AN INTEGRATED UAS DESIGN OPTIMIZATION BASED ON MISSION ASSESSMENT AND EVALUATION

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Abstract

Unmanned aerial systems can be used in number of civil applications, such as surveillance, search and rescue, precision agriculture, civil infrastructure inspection, remote sensing and etc. The mission fulfillment grade of these missions depends on UAV flight performance, sensor parameters, energy consumption, communication abilities and is determined by the initial mission requirements. To get an effective UAS solution it is necessary to take into account all elements of the system, e.g. to bring together aircraft design, payload, communication and other elements into one multidisciplinary design process.

Owing to the elevation model and realistic representation of the terrain, the visualization environment models the sensor payload performance, communication capabilities and the physical world where the UAS is performing the mission. It provides information concerning sensor coverage area, probabilities of object detection, number of detected objects, slant range between the UAV and search objects, obstacles detection in the line-of-sight and time of communication losses. These information are involved into the mission evaluation process and into the UAS design optimization.

An application study for the methodology is presented by a civil UAS search and rescue mission in a mountain area. During the mission simulation in the virtual operational environment the key evaluation criteria are obtained and involved into the UAS assessment and design process. Using the methodology presented in the paper, an UAV can be optimized with regard to mission requirements already in the early stages of the design process.

Keywords

UAS design; UAS mission simulation; operational analysis; UAS optimization; mission assessment and evaluation

1. INTRODUCTION

Unmanned aerial systems (UAS) can be used in a number of civil applications, such as surveillance, search and rescue (SAR), precision agriculture, civil infrastructure inspection, remote sensing and etc. [1].

Compared to manned aircrafts, an Unmanned Aerial Vehicle (UAV) interacts with the environment through the onboard sensors. Therefore, the sensor and communication performances as well as their implementation in the whole system play an important role in mission fulfillment grade [2]. Furthermore, an UAV design is strongly driven by the mission, sensors and communication systems requirements, FIG. 1.

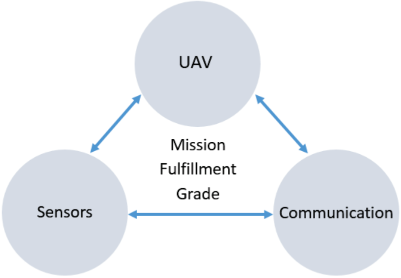


FIG. 1. Interrelation of UAV, sensors, communication and mission fulfillment grade

In classic aircraft design approaches the sensor and communication performances are not part of the primary requirements and are taken into account on the operational analysis stage only, when the aircraft concept is already quite detailed [2]. Owing to the elevation model and realistic representation of the terrain, the visualized operational environment simulates the sensor payload and communication performances in the physical world where the UAS is performing the mission. Thus, it provides the information concerning sensor coverage area, probabilities of object detection, number of detected objects, slant range between the UAV and search objects, communication range, obstacles detection in the line-of-sight and time of communication losses. These information are involved into the mission evaluation process and into the UAS design optimization. Using the methodology presented in this paper, an UAV is optimized with regard to mission requirements already in the early stages of the design process [2, 3].

The next sections present the methodology approach and the environment used for the UAS mission simulation and evaluation. An application study for the methodology is presented by a civil UAS search and rescue mission in a mountain area.

2. METHODOLOGY INTRODUCTION

The presented methodology is based on the enhanced mission simulation and evaluation of the UAS in the visualized operational environment.

2.1. Overview of the mission simulation and evaluation environment

The presented environment consists of several connected parts: UAV design, UAS simulation and assessment in the visualized operational environment and UAS optimization. The overall structure of the mission simulation and evaluation environment is presented in FIG. 2 [3].

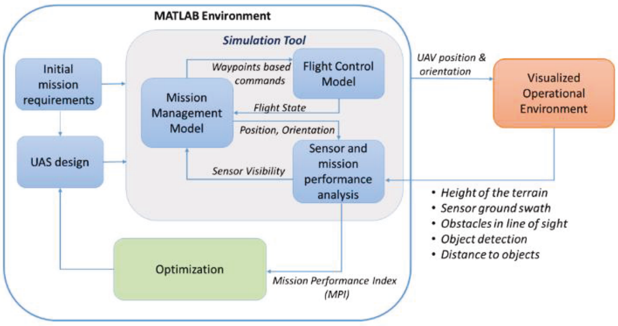


FIG. 2. Structure of the mission simulation and evaluation environment [3].

2.1.1. Initial mission requirements and UAS design

As a first step of the presented approach the key mission performance criteria, the design parameters together with the mission requirements are defined. Afterwards an initial set of UAS configurations based on a genetic algorithm [4] is calculated and simulated in the simulation and visualization environment.

A consistent design of an UAV is created taking into account general geometric data, weights, aerodynamic polar and propulsion system data. Simplified physical methods, especially for aerodynamics and structural weight estimation, are used where applicable. An overview of the UAS design process is presented in FIG. 3 [5].

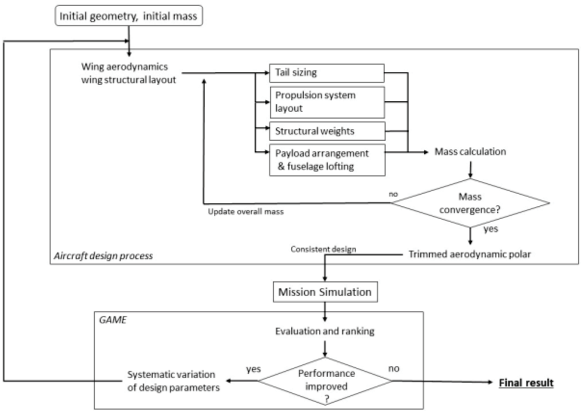


FIG. 3. Design process for calculation of a consistent aircraft dataset [5].

