酸化剤流量制御によるハイブリッドロケット消炎再着火の有効運用

Effective operations of hybrid-rocket extinction-reignition via oxidizer-mass-flow control

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The objective of this study is to reveal extinction-reignition ascendancy, which is one of the beneficial points of hybrid rocket, for expanding downrange and duration in the lower thermosphere in view of simple control of oxidizer mass flow. Swirling-flow oxidizer is furnished with solid fuel; we adopt polypropylene for solid fuel and liquid oxygen for oxidizer. A multidisciplinary design optimization has been implemented by using a hybrid evolutionary computation; data mining has been also conducted by using a scatter plot matrix to efficiently perceive the entire design space. It is consequently revealed that the hypothesis in the prior study is proved; extinction-reignition extends not only duration but also, downrange. Scatter plot matrix results express physical mechanisms of design-variable behaviors for the objective functions and also the roles of the design variables via bird's-eye visualization of the entire design space constitution.

1. Introduction

Single-stage rockets have been researched and developed for scientific observations and experiments of high-altitude zero-gravity condition, whereas multi-stage rockets have been for orbit injections of payloads. Institute of Space and Astronautical Science (ISAS)/Japan Aerospace Exploration Agency (JAXA) has been operating Kappa, Lambda, and Mu series rockets as the representatives of solid rocket to contribute to space science researches. Although Epsilon series began to be operated from September 2013, a next-generation rocket is necessary to fulfill higher-frequent and lower-cost space transportations.

Hybrid rocket engines (HREs) using different phases between fuel and oxidizer (solid fuel and liquid/gas oxidizer is generally used) have been researched and developed as an innovative technology in mainly the E.U. [1)] and the U.S. [2)] Each country has plans to adopt an HRE to a main engine of space transports because of several advantages: lower cost, higher safety (especially important for manned mission), and pollution free flight due to no gunpowder use. In contrast, disadvantages of HREs proceed from their combustion. Since HREs have low regression rate of solid fuel due to turbulent boundary layer combustion, the thrust of HREs is less than that of pure-solid/liquid engines which premixed combustion [3)] is implemented. Moreover, since the mixture ratio between solid fuel and liquid/gas oxidizer (O/F) is temporally fluctuated, thrust changes with time. Research topics of HREs are improving those performances via experiments.

Now in Japan, ISAS/JAXA recently researches HREs to develop a next-generation space transportation. Research topics are vaporization of liquid oxygen, advancement of exhaust velocity c^* efficiency, progress of regression rate, stable ignition, and numerical simulations of turbulent boundary layer combustion. In contrast, we will investigate hybrid-rocket ascendancy via design optimizations as a part of ISAS/JAXA's hybrid rocket project. The objective of the design optimizations in this project is to quantitatively indicate hybrid-rocket advantage compared with the current rockets via design optimizations; multidisciplinary design requirements: chemical equilibrium, thrust, structural, aerodynamics, and trajectory analyses are driven. Furthermore, exhaustive design information will be obtained to additionally consider manufacturing, productive, and market factors for practical problems (optimization is difficult to deal with them due to the difficulty of quantitative definition).

Design informatics (DI) has essential for not only an operating system itself but also its applications to practical problems so that science contributes toward the real world. Results themselves do not possess versatility in application problems due to their particularity; system versatility is indeed critical in application problems because it is revealed that application range is expanded. Furthermore, the application results indicate the guidance for system improvements. In this study, we conceptually explore a design optimization of a single-stage sounding hybrid rocket using DI approach. The objective is that extinction-reignition advantage in the science mission for aurora observation on hybrid rocket will be quantitatively revealed. Since HREs are comparatively easy to perform multi-time ignition [4)], extinction-reignition supremacy is especially predicted by using design informatics approach.

We researched step by step in the previous studies. As a first step, an optimization problem on single-time ignition, which is the identical condition of the current solid rocket, was defined to obtain the design information [5)]. As a second step, the implication of solid fuels in the performance of hybrid rocket was revealed because the regression rate is one of the key elements for hybrid-rocket performance [6)]. Finally, this study investigates an extinction-reignition sequence to reveal a hybrid-rocket ascendancy as multi-time ignition. We acquired a hypothesis regarding the difference between 1st and 2nd combustion characteristics in the previous study for investigating extinction-reignition advantage on a hybrid rocket system [7]. The objective of this study is to verify it.

The constitution of this paper is as follows. The optimization and data-mining techniques used in DI are explained in Chapter 2. The problem definition for designing a hybrid rocket are shown in Chapter 3. Otimization and data-mining results are revealed; the knowledge is also discussed in Chapter 4.

