Multicriteria Parametrical Identification of the Parafoil-Load Delivery System

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This paper addresses the problem of multicriteria (versus single-criterion) parametrical identification of the autonomously controlled cargo parafoil. Based on the structural identification as an initial step toward creation of an adequate model of the parafoil, a high-fidelity model including several dozens of optimization parameters has been developed. The present paper proposes the correct statement of the multicriteria parametrical identification problem including the necessity to investigate the feasible set of variable parameters. The paper advocates the use of the Parameter Space Investigation method and Multicriteria Optimization / Vector Identification software package to solve the problem.

I. Introduction

AS well known, the problem of the development of the mathematical model of some dynamic object includes two necessary stages. First, the equations of motions governing system's dynamics should be derived from the nature of the system. Once this first step in constructing a mathematical model, the so-called structural identification (defining a number and type of equations of motions), has been completed, the next step, the known as a parametrical identification, i.e. finding numerical values of variable parameters to better match experimental data should be carried on.

While the structural identification for parachute- and parafoil-based payload delivery systems is considered to be more or less settled,[1-5] the parametrical identification (defining aerodynamic and control coefficients, apparent-mass-tensor elements, etc.), especially for those high-degree-of-freedom models developed in the past decade[1,3,5] still needs to be addressed and it is being addressed by different group of researches for different aerodynamic deceleration systems.

By their nature, applied identification problems are multicriteria problems. However, as a rule these problems have been treated as single-criterion problems.[6,7] Usually it is done by using the most important criterion, or by using several criteria, but one at a time. The standard approach however is to develop a single compound criterion that weighs criteria relative to their importance.

By present time, several single-criterion approaches have been developed and used to identify the parameters of different payload delivery systems. Kurashova and Vishnyak[8] used maximum likelihood method to determine the aerodynamic characteristics of gliding parachute. They suggested identification of longitudinal parameters using experimental data obtained from lorry equipped with attachment points, measurement and control system. Their method exhibited verification errors of less then 10-15 percent.

Jann[9] discussed application of system identification methods (maximum likelihood as well) to the acquired database of the parafoil-load system (ALEX-I). Thereafter, he determined the essential parameters of the autonomous landing system. He described how the incorporated parameters were estimated and discussed the results and their applicability. He developed two different mathematical models which describe the real system. One was a 3-DoF model and another - a 4-DoF model. However capabilities of these were limited as they do not account for the distance between center of mass and aerodynamic reference point. Later, these models accounted for the actuators which move the control lines. Jann also presented an approach for theoretical calculations of the aerodynamic coefficients based on the extended lifting theory and validated those using real flight test data on powered parafoil ALEX[10].

Kothandaraman and Rotea[11] developed a SPSA (Simultaneous Perturbation Stochastic Approximation) algorithm for parameter estimation used for nonlinear parachute model. The SPSA is a tool for optimization that doesn't rely on a costly gradient computation. They claimed their method is useful where many parameters are to be

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optimized. They used this method to determine three aerodynamic coefficients, four apparent mass coefficients, and the initial states of the G-12 parachute model.

Rogers[12] used an extended Kalman filter algorithm implementation to estimate the aerodynamic, wind, mass property and measurement errors for controlled low-glide parachutes. This implementation incorporated two new approaches: i) attitude error formulation, to eliminate the mathematical singularity associated with vertical flight, and ii) incorporation of apparent masses as a part of motion dynamics. Rodgers presented details of the linearization of the nonlinear equations of motion and measurement equations, as well as a summary of the system error dynamics. His results based on simulated data showed that aerodynamic characteristics and winds can be estimated separately from apparent mass coefficients.

Hur and Valasek[13] also chose the Observer/Kalman Filter Identification (OKID) methodology for identification of the longitudinal and lateral/directional dynamical models of the Buckeye parafoil-vehicle system. OKID is a time domain technique which identifies a discrete input/output mapping from known input output data records. Since first being developed by Juang in the early 1990's,[14] the method has been successfully employed to identify linear system models of flexible spacecraft structures and aircraft. The dynamics of the Buckeye vehicle were modeled with 8 DoF: six for the parafoil, and two for the relative pitch and yaw attitudes of the vehicle. Based on preliminary results the authors drew a conclusion that the OKID method can identify the parafoil-vehicle dynamic system effectively and accurately.

Analysis of these attempts that address model verification leads to the conclusion that major differences between them lie in the way the authors account for the influence of numerous interrelated parameters on the motion of entire system. The present paper does not intend to discuss various numerical techniques of parameter identification, but addresses the physical issues (multicriteria essence) behind the identification process and is organized as follows. Section 2 introduces the cargo parafoil model developed during a structural identification[5] and names several groups of parameters to be identified. Because of the different nature of these groups of parameters several adequacy criteria are suggested to be used. That raises the necessity to employ a multicriteria parametrical identification technique. First, Sections 3 and 4 formulate multicriteria optimization problem and introduce the PSI method developed to manage such problems. Then, Section 5 shows how multicriteria optimization routine can be converted to a multicriteria identification algorithm. The paper continues with Section 6 where corresponding software is introduced. While an extensive identification experiment is still continues, the results of preliminary runs are discussed in Section 7.

II. Structural versus Parametrical Identification

For some generic parafoil-payload system Pegasus, the issue of parametrical identification has already been addressed earlier.[5] Two additional degrees of freedom (payload pitching and yawing) added to the existing set of six differential equations yields 8-DoF model that can be concisely represented in the following form:

$$\dot{\mathbf{V}}^{*T} = \mathbf{A}^{-1} \left\{ \begin{bmatrix} \mathbf{F} \\ \mathbf{M}_c \\ \mathbf{M}_p \end{bmatrix} - \mathbf{\Sigma} \mathbf{A} \mathbf{V}^* \right\} \tag{1}$$

$$\dot{\mathbf{\Lambda}}_c = \tilde{\mathbf{R}}_E(\mathbf{\Lambda}_c)\mathbf{\omega}_c , \quad \dot{\mathbf{\Lambda}}_p = \tilde{\mathbf{R}}_E(\mathbf{\Lambda}_p)\mathbf{\omega}_p \tag{2}$$