2.1.2. Simulation Tool

The simulation part consists of the Mission Management Model, the Flight Control Model and the Sensor and Mission Performance Analysis block. The Mission Management Model is a central element of the simulation model. It generates waypoint navigation commands, distributes input data to Flight Control Model and sends flight state information to the sensor model. After performing the simulation it stores the results into the data base for further evaluation. The aircraft's current position, velocity and attitude angles are calculated using linearized equations of motions in the Flight Control Model block. In the Sensor and Mission Performance Analysis block sensor results are calculated according to the mission type [3, 5].

2.1.3. Optimization

During the mission simulation in the virtual operational environment the key evaluation criteria are obtained. To compare different UAS configurations in terms of overall mission performance a Mission Performance Index (MPI) is introduced. It allows to take into account the correlation between the performance capabilities of the system elements, air vehicle design and system effectiveness [6]. It is discussed in more details in section 2.2.2.

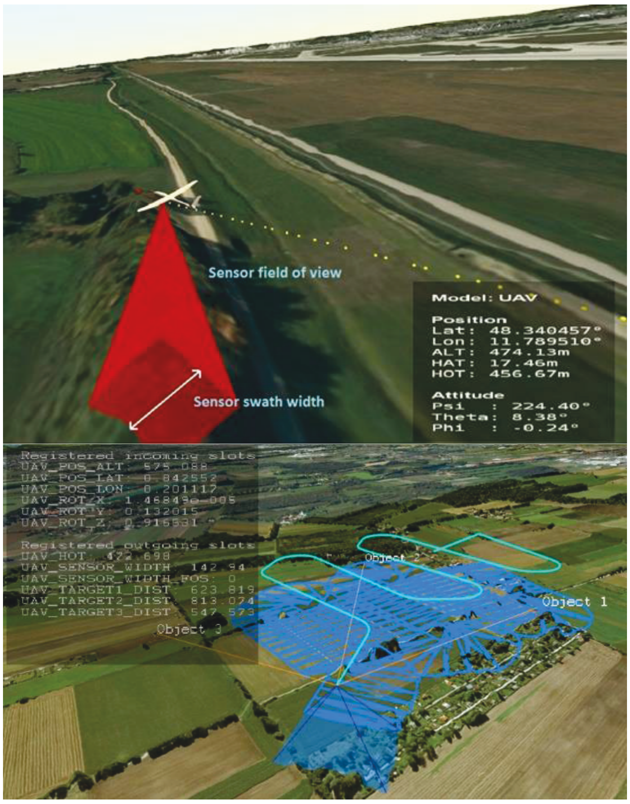
The goal of the UAS optimization process is to tailor the system configuration to the mission requirements. The objective function is to maximize the scalar MPI by varying aircraft geometry and sensor parameters using a genetic optimization algorithm. A finite number of UAS configurations is generated from randomized values of the design variable. Afterwards they are evaluated by the ability to fulfill the mission and ranked by the MPI. Next a new "generation of children" by using methods of randomized recombination, mutation and saving best individuals of "parents" are created. This process is repeated until no further improvements of the MPI is achieved [3, 5].

2.2. Mission performance assessment

2.2.1. Visualized operational environment

The visualization part of the tool chain simulates the operational environment where the UAS performs a mission. It receives information about the UAV position and orientation, as well as the orientation of the sensor installed on the platform from the simulation model. By means of high-resolution texture data, elevation model-based landscape, simulation of interaction of the UAS elements with each other and the environment the following information are obtained from the visualization environment [2]:

- Sensor ground swath
- Detection probability of search objects
- Slant range between UAV and search objects
- Communication range and obstacles detection in the line-of-sight
- Time of communication losses
- Height of the terrain



```
Model: UAV

Position
Lat:  48.340457°
Lon:  11.789510°
ALT:  474.13m
HAT:  17.46m
HOT:  456.67m

Attitude
Psi   :  224.40°
Theta:  8.38°
Phi   :  -0.24°
```

```
Registered incoming slots
UAV_POS_ALT: 575.088
UAV_POS_LAT: 0.842552
UAV_POS_LON: 0.201117
UAV_ROT_X: 1.46849e-005
UAV_ROT_Y: 0.132015
UAV_ROT_Z: 0.916531

Registered outgoing slots
UAV_HOT: 472.698
UAV_SENSOR_WIDTH: 142.94
UAV_SENSOR_WIDTH_POS: 0
UAV_TARGET1_DIST: 623.819
UAV_TARGET2_DIST: 813.074
UAV_TARGET3_DIST: 547.573
```

FIG. 4. UAS mission representation in the visualized operational environment [2, 3]

A general UAS mission representation in the visualized operational environment is shown in FIG. 4. The field of view of the camera installed on the UAV is depicted in form of a pyramid, which is determined by the horizontal and vertical angles of the sensor's field of view [3].

The sensor swath width is calculated by taking into account the elevation of the terrain and geometry representation of the sensor field of view, FIG. 5. In the regions especially where terrain heights are varying, the sensor swath width derived by the presented approach would make a significant difference compared to the sensor swath width on the flat terrain [2].