2. Problem definition

We consider a design optimization for a single-stage sounding hybrid rocket, simply composed of a payload chamber, an oxidizer tank, a combustion chamber, and a nozzle [8] shown in Fig. 1. A launch vehicle for aurora scientific observation will be focused because more efficient sounding rockets are desired due to successful obtaining new scientific knowledge on the aurora observation by ISAS/JAXA in 2009. In addition, a single-stage hybrid rocket problem fits for resolving fundamental physics regarding HREs and for improving the problem definition.

The problem definition is identical with the previous study [7] except for the design variables. Since the acquired hypothesis indicates that 2nd combustion should be feeble to merely sustain vehicle gross weight, we anew prepare design variables regarding oxidizer mass flow for each combustion.

2.1. Objective functions

Three objective functions are defined. First objective is maximizing the downrange in the lower thermosphere (altitude of 90 to 150 [km]) R_d [km] (obj1). Second is maximizing the duration in the lower thermosphere T_d [sec] (obj2). It recently turns out that atmosphere has furious and intricate motion in the lower thermosphere due to energy injection, from which derives aurora, from high altitude. The view of these objective functions is to secure the horizontal distance and time for competently observing atmospheric temperature and the wind so that thermal energy balance is elucidated on atmospheric dynamics. Third objective is minimizing the initial gross weight of launch vehicle $M_{\mathrm{tot}}(0)$ [kg] (obj3), which is generally the primary proposition for space transportations.

2.2. Design variables

We use 10 design variables: oxidizer mass flow on 1st combustion $\dot{m}_{\mathrm{ox}}^{(1\mathrm{st})}$ [kg/sec] (dv1), oxidizer mass flow on 2nd combustion $\dot{m}_{\mathrm{ox}}^{(2\mathrm{nd})}$ [kg/sec] (dv2), fuel length L_{fuel} [m] (dv3), initial radius of port $r_{\mathrm{port}}(0)$ [m] (dv4), total combustion time $t_{\mathrm{burn}}^{(\mathrm{total})}$ [sec] (dv5), first combustion time $t_{\mathrm{burn}}^{(1\mathrm{st})}$ [sec] (dv6), extinction time from the end of first combustion to the beginning of second combustion t_{ext} [sec] (dv7), initial pressure in combustion chamber $P_{\mathrm{cc}}(0)$ [MPa] (dv8), aperture ratio of nozzle ϵ [-] (dv9), and elevation at launch time $\phi(0)$ [deg] (dv10).

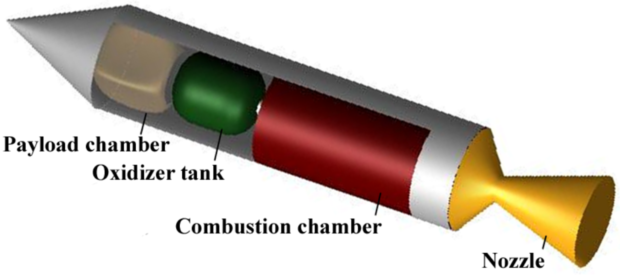

Fig. 1. Conceptual illustrations of hybrid rocket.

We set two combustion times as follows:

$$
\begin{aligned}
t_{\mathrm{burn}}^{(1\mathrm{st})} &= \begin{cases} t_{\mathrm{burn}}^{(\mathrm{total})} & (t_{\mathrm{burn}}^{(\mathrm{total})} < t_{\mathrm{burn}}^{(1\mathrm{st})}) \\ t_{\mathrm{burn}}^{(1\mathrm{st})} & (t_{\mathrm{burn}}^{(\mathrm{total})} \geq t_{\mathrm{burn}}^{(1\mathrm{st})}) \end{cases}, \\
t_{\mathrm{burn}}^{(2\mathrm{nd})} &= \begin{cases} 0 & (t_{\mathrm{burn}}^{(\mathrm{total})} < t_{\mathrm{burn}}^{(1\mathrm{st})}) \\ t_{\mathrm{burn}}^{(\mathrm{total})} - t_{\mathrm{burn}}^{(1\mathrm{st})} & (t_{\mathrm{burn}}^{(\mathrm{total})} \geq t_{\mathrm{burn}}^{(1\mathrm{st})}) \end{cases}.
\end{aligned} \tag{1}
$$

Under $t_{\mathrm{burn}}^{(\mathrm{total})} < t_{\mathrm{burn}}^{(1\mathrm{st})}$ condition, it is defined that $t_{\mathrm{burn}}^{(1\mathrm{st})}$ is set to be $t_{\mathrm{burn}}^{(\mathrm{total})}$ and second-time combustion is not performed. Note that there is no constraint except upper/lower limits of each design variable summarized in Table 1. These upper/lower values are exhaustively covering the region of the design space which is physically admitted. When there is a sweet spot (the region that all objective functions proceed optimum directions) in the objective-function space, the exploration space would intentionally become narrow due to the operation of range adaptation on the evolutionary computation.