$$\dot{\mathbf{P}}_i = {}_b^i\mathbf{R}\mathbf{V} , \tag{3}$$

where vector $\mathbf{V}^* = \left[\mathbf{V}^T, \mathbf{\omega}_c^T, \mathbf{\omega}_p^T \right]^T$ consists of a velocity vector of the system's center of gravity $\mathbf{V} = \left[u, v, w \right]^T$, angular velocity vectors of parafoil (canopy) $\mathbf{\omega}_c = \left[p_c, q_c, r_c \right]^T$ and payload $\mathbf{\omega}_p = \left[0, q_p, r_p \right]^T$, vectors $\mathbf{\Lambda}_c$ and $\mathbf{\Lambda}_c$ ($\mathbf{\Lambda} = \left[\varphi, \theta, \psi \right]^T$) constitute Euler angle triads for the canopy and payload respectively, $\mathbf{P}_i$ presents an inertial position of the system. On the right-hand side of Eq.(1), block 3-by-3 matrix $\mathbf{A}$ (where each element is a 3-by-3 matrix itself) represents a mass-inertia matrix of the system, vectors $\mathbf{F}$, $\mathbf{M}_c$ and $\mathbf{M}_p$ constitute aerodynamic force and moment acting on the system and its two components (canopy and payload respectively), and matrix $\mathbf{\Sigma}$ is a block 3-by-3 matrix where each element is a 3-by-3 matrix too. In Eqs.(2),(3), notations $\tilde{\mathbf{R}}_E(\mathbf{\Lambda})$ and ${}_b^i\mathbf{R}$ stand for the matrix operator acting on a vector $\mathbf{\Lambda}$ and rotation matrix respectively. The reference values of the major aerodynamic and control coefficients are determined by the wind-tunnel data and other previous studies. Reference values for parameters characterizing the bundle and some other uncertain variables are also added.

What is of most importance from the standpoint of identification is that some of these vectors and matrices depend parametrically on different sets of variable parameters.[5] Yet, since the coefficients in these series are known with some probability only, it is suggested to multiply these reference values by gain factors. Thus tuning the model means adjusting values of these gains within the certain (feasible) range.

By analyzing the model, sets of variable parameters were gathered into the following groups: i) a group of aerodynamic force coefficients $\mathbf{k}_F$; ii) a group of moment coefficients $\mathbf{k}_M$; iii) a group of mass-geometry coefficients $\mathbf{k}_G$; and iv) a group of apparent mass coefficients $\mathbf{k}_\alpha$. For instance, the aerodynamic-force-coefficients vector $\mathbf{k}_F$ includes following coefficients: k_{α_0}, $k_{CL\alpha}$, $k_{CL\delta_f}$, k_{CD_0}, k_{CD_0}, k_{A_2}, $k_{A\delta_f}$, $k_{CY\beta nom}$, $k_{CY\beta grad}$, $k_{CY\delta_a nom}$, $k_{CY\delta_a grad}$; group of mass-geometry coefficients $\mathbf{k}_M$ contains k_{rig}, $k_{x_{CG}}$, etc.

Another feature is that during real drops the wind profile cannot be measured simultaneously with the rest of the states, therefore creating an obvious uncertainty for the identification algorithm. This uncertainty together with some other uncertainties in the system geometry and state of control surfaces (not all state variables were observed and/or are available) produce one more set of variable parameters $\mathbf{k}_U$. In total as much as several dozen variable parameters derived from the model (1)-(3) need to be identified.

Consider now the adequacy criteria that can be used. Of course they are completely based on the flight test data available. To this end the flight test data acquired at different (from $4Hz$ to $100Hz$) rate by the global positioning system receiver and inertial measurement unit installed atop of payload contains the following information:

- local tangent plane coordinates;
- components of inertial velocity;
- attitude of the measurement unit;
- angular rates;
- state of the control surfaces (flaps).

As mentioned the uncontrolled dropsonde released together with the parafoil gathers current wind profile (horizontal speed components versus altitude).

Analyzing this available data one can think of the following adequacy criteria:

- proximity of simulated trajectory to the real one (that can be further split into the horizontal and vertical components);
- closeness of the speed/heading profiles;
- adequacy of the natural eigenvalues for all channels;
- closeness of system response to control actions.

Therefore, rather than using a single-criterion identification as it was done by other researchers it is proposed to use a multiple-criterion identification with several sets of different parameters grouped by their influence onto the general parafoil-based cargo system performance (see Fig.1).
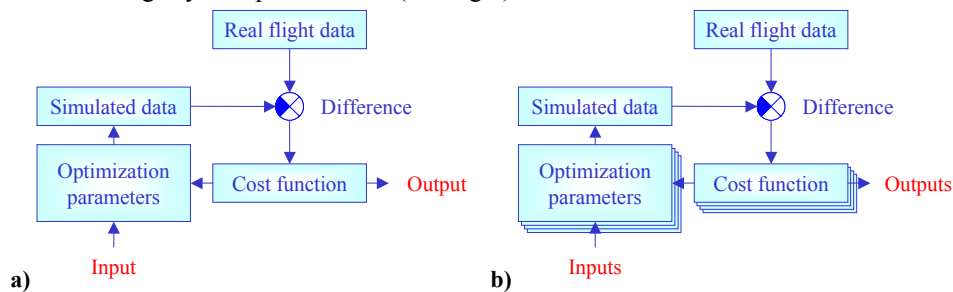

Figure 1. Single-criteria identification (a) and multi-criteria identification (b).

Necessity of employing multicriteria (or vector) identification technique can be understood from the following:

1. Although the developed model of a cargo parafoil system[5] seems to work fairly well and reflect all major features of the real object dynamics, generally we cannot assert a sufficient correspondence between the model and the object. This obviously limits utility of the single-criterion identification to evaluate adequacy of the model. In multicriteria identification there is no necessity of artificially introducing a single criterion to the detriment of the physical essence of the problem;

2. The richness of the flight test data allows using several particular proximity criteria to evaluate adequacy of the mathematical model, i.e. determining to what extent the mathematical model corresponds to the physical system in principle;

3. The fact is that there is not enough preliminary information about lower and upper limits for many of the variables meaning that prior to finding the optimal ones, we should be interested in determining the feasible set of these parameters, as well as performing sensitivity analysis.