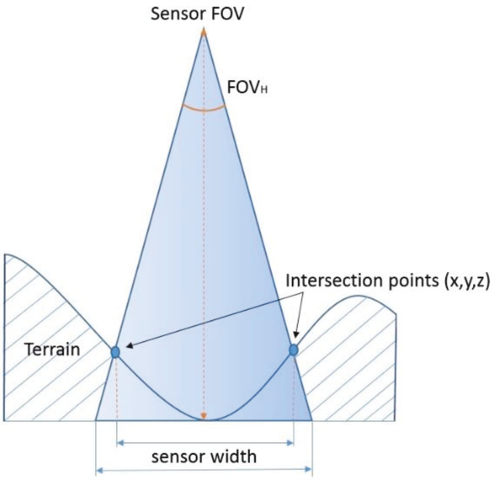


FIG. 5. Sensor width calculation in the visualized operational environment [2].

The visualization environment allows to detect intersections between objects in the scenery by means of ray tracing method. Therefore, by using geometric representation of the UAS elements in the scenery it is possible to detect exactly when the search objects will occur in the field of view of the sensor. The detection probability is based on the slant range distance between the sensor and the object and is then calculated according to the Johnson criteria [7]. Therefore, it is possible to simulate and evaluate the probability that the search objects will be detected by an operator [3].

2.2.2. Mission Performance Index

To incorporate a mission evaluation method into a multidisciplinary design process the following requirements have to be fulfilled:

- MPI has to be quantified with a scalar value in order to be used as the result of an objective function for numerical optimization
- Each contributing parameter should be normalized by a referenced value in order to facilitate comparability between mission evaluation results
- Performance parameters should be normalized with reference values of the same physical unit
- Each performance parameter is weighted by importance coefficients, which have to sum together to unity

The most commonly used method to handle more than one decision criteria and which allows to obtain an overall performance score is the Weighted Sum Model (WSM). In WSM method each attribute is multiplied with a weighting factor and added together. This approach is used as a base in MPI calculation [5, 6].

The MPI consists of the key evaluation criteria for a general civil mission and is represented in a form [3]:

$$(1)\quad MPI = \alpha \cdot \frac{ACR}{ACR_{ref}} \cdot f_{deg}(GSD) + \beta \cdot \frac{E_{ref}}{E} + \gamma \cdot \frac{P_{det}}{P_{detref}} + \delta \cdot \frac{T_{m\,ref}}{T_m} + \varepsilon \cdot \frac{CA}{CA_{ref}} + \zeta \cdot \frac{UOI}{UOI_{ref}}$$

where ACR is area coverage rate, $f_{\deg}$(GSD) degradation factor, E amount of used fuel or energy, P_{det} detection probability, T_m mission time, CA communication abilities and UOI user operating issues parameters.

The weighting coefficients of the key evaluation criteria $\alpha, \beta, \gamma, \delta, \varepsilon, \zeta$ have to sum to unity. Each factor is normalized to its reference value and weighted according to its importance [3].

The area coverage rate (ACR) is given by:

$$(2)\quad ACR = \frac{1}{T} \cdot \int_0^T w_{swath} \cdot V dt$$

where w_{swath} is the ground sensor swath width and V is the airspeed during the mission.

To evaluate the quality of the collected images by the camera a Ground Sample Distance (GSD) is introduced. The GSD is a function of the camera focal plane array (f), optics, and collection geometry (D) and represents the distance between the pixels projected on the ground at slant range (R), FIG. 6 [1].

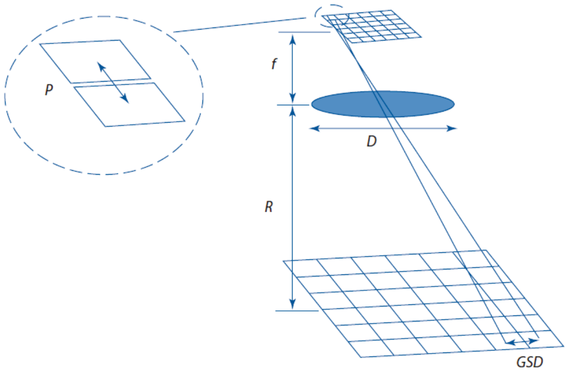


FIG. 6. Ground Sample Distance and optics geometry [1]

Assuming that the horizontal row in the focal plane array is aligned with the horizon, the horizontal GSD at the center of the image GSD_H is given by [1]:

$$(3)\quad GSD_H = \frac{P}{f} \cdot R$$

where P is the distance between pixels.

Alternatively using the field of view angles and resolution of the sensor, the GSD_H is obtained as:

$$(4)\quad GSD_H = 2 \cdot tan\left(\frac{FOV_H}{2 \cdot H_{Pix}}\right) \cdot R$$

where FOV_H is the horizontal field of view, H_{pix} is the number of horizontal pixels of the camera and R the current altitude over ground of the aircraft.

To take into account the limits of the GSD, within which the gathered information is valuable, a degradation factor $f_{deg}(GSD)$ in form of an exponential function is introduced in EQ. 1.

However, with such a representation of the MPI as described in EQ. 1. mission time is taken into account twice. The same holds true for the GSD, which is taken into account in the degradation factor and in the detection probability. Therefore, the ACR and $f_{deg}(GSD)$ are replaced by the area coverage (AC) to consider the mission time only as a separate evaluation criteria and the GSD only in the detection probability.