2.3. Evaluation method of hybrid rocket

First of all, $O/F(t)$ is computed by the following equation.

$$
O/F(t) = \frac{\dot{m}_{\mathrm{ox}}(t)}{\dot{m}_{\mathrm{fuel}}(t)}, \tag{2}
$$

where $\dot{m}_{\mathrm{ox}}(t)$ is set from dv1 and dv2 as well as

$$
\begin{aligned}
\dot{m}_{\mathrm{fuel}}(t) &= 2\pi r_{\mathrm{port}}(t) L_{\mathrm{fuel}} \rho_{\mathrm{fuel}} \bar{\dot{r}}_{\mathrm{port}}(t), \\
r_{\mathrm{port}}(t) &= r_{\mathrm{port}}(0) + \int \dot{r}_{\mathrm{port}}(t) \mathrm{d}t.
\end{aligned} \tag{3}
$$

$\dot{m}_{\mathrm{ox}}(t)$ and $\dot{m}_{\mathrm{fuel}}(t)$ are the mass flow of oxidizer/fuel [kg/sec] at time t, respectively. $r_{\mathrm{port}}(t)$ is port radius [m] at t, L_{fuel} describes fuel length, and ρ_{fuel} is fuel density [kg/m^3]. $\dot{r}_{\mathrm{port}}(t)$ describes the regression rate. Note that since HREs perform no premixed combustion which conventional rocket engine implements but turbulent boundary layer combustion, $O/F(t)$ is not constant but timely fluctuated. After that, an analysis of chemical equilibrium is performed by using NASA-CEA (chemical equilibrium with applications) [9], then trajectory, thrust, aerodynamic, and structural analyses are respectively implemented. A body is assumed as rigidness. As the time step is set to be 0.5 [sec], it takes roughly 10 [sec] for an individual evaluation on a general desktop computer.

A combustion chamber is filled with solid fuel with a single port at the center to supply oxidizer. As the regression rate to the radial direction $\dot{r}_{\mathrm{port}}(t)$ [m/sec] generally governs thrust power of HREs, it is a significant parameter. This study uses the following experimental model [10, 11];

$$
\begin{aligned}
\dot{r}_{\mathrm{port}}(t) &= a_{\mathrm{fuel}} \times G_{\mathrm{ox}}^{n_{\mathrm{fuel}}}(t) \\
&= a_{\mathrm{fuel}} \times \left(\frac{\dot{m}_{\mathrm{ox}}(t)}{\pi r_{\mathrm{port}}^2(t)} \right)^{n_{\mathrm{fuel}}},
\end{aligned} \tag{4}
$$

where $G_{\mathrm{ox}}(t)$ is oxidizer mass flux [kg/m^2/sec]. a_{fuel} [m/sec] and n_{fuel} [-] are the constant values experimentally determined by fuels. Swirling oxidizer flow is carried out; we adopt liquid oxygen for oxidizer and polypropylene as thermoplastic resin for solid fuel. Experiments [10, 11] respectively indicate $a_{\mathrm{fuel}} = 8.26 \times 10^{-5}$ [m/sec] and $n_{\mathrm{fuel}} = 0.5500$ [-] for polypropylene.

Table 1. Upper/lower limits of each design variable.

serial number	*design variable*	*unit*	*design space*		
dv1	oxidizer mass flow on 1st combustion	[kg/sec]	1.0 ≤	$\dot{m}_{\rm ox}^{\rm (1st)}$	≤ 30.0
dv2	oxidizer mass flow on 2nd combustion	[kg/sec]	1.0 ≤	$\dot{m}_{\rm ox}^{\rm (2nd)}$	≤ 30.0
dv3	fuel length	[m]	1.0 ≤	$L_{\rm fuel}$	≤ 10.0
dv4	initial radius of port	[m]	0.01 ≤	$r_{\rm port}(0)$	≤ 0.30
dv5	total combustion time	[sec]	20.0 ≤	$t_{\rm burn}^{\rm (total)}$	≤ 60.0
dv6	1st combustion time	[sec]	10.0 ≤	$t_{\rm burn}^{\rm (1st)}$	≤ 40.0
dv7	extinction time	[sec]	1.0 ≤	$t_{\rm ext}$	≤ 300.0
dv8	initial pressure in combustion chamber	[MPa]	3.0 ≤	$P_{\rm cc}(0)$	≤ 6.0
dv9	aperture ratio of nozzle	[-]	5.0 ≤	ϵ	≤ 8.0
dv10	elevation at launch time	[deg]	60.0 ≤	$\phi(0)$	≤ 90.0

3. Design informatics

DI is essential for practical design problems. Although solving design optimization problems is important under many-discipline consideration on engineering [12], the most significant part of the process is the extraction of useful knowledge of the design space from results of optimization runs [13), 14]. The results produced by multiobjective optimization (MOO) are not an individual optimal solution but rather an entire set of optimal solutions due to tradeoffs. That is, MOO results are not sufficient from the practical point of view as designers need a conclusive shape and not the entire selection of possible optimal shapes. But optimal-solution set produced by an MOO can be considered a hypothetical design database for design space. Thereupon, data mining techniques can be applied to a hypothetical database to acquire not only useful design knowledge but also structurizing and visualizing design space for conception support. This approach was suggested as DI [15].

