolutionary Computation*, pages 804–809. IEEE, 1996.

[20] Jose D Martinez-Morales, Ulises Pineda-Rico, and Enrique Stevens-Navarro. Performance comparison between madm algorithms for vertical handoff in 4g networks. In *2010 7th International Conference on Electrical Engineering Computing Science and Automatic Control*, pages 309–314. IEEE, 2010.