Thus, the new MPI is presented in the following form:

$$(5)\quad MPI = \alpha \cdot \frac{AC}{AC_{ref}} + \beta \cdot \frac{E_{ref}}{E} + \gamma \cdot \frac{P_{det}}{P_{det\,ref}} + \delta \cdot \frac{T_{m\,ref}}{T_m} + \varepsilon \cdot \frac{CA}{CA_{ref}} + \zeta \cdot \frac{UOI}{UOI_{ref}}$$

The object detection probability is calculated according to the Johnson criteria (J_p) [7], direction of the field of view of the camera (FOV_{det}) and the duration of detection time [3, 6]:

$$(6)\quad P_{det} = f(J_p, FOV_{det}, t_{det})$$

As the direction of the field of view of camera is simulated in the visualized operational environment, it is possible to calculate the time of the object being in the field of view of the sensor. This time is taken as detection time.

The Johnson criteria is a method for determining the probability of detection, recognition, and identification based on the sensor's resolution. For this the targets are replaced by black and white line pairs, each of which constitutes a cycle, which corresponds to two pixels [1]:

$$(7)\quad J_p(N) = \frac{(N/N_{50})^{2,7+0,7\cdot(N/N_{50})}}{1+(N/N_{50})^{2,7+0,7\cdot(N/N_{50})}}$$

N_{50} stands for number of cycles across the target providing a 50% probability of a successfully detection task. It is defined that for detection N_{50} = 0.75, for recognition N_{50} = 3.0 and for identification N_{50} = 6.0. N is a given number of cycles across the object of interest and is defined as an object characteristic dimension d_c divided by twice the GSD:

$$(8)\quad N = \frac{dc}{2 \cdot GSD}$$

The two-dimensional objects characteristic dimension d_c is given by [1]:

$$(9)\quad d_c = \sqrt{W \cdot H}$$

where W is the width and H is the height of the object of interest.

The detection time acts as a degradation factor for the calculation of the probability of detection by the Johnson criteria. The dependence is depicted in FIG. 7. Based on the data that in average a human needs 0,25 s to notice visual changes [8], it is assumed that an operator needs minimum 2 s to notice an object and to give a value to it. Therefore, the probability of detection at that moment would be considered as 70% of the Johnson probability. With increased time the detection probability is linearly rising and achieves 100% of the Johnson probability at a time of 10 s [3].

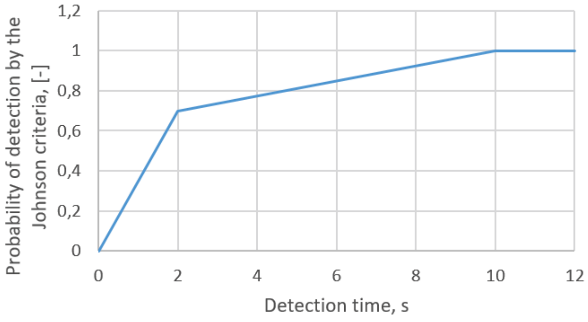


FIG. 7. Dependence of detection probability by the Johnson criteria and detection time [3]

The Communication Abilities (CA) parameter represents time of communication losses (T_{cl}) and the possibility to store data on board during the losses. It is obtained as ratio between the mission time and time of communication losses:

$$(10)\quad CA = \frac{T_{mission} - T_{cl}}{T_{mission}}$$

User Operating Issues (UOI) evaluation criteria takes into account information about additional requirements to the UAS. It is represented in form of a scalar value within the range from 0 to 1 and can contain information about launch/landing options according to the system weight, how easy it is to use the system, if it needs any special handling or storage facilities and how environmental sensitive the systems is [3].

A complicated part of the MPI definition is the assignment of the weighting coefficients $\alpha, \beta, \gamma, \delta, \varepsilon, \zeta$. Despite the fact that there are many methods for weight assignment, this process still stays subjective and has to be adjusted to every mission case by the design engineer based on engineering insight and experience [3].

3. UAS SEARCH AND RESCUE APPLICATION STUDY

UAS can be very useful in a number of search and rescue scenarios, such as search for missing hikers, mountain climbers or rescue of persons in danger after disaster [9]. To show the capabilities of the presented approach a search and rescue application study in a mountain area is presented in this section.

3.1. Description of the application study

For SAR type of missions it is important to survey a certain area of interest within the shortest period of time and with required resolution of the gathered images, so that the missing person can be detected by an operator.

In order to take into account the uncertainty of the missing person's location three possible spots are defined at the beginning of the simulation. During the simulation it is determined whether the person can be detected or recognized by an operator in one of these locations. The overall detection probability considered in the MPI is obtained as:

$$P_{det} = \frac{\frac{\sum_i^n P_{deti}}{n}}{\left(\frac{\sum_i^n P_{deti}}{n}\right)_{ref}} \tag{11}$$

where n is the number of possible spots simulated, e.g. in the presented case 3.

The goal of the presented mission design study is to search for a missing hiker on an area of 11 km² on the Watzmann mountain in southern Germany. The elevation difference of the search area is about 552 m, where the lowest point is located at an altitude of 755 meters above sea level and the highest at an altitude of 1307m.

3.2. Mission simulation

The designed UAS consists of a platform, a sensor camera, a flight control system, a generic data link and a data recorder element. The weights of these payload elements, except the UAV and the camera, are defined in TAB 1.