The goal of this approach is the conception support for designers to materialize innovation. This methodology is constructed by three essences: problem definition, efficient optimization, and data mining for structurization and visualization of design space. A design problem including objective functions, design variables, and constraints, is strictly defined in view of the background physics for several months. Note that problem definitions are the most important process because it directly gives effects on design space qualities. If we garrulously define a problem, unnecessary evolutionary exploration should be performed; needless mining will be also carried out because it is conceived to be low-quality design space. Then, optimization is implemented to acquire nondominated solutions (quasi-Pareto solutions) to become hypothetical database. Finally, data mining is implemented for this database to obtain design information. Mining has a postprocess role for optimization. Mining results might include significant knowledge for next design phase and also becomes the material to redefine a design problem.

3.1. Optimization method

DI second phase is optimization; we use evolutionary computations (ECs). Although we can employ a surrogate models [16]: the radial basis function and the Kriging model [17], which is a response surface model developed in the field of spatial statistics and geostatistics, we will not select them because they are generally difficult to deal with a large number of design variables. In addition, we would like to generate a hypothesis database using exact solutions. We also employ ECs so that plural individuals are parallel conducted. We use a hybrid EC between the differential evolution (DE) and the genetic algorithm (GA) [18].

First, multiple individuals are generated randomly as an initial population. Then, objective functions are evaluated for each individual. The population size is equally divided into subpopulations between DE and GA [*]. New individual candidates generated via DE and GA are combined. The nondominated solutions in the combined population are archived in common. Note that only the archive data is in common between DE and GA. The respective optimization methods are independently performed in the hybrid EC.

The hybrid EC is a real-coded optimizer [19]. Although GA is based on the real-coded NSGA-II (the elitist nondominated sorting genetic algorithm) [20], it is made several improvements on to be progressed with the diversity of solutions. Fonseca's Pareto ranking [21] and the crowding distance [20] are used for fitness values. The stochastic universal sampling [22] is employed for parents selection. Crossover rate is 100%; the principal component analysis blended crossover-α (PCABLX) [23] and the confidence interval based crossover using L_2 norm (CIX) [24] are used because of the high performance for convergence and diversity as well as the strength for noise [18]. The subpopulation size served by GA is equally divided for these two crossovers. Mutation rate is set to be constant as the reciprocal of the number of design variables. For alternation of generations, we employ a cross-generational elitist selection model, which uses the crowding distance for clustering; it selects N solutions from all parents and offspring. Thereupon, candidates of the next generation are $2N$. We will estimate fitness to be low for maintaining diversity if crowding distances are small due to falling into local optima. DE is used as the revised scheme [25] for multiobjective optimization from DE/rand/1/bin scheme. The scaling factor F is set to be 0.5. The hybrid EC has a range-adaptation function [26], which changes the search region according to the statistics of better solutions, for all design variables. Range adaptations are implemented at every 20 generations.

3.2. Data mining

DI third phase is data mining. Scatterplot matrix (SPM) [27] or be simply named scatterplots remains one of the general vi-

[*] although sub-population size can be changed at every generations on the optimizer, the determined initial sub-populations are fixed at all generations