The multicriteria identification is a relatively new direction that is of great value in modern engineering applications.[15] The numerical technique to solve such kind of problems has usually been adopted from multicriteria optimization. Multicriteria optimization methods have been considered in many articles, monographs and handbooks.[16-18] However, experts continue to experience difficulties in correctly stating optimization problems in engineering. These troubles typically emerge when trying to define the set of feasible solutions, i.e. the constraints imposed on the design variables, functional relationships, and criteria. The Parameter Space Investigation (PSI) method[19] was developed specifically for the correct statement and solution of engineering optimization problems. The PSI method has already been used successfully for the statement and solution of the different types of multicriteria problems such as design, design with control, optional development of prototypes, finite element models, and decomposition and aggregation of large-scale systems. It was also implemented for identification of the static systems. Naturally, we would like to employ this method for the problem at hand.

The following briefly describes the essence of the PSI-method developed initially for multicriteria optimization problems and shows how it can be used for identification problem at hand.

III. Formulation of Multicriteria Optimization Problem

Notice, the model (1)-(3) can be reduced to:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \boldsymbol{\alpha}, t) , \ t \in [t_0; t_f] , \ \mathbf{x}_{t=t_0} = \mathbf{x}_0 . \tag{4}$$

In this model $\mathbf{x} = \{x_1,...,x_n\}$ is a state vector with initial conditions $\mathbf{x}_0$, and $\boldsymbol{\alpha} = \{\alpha_1,...,\alpha_p\}$ is a vector of variable parameters to be optimized.

Consider next three types of constraints one should account for in order to formulate a multicriteria optimization problem correctly. They are: i) parametric, ii) functional, and iii) criteria constraints.

The parametric constraints in general have the form

$$\alpha_j^* \leq \alpha_j \leq \alpha_j^{**} , \ j = 1,...,p . \tag{5}$$

(For mechanical systems α_j usually represent geometrical dimensions, stiffnesses, masses, moments of inertia, damping factors, etc., and define a parallelepiped $\boldsymbol{\Pi}$ in the p-dimensional space.)

The functional constraints may be written in the similar form as

$$c_j^* \leq f_j(\boldsymbol{\alpha}) \leq c_j^{**} , \ j = 1,...,q \ \text{ for } t \in [t_0; t_f] . \tag{6}$$

The third group of constraints involves local quality criteria

$$\Phi_l(\boldsymbol{\alpha}) , \ l = 1,...,\nu \tag{7}$$

that should be minimized/maximized. Because of the multicriteria nature of the problem to decrease the total number of the reasonable candidate solutions (avoid the situations when the values of certain criteria are unacceptable from the expert's standpoint) the criterial constraints must be introduced

$$\Phi_l(\boldsymbol{\alpha}) \leq \Phi_l^{**} , \ l = 1,...,\nu . \tag{8}$$

Here Φ_l^{**} is the worst value of a particular criterion expert can tolerate while ameliorating other criteria. (Without loss of generality here and further on we consider a minimum problem.)

The functional dependences $f_j(\boldsymbol{\alpha})$ and the quality criteria $\Phi_l(\boldsymbol{\alpha})$ may be functionals of the interval curves of the analyzed differential equations (or alternative mathematical models) or just functions of $\boldsymbol{\alpha}$.

The major difference between criterial and hard functional constraints is that the values of Φ_l^{**} are not known beforehand and have to be determined while solving the problem. They are subject to expert's revision (he either tightens or loosens them). For the sake of flexibility the functional constraints can also be represented in the form of pseudocriteria, especially when they are not firm.

Obviously, two last types of constraints limit initial space $\mathbf{\Pi}$ to subspace $\mathbf{G}$, $\mathbf{G} \subseteq \mathbf{\Pi}$ and finally to some feasible set $\mathbf{D}$, $\mathbf{D} \subseteq \mathbf{G} \subseteq \mathbf{\Pi}$ as is shown on Fig.2.

We are now ready to formulate the multicriteria optimization problem for system (4) and sets of constraints (5), (6), and (8).

The multicriteria optimization problem is to find an Edgeworth-Pareto set $\mathbf{EPS}$, $\mathbf{EPS} \subseteq \mathbf{D}$, so that the following holds:

$$\mathbf{\Phi}_l(\mathbf{EPS}) = \min_{\alpha \in \mathbf{D}} \mathbf{\Phi}_l(\alpha) \, , \; l = 1,...,\nu \, . \tag{9}$$

After finding $\mathbf{EPS}$ the most preferable or optimal vector α_0, $\alpha_0 \in \mathbf{EPS}$ can be finally determined (chosen).

At this point is important to point out the following. Unlike well-conditioned traditional single-criteria optimization we are not only interesting in finding α_0 but in defining the feasible and Edgeworth-Pareto sets first.
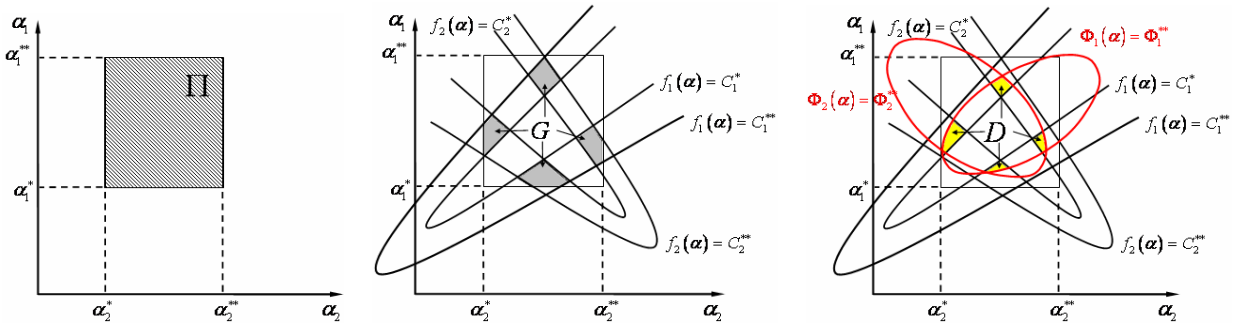

Figure 2. Illustration of subsets Π, G, and D in 2D space.