Component	Weight
Flight Control System	0.62 kg
Generic Datalink	0.58 kg
Data Recorder	0.3 kg
Mission Management Computer	0.4 kg

TAB 1. Weights of UAS basic payload elements

The platform is designed for each UAS configuration in the optimization process according to the chosen design variables, which are presented in TAB 2. These are wing area and aspect ratio of the designed UAV, design speed and possible cameras installed on the platform. Selected cameras differ from each other in resolution, field of view and weight as presented in TAB 3.

Design variables	Range	
Wing area	0.2 … 3	[m²]
Aspect ratio	5 … 15	[-]
Design speed	10 … 30	[m/s]
Camera Index	1… 4	[-]

TAB 2. Design variables for UAS optimization

Camera Index	Sensor Resolution	Max horizontal field of view	Weight
Cam 1	1920 x 1080	59°	1.2 kg
Cam 2	1280 x 720	31.5°	4 kg
Cam 3	1280 x 720	30°	6.8 kg
Cam 4	1920 x 1080	31.2°	16 kg

TAB 3. Selected camera types for UAS optimization

The required GSD for the presented mission design study is taken as 30 cm. With this quality of derived images it would be possible to detect a lost person in the mountains region. Sensors with bigger resolution allow to fly at higher altitudes and with higher area coverage rate, while sensors with smaller resolution achieve the desired GSD at lower altitudes and smaller area coverage rate. Moreover sensors with better performance are more expensive and can be also heavier and therefore requiring also more fuel. This tradeoff is considered when choosing a sensor payload for the UAS.

The altitude of flight waypoints, Alt_{wp}, is calculated for each UAS configuration during the optimization according to the desired GSD and the sensor resolution as:

$$(12)\ Alt_{wp} = \frac{SW_{req}}{2tan\left(\frac{HFOV_{max}}{2}\right)}$$

where $HFOV_{max}$ is the maximal horizontal field of view and SW_{req} is the required sensor ground swath width. The latter is determined as a product of the horizontal resolution H_{res} and the required GSD:

$$(13)\ SW_{req} = H_{res} \cdot GSD_{req}$$

The altitude of the trajectory waypoints is adjusted to the terrain elevation.

3.3. Evaluation of results

In the next two subsections the results of the mission simulation and evaluation are presented. As mentioned before the process of the weight assignment of the key evaluation criteria is very subjective. To show the influence of choosing weight coefficients, two simulations with different weighting coefficients are performed. In the first simulation the mission time and detection probability are considered as the prevailing evaluation criteria. In contrast in the second simulation the detection probability and area coverage are the prevailing criteria.

During the UAS optimization process 10 generations of configurations with 12 individuals each are designed, simulated and evaluated. The key evaluation criteria are obtained during the simulation for each individual. Reference values for each evaluation criteria are mean values of the first generation.

3.3.1. Prevailing criteria: mission time and detection probability

When a mission concerns human lives, mission time and probability of detection become the prevailing criteria. Therefore, for the first simulation of the application study it is assumed that mission time and detection probability are equally important and their weighting coefficients are $\delta = 0.4$, $\gamma = 0.4$. Area coverage is weighted then with the coefficient $\alpha = 0.15$, used energy with $\beta = 0.05$ and $\varepsilon = 0$, $\zeta = 0$.

During the optimization process 120 UAS configurations have been designed and evaluated. The progress of design variables and MPI during the optimization process is presented in FIG. 8 and FIG. 9.

In the first generation UAS configurations with all possible onboard cameras are calculated. The higher the value of MPI is, the better the mission is fulfilled by a system. The highest MPI values are obtained by systems with cameras 1 and 2. These systems are taken to the next generation as the best individuals. Already in the 4th generation it is determined that the highest MPI will be obtained with camera 1 on board. With each further generation the MPI is increasing and the range of the design variables is narrowed down.

The optimized UAS has a 1.7 m² wing area, 10.6 aspect ratio and 7.3 kg of total weight. The mission is fulfilled in 31 minutes, with the flight speed of 30 m/s and at the waypoints altitude of 254 m. In FIG. 10 are shown elevation of the terrain and the flight altitude profile above the mean sea level (MSL) obtained from the operational environment.

The missing person was successfully detected in all 3 possible locations.

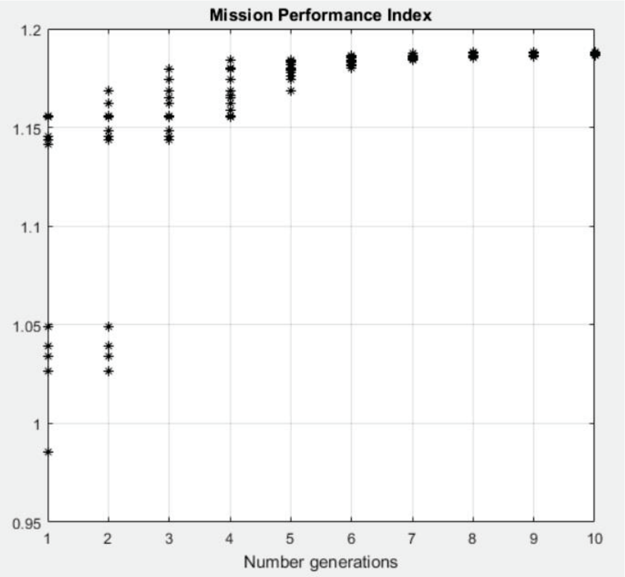


FIG. 8. Progress of the MPI during the optimization: mission time and detection probability are the prevailing criteria