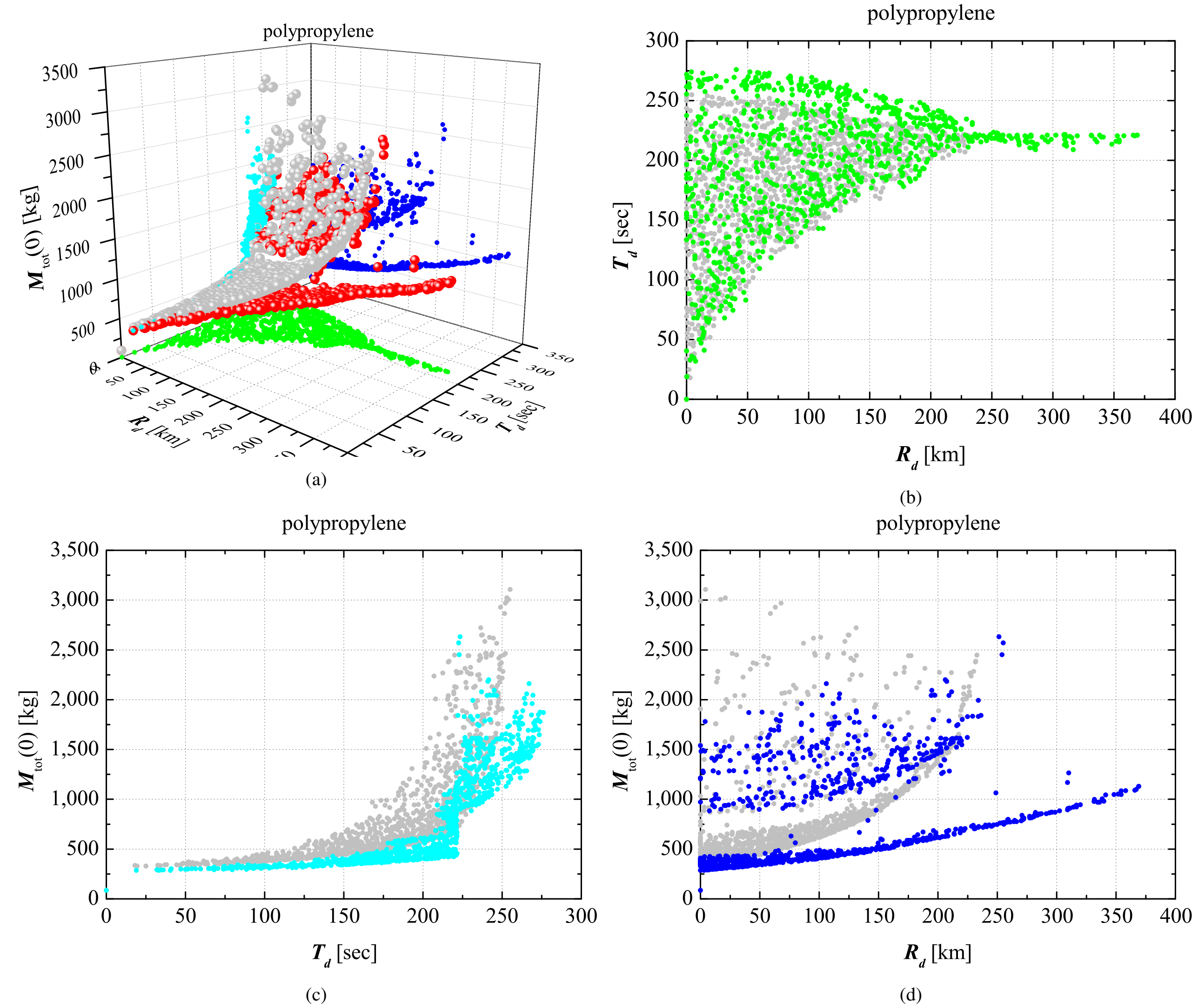

Fig. 2. Plots of nondominated solutions derived by optimization, (a) plotted in the three-dimensional objective-function space (red) and their plots projected onto two dimensions, (b) plots projected onto two dimension between R_d (obj1) and T_d (obj2) (light green), (c) plots projected onto two dimension between T_d (obj2) and $M_{tot}(0)$ (obj3) (light blue), and (d) plots projected onto two dimension between R_d (obj1) and $M_{tot}(0)$ (obj3) (blue). Note that gray-colored plots represent the results of previous work [7] in view of no oxidizer-mass-flow control.

sual descriptions for multidimensional data due to its simplicity. SPM is available to simultaneously visualize multidimensional data constructed by all of objective functions and design variables like as a bird's-eye view. Other data-mining techniques which have flexibility and effective visual expressiveness exist. However, we merely select SPM so that we will obtain first-step design information via observing design-space overview.

4. Results

4.1. Optimization results

Population size in the hybrid EC uses 18 individuals; we perform until 4,500 generations because hypervolume is converged. Figure 2 shows the optimization result. Figure 2(a) indicates consequently obtained nondominated solutions in the objective-function space. We can confirm that the present result improves all objective functions and expands the feasible region compared with the former result which the problem gave a same oxidizer mass flow for 1st and 2nd combustions. Note that red plot denotes the present result; gray plot describes the former results. We observe the figure to project the nondominated solutions onto 2 dimensions so that we will confirm the detailed nondominated-solution structure.

Figure 2(b) shows 2 dimensional plots between R_d and T_d. This figure indicates the difference of philosophy for between extending R_d and T_d; we cannot simultaneously fulfill both. Although the previous study did not realize R_d expansion [7], oxidizer-mass-flow control can achieve; the extension rate is roughly 70%. Moreover, it is considerable that T_d is approximately mere constant value at that time due to high horizontal velocity. In contrast, we can expand T_d using oxidizer-mass-flow control rather than the previous upper limit, but the extending effect for T_d is smaller than that for R_d: roughly 10%.