IV. Essence of the PSI-Method

The PSI-method is based on populating the search region $\mathbf{\Pi}$ with a uniformly distributed sequence of points. To produce such sequence a set of auxiliary uniformly-distributed on the unit p-dimensional cube points Q_i, $i = 1,...,M$ is generated first (each point Q_i has p components). It is done using the Latin square or Latin hypercube sampling,[20] which is useful when you must sample a p-dimensional space exceedingly sparsely, at M points. The approach is to partition each (normalized) design parameter (dimension) into M segments, so that the whole space is partitioned into M^p cells. The M cells to contain the sample points are chosen by the following algorithm: *i*) randomly choose one of the M^p cells for the first point, *ii*) eliminate all cells that agree with this point on any of its parameters (that is, cross out all cells in the same row, column, etc.), leaving $(M-1)^p$ candidates, *iii*) randomly choose one of these remaining candidates, eliminate new rows and columns, and continue the process until there is only one cell left, which then contains the final sample point. The result of this construction is that each design parameter will have been tested in every one of its subranges. Figure 3 provides with an example of "wise" population of two-dimensional search region $\mathbf{\Pi}$ as compared to that of "straightforward" population one might think of.

To generate the original sequence of points q_{ij}, $i = 1,...,M$, $j = 1,...,p$ (where q_{ij} is the j-th component of the i-th point Q_i) the PSI-method employs the so-called LP$_\tau$ sequence generation procedure,[21] which in turn inherits Sobol's quasi-random sequences[22] generator by Antonov and Saleev.[23] The Sobol' sequence generates quasirandom numbers q_{ij}, $i = 1,...,M$, $j = 1,...,p$ between zero and one directly as binary fractions of length w bits, from a set of w special binary fractions, v_k, $k = 1,...,w$, called direction numbers. In Sobol's original method, the i-th number Q_i is generated by XORing (bitwise exclusive or) together the set of v_k's satisfying the criterion on k, "the k-th bit of i is nonzero." In other words, as i increments, different ones of the v_k's flash in and out of q_{ij} on different time scales. By construction, the first direction number v_1 alternates between being present and absent most quickly, while v_k goes from present to absent (or vice versa) only every 2^{k-1} steps.

The advantage of Sobol's approach (LP$_\tau$ sequence generation procedure) is that the sequence is generated number-theoretically, rather than randomly (as for other known approaches[24]), so successive points at any stage sort of "know" how to fill in the gaps in the previously generated distribution and keep filling them in, hierarchically

(see example on Fig.4). Figure 5 shows that the coverage of LP$_\tau$ sequence is also much more equally distributed in comparison to the embedded Microsoft Windows random numbers generator (RNG).)

Finally, the unit p-dimensional cube is stretched to the parametric constraints (5) by following scaling procedure

$$\alpha_j^i = \alpha_j^* + q_{ij}(\alpha_j^{**} - \alpha_j^*) , \;\; j = 1,...,p , \;\; i = 1,...,M . \tag{10}$$
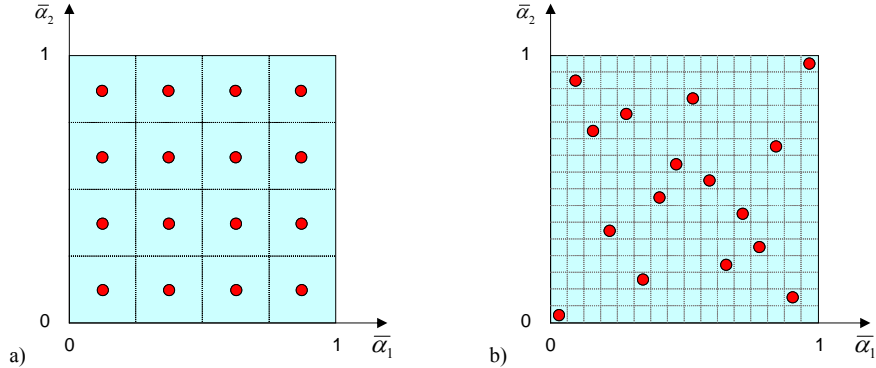

Figure 3. Example of straightforward (a) versus "wise" Latin-cube (b) sampling.

Values of functional dependencies are being computed for these M trial points. If they satisfy corresponding constraints (6), the quality criteria $\Phi_l(\boldsymbol{\alpha}^i)$, $l = 1,...,\nu$ are also being calculated at each trial point $i = 1,...,N$, $N \leq M$.

points 1-128 *points 129-512* *points 512-1024* *points 1-1024*
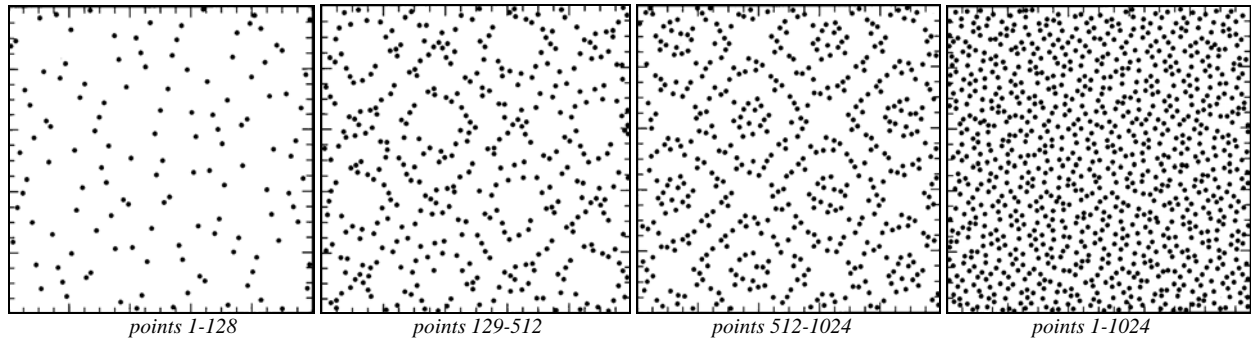
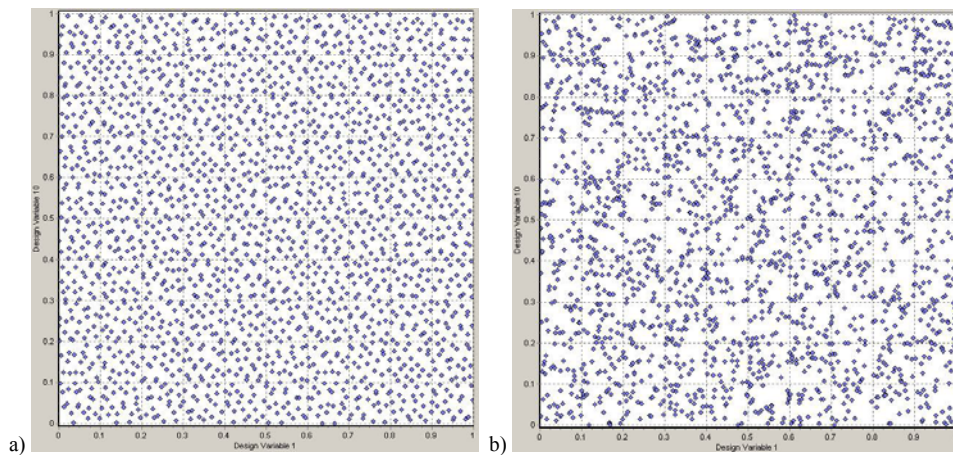**Figure 4. First 1024 points of the two-dimensional Sobol' sequence.**