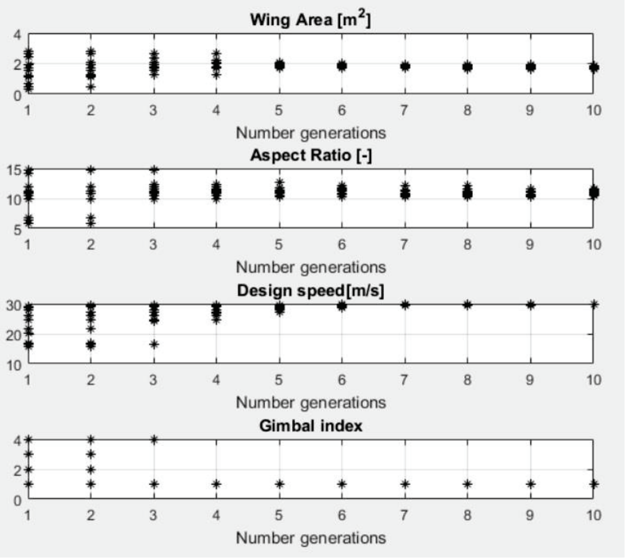


FIG. 9. Progress of design variables during the optimization: mission time and detection probability are the prevailing criteria

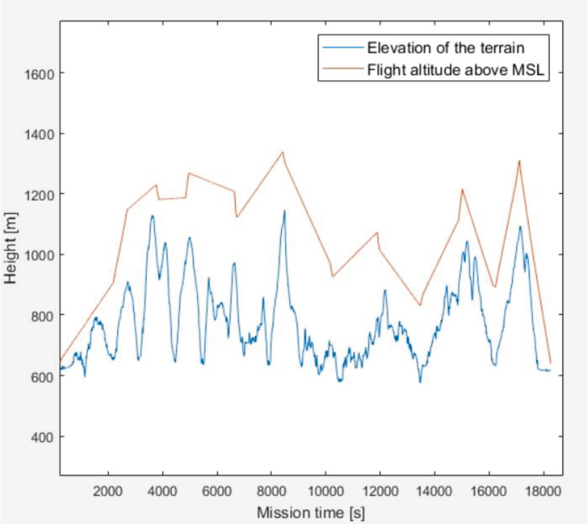


FIG. 10. Simulation 1: Elevation of the terrain and the flight altitude above MSL

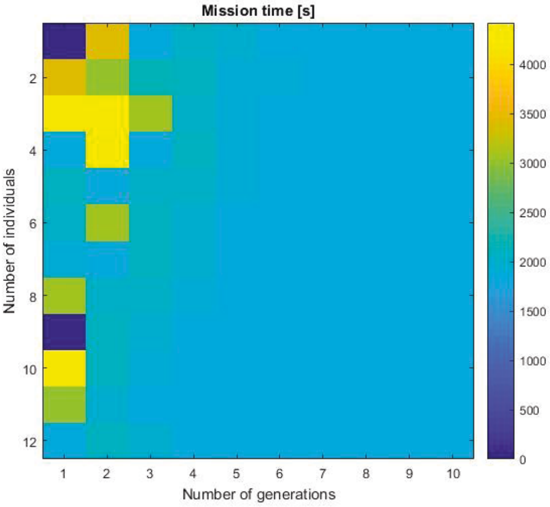


FIG. 11. Key evaluation parameter for 10 generations with 12 individuals each: mission time

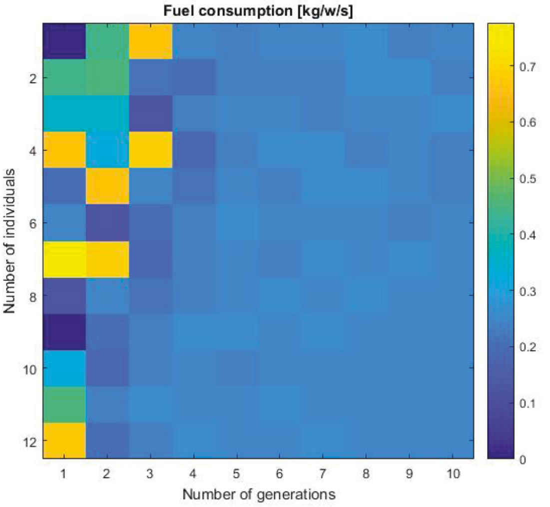
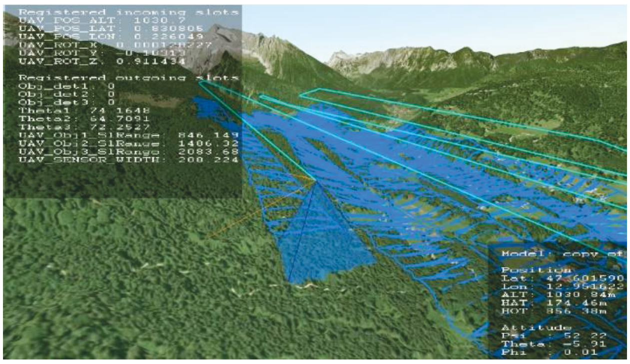


FIG. 12. Key evaluation parameter for 10 generations with 12 individuals each: fuel consumption