Figure 2(c) shows 2 dimensional plot between T_d and $M_{tot}(0)$. This figure describes the specific nondominated surface which generates a difference in level near 225 [sec], i.e., we should different design strategies in the feasible regions between under T_d of 225 [sec] and over that of 225 [sec]. Extinction-reignition is

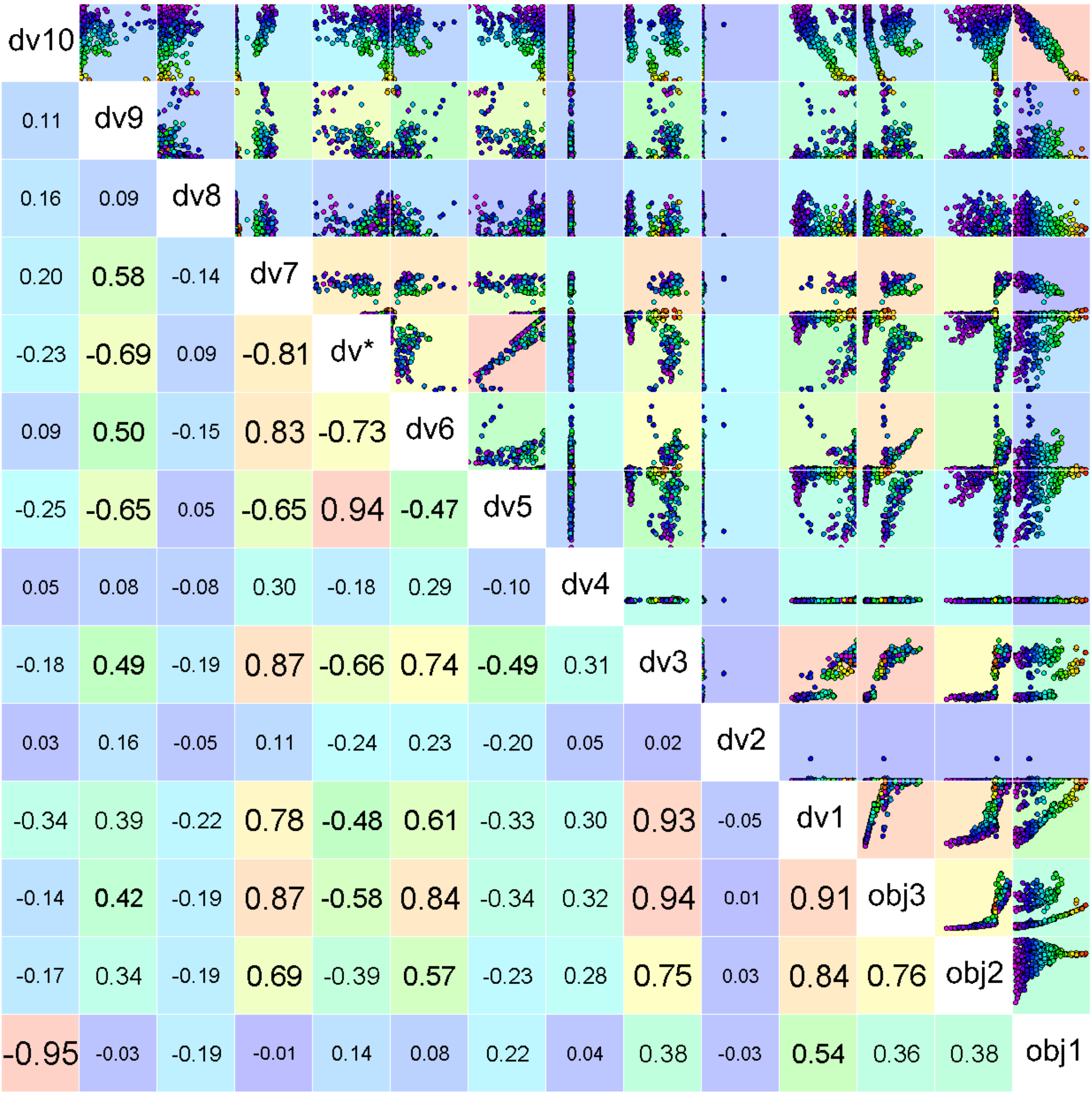

Fig. 3. Scatterplots of the optimization results and their correlation coefficients. The upper/lower values of the axes of the design variables on graphs are set to be the upper/lower limits of each design variables shown in Table 1. Plots are colored by R_d as obj1; each block is colored by the absolute value of their correlation coefficients. "dv*" denotes dv5−dv6, i.e., 2nd combustion time $t_{\rm burn}^{\rm (2nd)}$; dv* range is from 0 to 50 [sec].

not performed under T_d of 225 [sec] or lower condition; it is implemented under T_d of 225 [sec] or upper condition. Both of the regions have a tradeoff, but we should permit drastic $M_{\rm tot}(0)$ rise so that we effectively employ extinction-reignition. Furthermore, inclination $\partial M_{\rm tot}(0)/\partial T_d$, which describes the growth rate of $M_{\rm tot}(0)$ for T_d, becomes larger than single ignition case under extinction-reignition condition. We should abandon $M_{\rm tot}(0)$ restriction for extending T_d using extinction-reignition.