Figure 5. Comparison of LP$_\tau$ sequence coverage (a) with Windows RNG coverage (b) in the plain of two (1st vs. 10th) out of 25 parameters for 2048 trials.

The parameter space is investigated in three stages. First, a table of trials is ascribed to each l-th criterion $\Phi_l(\boldsymbol{\alpha})$, and the values of $\Phi_l(\boldsymbol{\alpha}^1),\ldots,\Phi_l(\boldsymbol{\alpha}^N)$ are arranged in ascending order (assuming that all the criteria must be minimized).

At the second stage, the expert chooses preliminarily the criterial constraints Φ_l^{**} (8). During the third stage the problem's solvability is checked meaning that the set of all $\boldsymbol{\alpha}^i$ satisfying all inequalities (9) simultaneously is determined. If the set of these vectors $\boldsymbol{\alpha}^i$ is nonempty, then the problem of the feasible set construction is solvable. Otherwise, one has to either correct the values of Φ_l^{**} or to return to the first stage and increase the number of trials to repeat the second stage with a larger table. The procedure is continued until $\mathbf{D}$ proves to be nonempty and the maximum values of Φ_l^{**} are specified. After that, the Edgeworth-Pareto set EPS is constructed and analyzed.

V. From Multicriteria Optimization to Multicriteria Identification

Obviously, the problem formulation in Section 3 can be easily adapted to the multictriteria parametrical identification problems. To start with we note that in the problem of multictriteria parametrical identification or matching experimental data to the predefined mathematical model vector of variable parameters $\boldsymbol{\alpha}$ to be optimized may include t_0 and t_f.

We denote by $\Phi_l^m(\boldsymbol{\alpha})$, $l=1,\ldots,\nu$ the indices (criteria) resulting from the analysis of the mathematical model that can be represented by the Eq.(4). The model (4) can include some random perturbations like white noise or any other disturbances (inaccurate wind in our case). In this case we will consider $\Phi_l^m(\boldsymbol{\alpha})$ being a mathematical expectation of corresponding index.

On the contrary, let $\Phi_l^{\exp}$, $l=1,\ldots,\nu$ denote experimental values of the l-th criterion measured on the prototype. Of course we assume the experiment to be sufficiently accurate and complete as well as amount of measured data available to be sufficient for correct formulation on the identification problem at hand. If the data for several experiments is available then $\Phi_l^{\exp}$ will represent the mathematical expectation or some other estimate of the random variable.

Now instead of quality or performance criteria (7) we will use the following adequacy (proximity, closeness) criteria

$$\Re_l\left(\Phi_l^m(\boldsymbol{\alpha}),\Phi_l^{\exp}\right),\ l=1,\ldots,\nu, \tag{11}$$

where $\Re_l\left(\Phi_l^m(\boldsymbol{\alpha}),\Phi_l^{\exp}\right)$ denotes some operator applied to simulated and experimental indices (it might be their ratio, module of the difference, etc.).

Therefore, criterial constraints (9) can now be rewritten as

$$\Re_l\left(\Phi_l^m(\boldsymbol{\alpha}),\Phi_l^{\exp}\right)\le\Phi_l^{**},\ l=1,\ldots,\nu. \tag{12}$$

For this problem to a considerable extent the values of Φ_l^{**} depend on the accuracy of the experiment and physical sense of the proximity criteria (11).

This brings us to the following formulation of multicriteria parameter identification problem for system (4) and sets of constraints (5), (6), and (12). The multicriteria parameter identification problem is to find an Edgeworth-Pareto set **EPS**, $\mathbf{EPS}\subseteq\mathbf{D}$, so that:

$$\Phi_l(\mathbf{EPS})=\min_{\boldsymbol{\alpha}\in\mathbf{D}}\Re_l\left(\Phi_l^m(\boldsymbol{\alpha}),\Phi_l^{\exp}\right),\ l=1,\ldots,\nu. \tag{13}$$

After finding **EPS**, the most preferable or optimal vector $\boldsymbol{\alpha}_0$, $\boldsymbol{\alpha}_0\in\mathbf{EPS}$ matching the physical sense of the object and/or results of the experiments can be finally determined (chosen). If not, then the problem of identification has an ambiguous solution (one should keep in mind that as a rule, in practice some of the criteria are calculated with comparatively high accuracy, while others are determined with considerable errors). Theoretically, to resolve this ambiguity researcher can reconsider the rigidity of or maybe add more constraints. Additional experiments might help also. However, usually this can be done on rare occasions only, because basically the ambiguity of restored parameter is the price to be paid for incomplete simulation of a real object by a mathematical model, incompleteness of the full-scale experiment, etc.

VI. Software Description

The following briefly discusses possibilities of the usage of the PSI method within the frame of the MOVI 1.3 software package adapted to Mathwork's Matlab/Simulink. This package allows user to perform feasibility analysis/design in a fairly friendly form. The total number of variable parameters (they maybe both continuous and discrete) exceeds several hundreds. No other constraints are imposed on the program. Criteria can be either minimized or maximized. Some or even all of the criterial constraints if unknown a priori can be considered as pseudocriteria.

Figures 6-10 show the test runs of the identification problem where several rather then all variable parameters and four different adequacy criteria were used. Fig.6 demonstrates an example of test tables obtained after multiple runs of the model with different parameter vectors. Number N in the left-top corner indicates the total number of trials, while ND (ND≤N) – the number of design variable vectors in the feasible set. All functional failures (trials that did not meet the functional constraints) can be considered separately in another table. By softening constraints, part of them may be immediately returned to the feasible set.