Values of mission time and fuel consumption for 10 generations are presented in FIG. 11 and 12, respectively. According to the results in FIG. 11, the 4th, 5th, 6th, 7th and 12th UAS configuration in the first generation completes the mission in the shortest time. However FIG. 12 shows that some of them require almost 3 times more fuel compared to the optimized UAS. The MPI value for this systems configurations is not higher than 1.07 compared to the final UAS with MPI=1.19. Despite the fact that the fuel consumption weighting coefficient is 0.05 it still influences the optimization process. With each further generation values of the mission time as well as the fuel consumption are decreasing.



```
Registered incoming slots
UAV_POS_ALT: 1030.7
UAV_POS_LAT: 0.830805
UAV_POS_LON: 0.226049
UAV_ROT_X: 0.000128227
UAV_ROT_Y: -0.10313
UAV_ROT_Z: 0.911434

Registered outgoing slots
Obj_det1: 0
Obj_det2: 0
Obj_det3: 0
Theta1: 74.1648
Theta2: 64.7091
Theta3: 72.2527
UAV_Obj1_SlRange: 846.149
UAV_Obj2_SlRange: 1406.32
UAV_Obj3_SlRange: 2083.68
UAV_SENSOR_WIDTH: 208.224
```

```
Model: copy of

Position
Lat: 47.601590
Lon: 12.951622
ALT: 1030.84m
HAT: 174.46m
HOT: 856.38m

Attitude
Psi   : 52.22
Theta: -5.91
Phi   : 0.01
```

FIG. 13. Mission performance representation of the simulation 2 in the visualized operational environment

The result of the first mission simulation in the visualized operational environment is presented in FIG. 13. Despite the fact that for all derived UAS configurations the missing person was detected in 3 possible locations defined at the beginning, the covered area has gaps. Owing to the mountain landscape and terrain elevation the sensor swath width is varying during the mission simulation as presented in FIG. 14. Therefore, uncovered areas between the search paths occur. That means that the chosen flight altitude based on the required GSD is not sufficient for mountain areas, where the terrain elevation is quite different. In contrast, as shown in the previous studies [3, 6], in case of a flat terrain and when the flight altitude is based on the required GSD the search area will be completely covered.

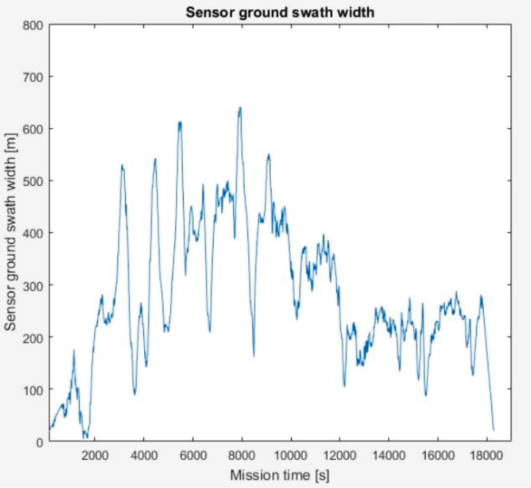


FIG. 14. Simulation 1: Sensor swath width variation during the mission simulation in the mountain area

To close the uncovered gaps the altitude of waypoints is increased by approx. 50 m to an altitude above ground of 300 m. Within this simulation the coverage of the search area is increased but in the areas with high elevation difference there are still gaps. The mission is fulfilled in 30 minute and the missing person is detected in all 3 possible locations. However, the increased altitude leads in general to an increased GSD, so that at some flight path locations the calculated GSD is larger than the required GSD for correct detection of the missing person.

3.3.2. Prevailing criteria: detection probability and coverage area

In the second simulation the weighting coefficients are changed. To increase the importance of the coverage area within the mission evaluation, its weighting coefficient in the MPI is increased.

Therefore, for this simulation of the application study detection probability and area coverage are taken as equally important with weighting coefficients $\alpha = 0.4$, $\gamma = 0.4$. Other weighting coefficients are taken as: $\delta = 0.15$, $\beta = 0.05$, $\varepsilon = 0$, $\zeta = 0$.

The progress of design variables and MPI during the optimization process for the second simulation is presented in FIG. 14 and FIG.15.

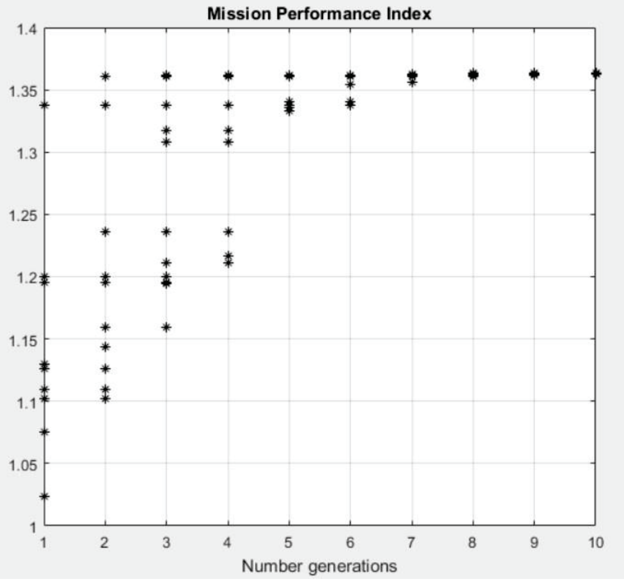


FIG. 15. Progress of MPI during the optimization: detection probability and coverage area are the prevailing criteria