Figure 2(d) shows 2 dimensional plot between R_d and $M_{\rm tot}(0)$. It is considerable that oxidizer-mass-flow control in extinction-reignition fulfills R_d expansion to restrain $M_{\rm tot}(0)$ increase rather than extending T_d. Moreover, when we compare single ignition and extinciton-reignition, inclination $\partial M_{\rm tot}(0)/\partial R_d$, which denotes an increasing rate of $M_{\rm tot}(0)$ for R_d gain, is approximately continuous.

4.2. Data mining results

Since we already performed the detailed consideration and discussion regarding the behavior of each design variable in design space on the previous study [7], we will consider to focus on the behavior of oxidizer mass flow for 1st and 2nd combustion which re-define in the present study. According to the hypothesis which we obtained from the data-mining result in the previous study to define oxidizer mass flow constant [7], the hybrid EC will actively employ extinction-reignition, however, the characteristics between 1st and 2nd combustions are entirely different; 1st needs powerful combustion to launch a body to the lower thermosphere; 2nd requires feeble combustion to merely sustain vehicle gross weight.

SPM shown in Fig. 3 demonstrates that 1st combustion needs a large value of oxidizer mass flow for maximizing R_d and T_d as well as generating substantial thrust. In contrast, 2nd combustion restrains a small number of oxidizer mass flow so that a hybrid rocket requires the combustion to generate minimum thrust for holding up its weight. That is, it is considerable that the hypothesis is correct.

5. Conclusions

We have studied the effective operations of hybrid-rocket extinction-reignition using oxidizer-mass-flow control via design informatics. The results consequently indicate that we have each appropriate setting for 1st and 2nd combustions; 1st needs powerful combustion to launch a body to the lower thermosphere; 2nd requires feeble combustion to merely sustain vehicle gross weight. Even if we perform no complicated but simple control of oxidizer mass flow to be respectively constant values for each combustion, oxidizer-mass-flow control is useful for effective operations of a hybrid-rocket system.