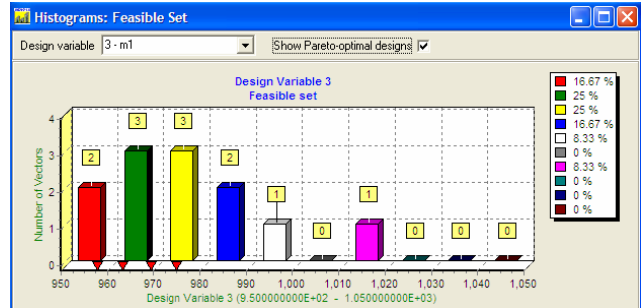Figure 6. Example of fully ordered test table.

Figure 7. Feasible set histogram for the single parameter.

The minimum and maximum numbers of each adequacy criterion are presented at the title of each table (vertical column). On this step MOVI software allows an expert to truncate the whole table achieving better results by working with the small portion of it at a time, and to correct the value of any criterial constraint to narrow/broaden the feasible set (it can be done for all columns from the left to the right decreasing ND value for every criterion). Finally, resulting table may be converted to the simplified form containing information on the subsets of feasible solutions and Pareto-optimal solutions (NP≤ND).

Further analysis involves graphical representation of the data (see examples on Figs.7-10). Fig.7 represents a histogram for the specific parameter (how many of the trials fall into the certain range). Fig.8 depicts an example of criteria versus criteria graph. Figure 9 shows the criteria versus single parameter plot for all trial points (meaning that each point corresponds to a single parameter vector). In addition the criteria versus single parameter plot can be obtained for any specified parameter by running some additional runs with all other parameters fixed (as it shown on Fig.10). It is possible to change ranges for the chosen parameter here. Moreover, the values of any other component of the parameter vector can be corrected also.
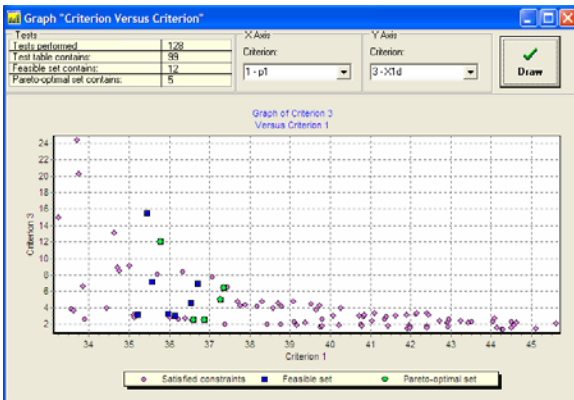
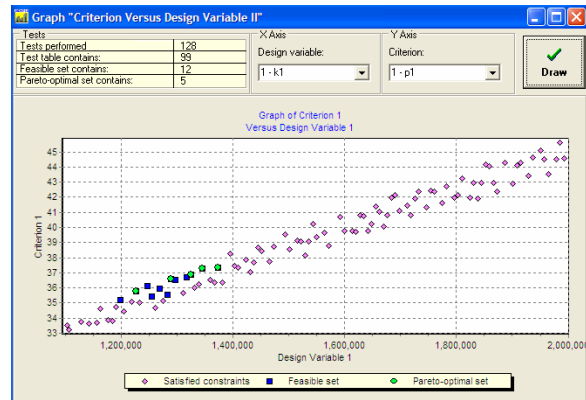

Figure 8. Criterion vs. criterion graph.

Figure 9. Criterion vs. parameter graph constructed using all feasible solutions.
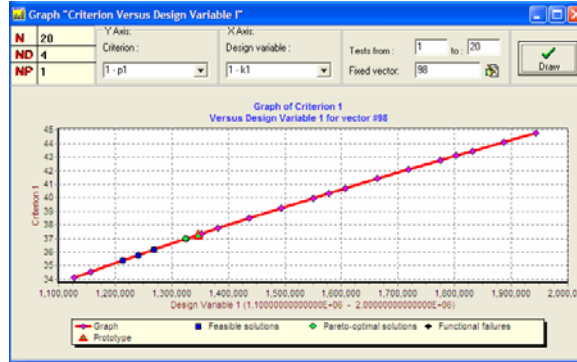
Figure 10. Criterion vs. parameter graph.

VII. Discussion of Parametric ID Results

As mentioned in Section 2, over 30 parameters were used along with eight different criteria. Among them there are two criteria describing the closeness of the horizontal and vertical projections of the trajectories, and three criteria relating to the adequacy of the natural eigenvalues (power spectrum) for all channels (roll, pitch and yaw).

Figure 11 shows the real drop trajectory, prototype trajectory (all gain factors are equal to unity) and the trajectories that were found to be the best with respect to the each specific criteria named above.
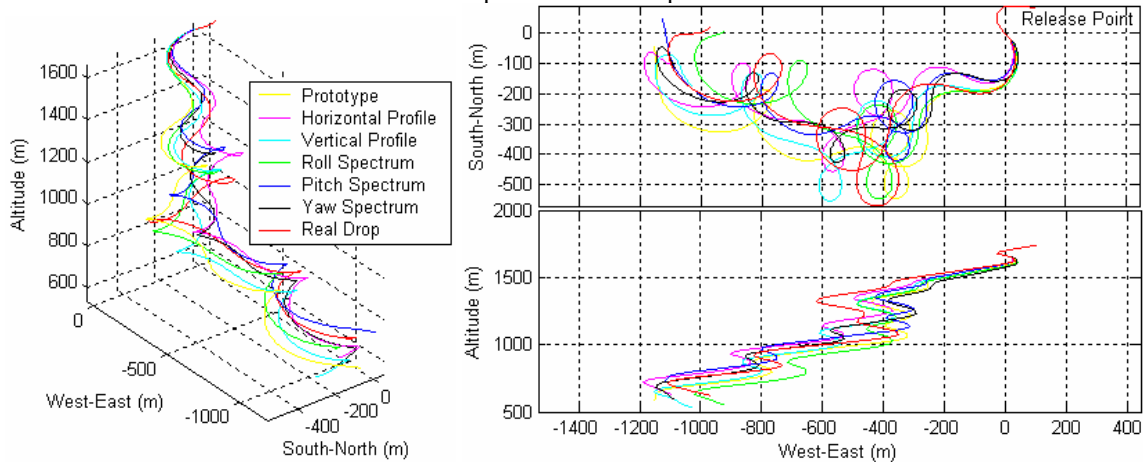

Figure 11. Optimal parafoil trajectories with respect to different criteria.