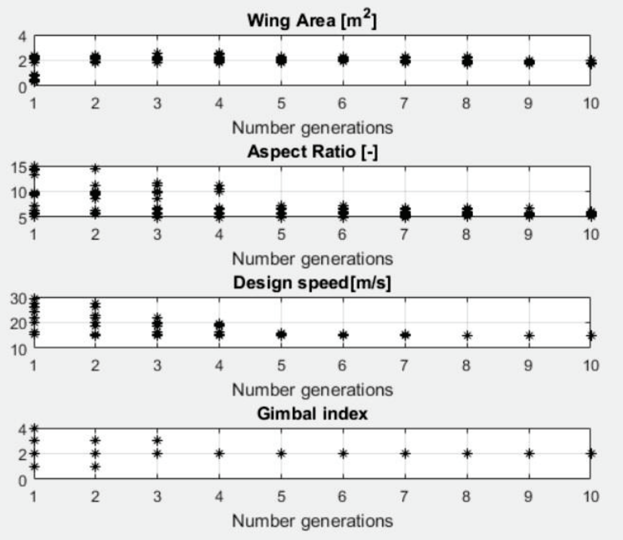


FIG. 16. Progress of design variables during the optimization: detection probability and coverage area are the prevailing criteria

It must be mentioned, that the absolute values of the MPI for simulation 1 and 2 cannot be compared, since the reference factors are taken from the first generation each and therefore are different. Nevertheless, the design variables are comparable.

The highest MPI value in simulation 2 is obtained by the system with camera 2 on board compared to camera 1 for the optimized UAS obtained from the first simulation. Furthermore, the size of the designed UAV in simulation 2 is bigger, than in the first simulation.

The optimized UAS has 10.4 kg of total weight, a 1.7 m² wing area, 5.6 aspect ratio. The mission is fulfilled by this system in 77 minutes with the flight speed of 15 m/s at the waypoints altitude of 340 m, FIG. 17.

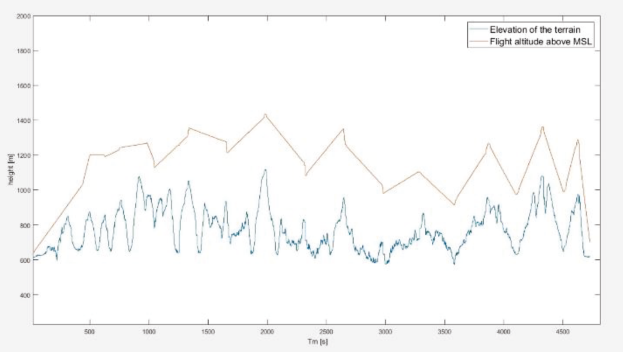
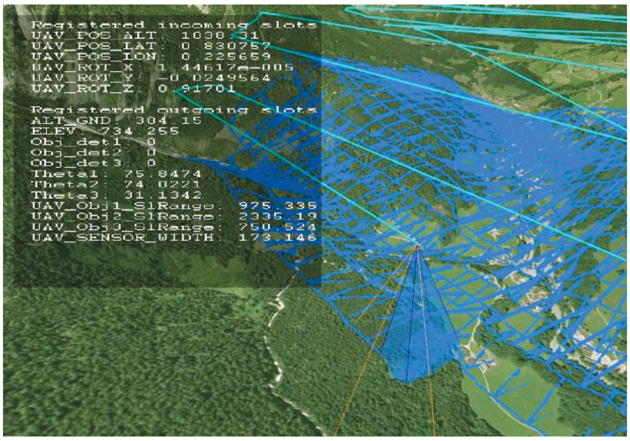


FIG. 17. Simulation 2: Elevation of the terrain and the flight altitude above MSL



```
Registered incoming slots
UAV_POS_ALT: 1038.31
UAV_POS_LAT: 0.830757
UAV_POS_LON: 0.225659
UAV_ROT_X: 1.44617e-005
UAV_ROT_Y: -0.0249564
UAV_ROT_Z: 0.91701

Registered outgoing slots
ALT_GND: 304.15
ELEV: 734.255
Obj_det1: 0
Obj_det2: 0
Obj_det3: 0
Theta1: 75.8474
Theta2: 74.0221
Theta3: 31.1342
UAV_Obj1_SlRange: 975.335
UAV_Obj2_SlRange: 2335.19
UAV_Obj3_SlRange: 750.524
UAV_SENSOR_WIDTH: 173.146
```

FIG. 18. Mission performance representation of the simulation 2 in the visualized operational environment

The result of the second mission simulation in the visualized operational environment is presented in FIG. 18. The area coverage was increased by 34% and no gaps have been detected. As well as in the first simulation, the missing person was successfully detected in all 3 possible locations and the obtained GSD is sufficient during the whole mission.

4. CONCLUSION

The introduced design environment allows to design, simulate, evaluate and optimize an UAS according to initial mission requirements. By simulating the visualized operational environment it is possible to indicate extensions to cover, obstacle in line-of-sight, communication losses and flight path flaws. These information are involved into the mission evaluation process and the UAS design. A genetic optimization algorithm is used to find an unmanned aircraft design that optimally fulfills a certain mission task.

The considered application design study showed the importance of taking the terrain data into account during the UAS optimization process. Systems and flight paths sufficient for the flat terrain would not give the same mission success in mountain areas. Selection of the mission performance evaluation criteria and assignment of weighting coefficients play a role in the UAS optimization process.

The presented design environment is flexible and modifications are possible. Therefore new algorithms such as trajectory path optimization, improved objects detection algorithms and others can be implemented into the simulation model in complex environment.

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