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References

1) Karabeyoglu, M. A., "Advanced Hybrid Rockets for Future Space Launch," *Proceedings on 5th European Conference for Aeronautics and Space Sciences*, EUCASS, 2013.
2) Simurda, L., Zilliac, G., and Zaseck, C., "High Performance Hybrid Propulsion System for Small Satellites," *AIAA Paper 2013-3635*, AIAA, 2013.
3) Karabeyoglu, M. A., Altman, D., and Cantwell, B. J., "Combustion of Liquefying Hybrid Propellants: Part 1, General Theory," *Journal of Propulsion and Power*, Vol. 18, No. 3, 2002, pp. 610–620.
4) Saraniero, M. A., Caveny, L. H., and Summerfield, M., "Restart Transients of Hybrid Rocket Engines," *Journal of Spacecraft and Rockets*, Vol. 10, No. 3, 1973, pp. 215–217.
5) Chiba, K., Kanazaki, M., Nakamiya, M., Kitagawa, K., and Shimada, T., "Conceptual Design of Single-Stage Launch Vehicle with Hybrid Rocket Engine for Scientific Observation Using Design Informatics," *Journal of Space Engineering*, Vol. 6, No. 1, 2013, pp. 15–27.
6) Chiba, K., Kanazaki, M., Nakamiya, M., Kitagawa, K., and Shimada, T., "Diversity of Design Knowledge for Launch Vehicle in View of Fuels on Hybrid Rocket Engine," *Journal of Advanced Mechanical Design, Systems, and Manufacturing*, Vol. 8, No. 3, 2014, pp. JAMDSM0023, 1–14.
7) Chiba, K., Yoda, H., Kanazaki, M., and Shimada, T., "Extinction-Reignition Superiority in a Single-Stage Sounding Hybrid Rocket," *Aerospace Science and Technology*, Vol. 58, 2016, pp. 437–444.
8) Kosugi, Y., Oyama, A., Fujii, K., and Kanazaki, M., "Multidisciplinary and Multi-Objective Design Exploration Methodology for Conceptual Design of a Hybrid Rocket," *AIAA Paper 2011-1634*, AIAA, 2011, pp. 1–13.
9) Gordon, S. and McBride, B. J., "Computer Program for Calculation of Complex Chemical Equilibrium Compositions and Applications I. Analysis," *NASA Reference Publication RP-1311*, NASA, 1994.
10) Hirata, K., Sezaki, C., Yuasa, S., Shiraishi, N., and Sakurai, T., "Fuel Regression Rate Behavior for Various Fuels in Swirling-Oxidizer-Flow-Type Hybrid Rocket Engines," *AIAA Paper 2011-5677*, AIAA, 2011.
11) Yuasa, S., Shiraishi, N., and Hirata, K., "Controlling Parameters for Fuel Regression Rate of Swirling-Oxidizer-Flow-Type Hybrid Rocket Engine," *AIAA Paper 2012-4106*, AIAA, 2012.
12) Arias-Montano, A., Coello, C. A. C., and Mezura-Montes, E., "Multiobjective Evolutionary Algorithms in Aeronautical and Aerospace Engineering," *IEEE Transactions on Evolutionary Computation*, Vol. 16, No. 5, 2012, pp. 662–694.
13) Chiba, K., Obayashi, S., and Nakahashi, K., "Design Exploration of Aerodynamic Wing Shape for Reusable Launch Vehicle Flyback Booster," *Journal of Aircraft*, Vol. 43, No. 3, 2006, pp. 832–836.
14) Chiba, K. and Obayashi, S., "Knowledge Discovery in Aerodynamic Design Space for Flyback-Booster Wing Using Data Mining," *Journal of Spacecraft and Rockets*, Vol. 45, No. 5, 2008, pp. 975–987.
15) Chiba, K., Makino, Y., and Takatoya, T., "Design-Informatics Approach for Intimate Configuration of Silent Supersonic Technology Demonstrator," *Journal of Aircraft*, Vol. 49, No. 5, 2012, pp. 1200–1211.
16) Keane, A. J., "Statistical Improvement Criteria for Use in Multiobjective Design Optimization," *AIAA Journal*, Vol. 44, No. 4, 2006, pp. 879–891.
17) Jeong, S., Murayama, M., and Yamamoto, K., "Efficient Optimization Design Method Using Kriging Model," *Journal of Aircraft*, Vol. 42, No. 2, 2005, pp. 413–420.
18) Chiba, K., "Evolutionary Hybrid Computation in View of Design Information by Data Mining," *Proceedings on IEEE Congress on Evolutionary Computation*, IEEE, 2013, pp. 3387–3394.
19) Oyama, A., Obayashi, S., and Nakamura, T., "Real-Coded Adaptive Range Genetic Algorithm Applied to Transonic Wing Optimization," *Applied Soft Computing*, Vol. 1, No. 3, 2001, pp. 179–187.
20) Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T., "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, Vol. 6, No. 2, 2002, pp. 182–197.
21) Fonseca, C. M. and Fleming, P. J., "Genetic Algorithms for Multiobjective Optimization: Formulation, Discussion and Generalization," *Proceedings of the Fifth International Conference on Genetic Algorithms*, Morgan Kaufmann, 1993, pp. 416–423.
22) Baker, J. E., "Adaptive Selection Methods for Genetic Algorithms," *Proceedings of the International Conference on Genetic Algorithms and their Applications*, Lawrence Erlbaum Associates, 1985, pp. 101–111.
23) Takahashi, M. and Kita, H., "A Crossover Operator Using Independent Component Analysis for Real-Coded Genetic Algorithms," *Proceedings of IEEE Congress on Evolutionary Computation 2001*, IEEE, 2001, pp. 643–649.
24) Hervas-Martinez, C., Ortiz-Bayer, D., and Garcia-Pedrajas, N., "Theoretical Analysis of the Confidence Interval Based Crossover for Real-Coded Genetic Algorithms," *The 7th International Conference on Parallel Problem Solving from Nature, LNCS 2439*, Springer-Verlag, Berlin Heidelberg, 2002, pp. 153–161.
25) Robic, T. and Filipic, B., "DEMO: Differential Evolution for Multiobjective Optimization," *The 3rd International Conference on Evolutionary Multi-Criterion Optimization, LNCS 3410*, Springer-Verlag, Guanajuato, Mexico, 2005, pp. 520–533.
26) Sasaki, D. and Obayashi, S., "Efficient Search for Trade-Offs by Adaptive Range Multi-Objective Genetic Algorithms," *Journal of Aerospace Computing, Information, and Communication*, Vol. 2, No. 1, 2005, pp. 44–64.
27) Elmqvist, N., Dragicevic, P., and Fekete, J., "Rolling the Dice: Multidimensional Visual Exploration using Scatterplot Matrix Navigation," *IEEE Transactions on Visualization and Computer Graphics*, Vol. 14, No. 6, 2008, pp. 1539–1548.