The choice was made among the results of several thousand trials (about two months of continuous PC run). However the set of feasible (and Pareto-optimal) solutions included much fewer trials because of criterial constraints applied to some of the state variables (angle of attack, speed components, altitude). As seen from Fig.11, all trajectories are fairly close to each other which actually attests the high quality of the model. As expected and predicted by others,[25] not much difference was observed compared to the 6-DoF model the authors developed earlier.[5] The only noticeable difference was in slightly smaller discrepancy in the natural eigenvalues (power spectrum) for pitch and yaw channels. Of course the 8 DoF model exhibited closer match to that of real drop data. Analysis of the power spectrum exposed which frequencies were missing and therefore defined limitation of the 6-DoF versus 8-DoF model. It also allowed evaluating the accuracy and applicability of the wind data gathered by the dropsonde.

Yet, the trajectories on Fig.11 do not match completely. Of course, neither the values of variable parameters match well. Moreover, even if only cost function is considered (and maybe only a single-criterion ID method is applied), multiple near-optimal (local) variable data sets can be found as seen from Fig.12. This figure presents the values for 33 variable parameters (coefficients gains) for several sets for the certain cost function the value of which for each set is also shown on the bottom. Fig.13 represents the same data but graphically to show the variation of parameters with respect to their nominal unity values (after several preliminary runs the range for all gain factors was established as [0.2;2]).

While several preliminary trials when only a few parameters were allowed to be changed (corresponding to set 1-5 columns in the table of Fig.12) decreased the cost function from 10.44 dimensionless units to about 4 units,

further adjustment involving over thirty variable parameters was needed to decrease the value of the cost function further. Some of the resulting local optimum sets are shown in the last five columns of Fig.12. What's interesting is that having approximately the same value of the cost function (less than 2 units) and resulting in fairly close trajectories these sets differ from each other (sometime as much as twofold). That means that having so many variable parameters we can redistribute them in several ways to achieve approximately the same magnitude of the cost function.

	Parameter/Value		Set 0	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 6a	Set 7a	Set 33-1	Set 33-2
c1	delcon	1	1	1	0.23983	0.23983	0.23983	0.23983	0.2878	0.2865	0.2865	0.494613	0.349706
c2	xcg	0	0	0	0	0	0.386	0.386	0.4632	0.59664	0.59664	0.546635	0.535231
c3	Alpha0	10	1	1	1	1	1	0.936	1.1392	1.1739	1.1739	1.240674	1.255886
c4	CLalpha	0.0375	1	1	1	1	1	1.0022	0.91294	0.96735	0.96735	0.927995	0.941119
c5	CLDf	0.2	1	1	1	1	1	1.07	1.137	1.2707	1.2707	1.770711	1.769055
c6	CD0	0.14	1	1	1	1	1	1.062	0.86667	1.0494	1.0494	0.96331	0.961487
c7	A2	0.25	1	1	1	1	1	0.995	0.80066	0.4483	0.4483	0.634647	0.629522
c8	ADf	0.2	1	1	1	1	1	1.064	1.2	0.75852	0.75852	0.413619	0.406355
c9	Cm0	-0.33	1	1	1	1	1	1.0486	0.8	1.1106	1.1106	0.937026	0.940533
c10	Rig	8	1	1	1	1	1	1	1.0523	0.58525	0.58525	0.958859	0.957133
c11	Cmq	-6.39	1	1	1	1	1	0.894	0.8	1.2255	1.2255	0.588472	0.583637
c12	CYbnom	-0.005	1	1	1	1	1	1	0.8	1.1803	1.1803	0.461411	0.442807
c13	CYbgrad	-0.0001	1	1	1	1	1	1	1.2	0.86021	0.86021	1.440569	1.451131
c14	CYDanom	-0.007	1	1	1	1	1	1	1.2	0.2263	0.2263	1.132878	1.282393
c15	CYDagrad	0.0012	1	1	1	1	1	1	1.2	1.4006	1.4006	1.214801	1.340795
c16	Clbnom	-0.0014	1	1	1	1	1	1	0.95664	1.3619	1.3668	0.456535	0.462645
c17	Clbgrad	-0.001	0	0	0	0	0	0	0	0	0.000161	0.00013	8.98E-05
c18	ClDanom	-0.0063	1	1	1	1	1	1	1.2	0.74132	0.74518	0.530218	0.62248
c19	ClDagrad	-0.001	0	0	0	0	0	0	0	0	0.00011	-4.51E-06	-3.78E-06
c20	Clp	-0.15	1	1	1	1.0765	1.0765	1.0765	0.8612	1.3461	1.3476	1.060879	1.07091
c21	Clr	0.0775	1	1	1	1	1	1.0037	0.80296	0.68709	0.68807	0.56154	0.565489
c22	Cnbnom	0.007	1	1	1	1	1	1	0.8	0.57465	0.57465	0.473491	0.469812
c23	Cnbgrad	-0.0003	1	1	1	1	1	1	1.2	1.0893	1.0893	0.77051	0.774133
c24	CnDanom	0.03	1	0.94344	0.94344	0.94344	0.94344	0.94344	0.98673	0.89177	0.89177	0.963727	0.965694
c25	CnDagrad	-0.001	1	0.50087	0.50087	0.50087	0.50087	0.50087	0.4007	0.34391	0.34391	0.644465	0.540929
c26	Cnp	0.023	1	1	1	1	1	0.99	1.188	1.519	1.519	1.024963	1.022094
c27	Cnr	-0.0936	1	1	1	1	1	1.0012	1.2014	1.155	1.155	1.10557	1.108614
c28	kA	0.899	1	1	1	1	1	1	1	1	1	0.539401	0.548065
c29	kB	0.339	1	1	1	1	1	1	1	1	1	1.382761	1.384552
c30	kC	0.783	1	1	1	1	1	1	1	1	1	1.259202	1.278601
c31	kA*	0.63	1.43	1.43	1.43	1.43	1.43	1.43	1.43	1.43	1.43	1.798577	1.760393
c32	kB*	0.817	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.497986	0.525471
c33	kC*	1	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.402627	0.202126
	Cost Function		10,444	4,224	4,058	3,947	3,883	3,700	1,812	1,271	1,271	1,272	1,181

Figure 12. "Quasi-optimal" values for 33 variable parameters for different sets of variable parameters for a single criteria.
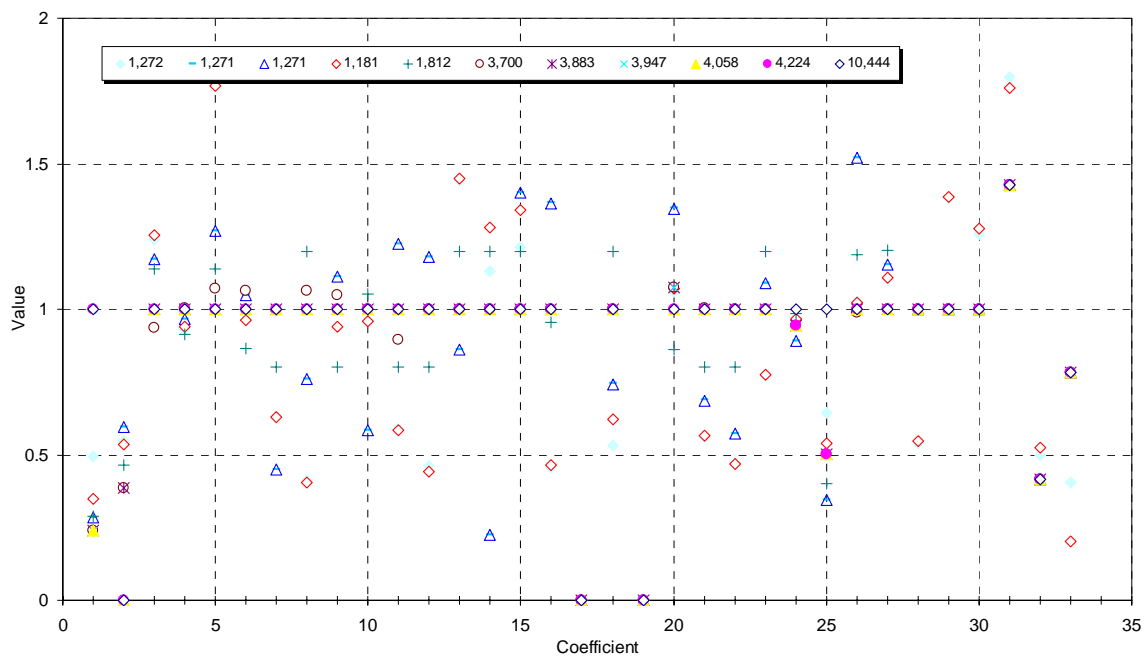

Figure 13. Graphical representation of parameters spread.

American Institute of Aeronautics and Astronautics

On the one hand, detailed analysis of solutions revealed explicit and implicit correlation between some variable parameters (darkened cells on Fig.14 show correlation between some of 25 variable parameters). That allows decreasing the original number of variable parameters by about 30% and alternatively (if needed) adding new parameters that were not considered in the original setup without increasing dimension of the problem.
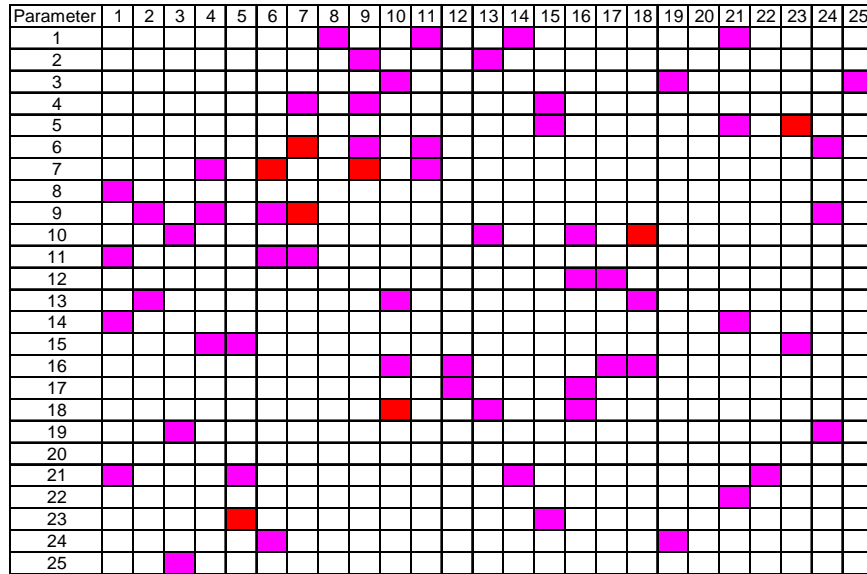
Figure 14. Strong correlation between some of variable parameters.

This also provides insight into the set of additional states of the system that need to be observed and recorded. The data on system's motion is usually obtained either with the help of GPS/IMU unit atop the payload or by tracking the payload using a cinetheodolite system with the following post analysis.[26] As shown by our previous study[4,5] having this data is almost enough for validation of 6-DoF models. For a more fundamental study including separate payload and parafoil behavior (higher fidelity models) and perhaps inflation dynamics, the canopy motion has to be investigated separately. Otherwise due to lack of experimental studies and measurements, the parafoil/payload interactions are often postulated in analytical modeling, resulting in theoretical predictions based on uncertain assumptions. Therefore, there is a need to experimentally investigate motion of the parafoil, employing for instance the technique of measuring two angles defining a direction of the riser with respect to the payload, offered by Lee et al.[27], video imaging of the canopy from the camera installed atop payload,[28,29] or by applying the algorithms originally developed to for payload[26] to estimate the pose of the parafoil.

VIII. Conclusion

Discussion presented in this paper persecutes the goal of correctly formulating the problem of multicretiria parametrical identification of the parafoil-based delivery system. It is suggested to implement the well-established PSI multicriteria optimization method to investigate the set of feasible parameters and solve the identification problem. The paper shows that in total the problem contains as much as several dozens variable parameters and several distinctive adequacy criteria. Different sets of parameters affect these criteria non-adequately. Moreover, minimum-criterion solutions do not coincide. Currently authors are performing more simulations with existing set of flight test data and expect to involve some more to be able to complete tweaking the model.

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