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COLLABORATIVE OPTIMIZATION OF REMOTE SENSING SMALL SATELLITE MISSION USING GENETIC ALGORITHMS*

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Abstract– This paper focuses on the development of an efficient distributed collaborative optimization method for the design of remote sensing small satellite mission in low earth orbit (LEO). The satellite mission requirement involves the duration in which the satellite is able to take images, send data to the ground station and the amount of information it can store. Conventionally, all at once methods are used in satellite mission analysis, however, design optimization of such systems are multidisciplinary task with multiple conflicting objectives such as cost, performance and reliability. The approach adopted in this paper is based on a distributed collaborative optimization (CO) framework. In this approach, the design optimization problem is divided into two levels; namely system and discipline levels. The discipline level optimization involves payload, power, mission and launch subsystems. The objective function of the system level is to minimize the resolution of the satellite imaging payload subject to equality constraints. The use of equality constraints at the system level in CO to represent the disciplinary feasible regions introduces numerical and computational difficulties, as the discipline level optima are non-smooth and noisy functions of the system level optimization parameters. As a result of these difficulties, derivative-based optimization techniques cannot be used for the system level optimization. To address these difficulties a robust optimization algorithm, genetic algorithms (GA), are used at the system level, whilst at the discipline level efficient gradient based techniques are utilized. The results show that distributed CO framework using GA has the same level of accuracy as with the conventional all at once approaches, while providing a potential approach for solving complex multidisciplinary design problems such as the design of satellite systems.

Keywords– Multidisciplinary design optimization, collaborative optimization, satellite mission, genetic algorithms, imaging payload

1. INTRODUCTION

The design of space systems is a multidisciplinary process with multiple and often conflicting objectives such as cost, performance and reliability. This, combined with the increasing demands of economic competition and the complexity of space systems has led to the rapid growth of the multidisciplinary design optimization (MDO) over the past two decades [1]. The design of such complex systems has traditionally involved a conceptual design phase, a preliminary design phase and a detailed design phase. For example, in the design of satellite, the most important and crucial decisions in a space mission life-cycle are made during the conceptual design phase. This initial design phase offers the best opportunity to make radical changes, preventing potential failures and anomalies before proceeding to detailed design phase and verification of the satellite design [2]. The conventional sequential approach to such complex satellite system design involves a large number of iterations, which it does not guarantee to achieve the

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best compromise and may even lead to non-optimal design. In the past few years, several research works have focused on the use of the conventional optimization techniques to the conceptual design of satellite. For example, Byoungsoo [3] used meta-heuristic algorithms to minimize the space system cost based on the technology choice at conceptual design phase, while Hassan [4] applied multiobjective optimization design using genetic algorithm (GA) for conceptual design of spacecraft systems. Similarly, Magnin [5] has presented a method for performing multiobjective optimization under uncertainty of satellite systems.

Over the past two decades, there has been significant progress in the application of MDO for solving such complex design problems. Several MDO approaches have been proposed that include multiple discipline feasible (MDF) [6], all-at-once (AAO) and individual discipline feasible (IDF) [7], collaborative optimization [8], bi-level integrated synthesis (BLISS) [9], concurrent subspace optimization (CSSO) [10] and analytical target cascading (ATC) [11].

CO is designed in such a way that it supports disciplinary autonomy while maintaining interdisciplinary compatibility, thus providing added design flexibility. These features make CO well suited for use in a practical multidisciplinary design environment such as space systems. CO has also been widely used to solve various complex multidisciplinary design problems including launch vehicle design [12], aircraft design [13], undersea vehicle design [14] and ship design [15]. In spite of these advantages, however, the CO methodology has not become a main stream design optimization tool in industry due to the high computational costs involved (a feature common to all MDO approaches). In addition, an important difficulty specifically associated with CO is its slow system level optimization convergence rate. This relates to the fact that CO ensures interdisciplinary compatibility by means of system level equality constraints and attempts to minimize the disagreement between the disciplines by sending targets to individual disciplines that their optimization runs are required to meet. The discipline level optima can be non-smooth and noisy functions of the system level variables. This, combined with the use of equality constraints at the system level to represent disciplinary feasible regions introduces computational difficulties [16]. These features make it difficult to use derivative-based optimization techniques at the system level optimization in CO. To address these challenges the present paper focuses on the implementation of an efficient system level optimization algorithm for solving satellite design problems within a distributed CO framework that (i) retains compatibility with subsystem (discipline) constraints, (ii) provides higher convergence rate at the system level using GA and exterior penalty method at the system level optimization and (iii) reduces computational effort associated with discipline optimization runs by using gradient-based optimization algorithms at disciplinary optimization runs within a distributed CO framework.

2. COLLABORATIVE OPTIMIZATION (CO) METHOD

CO is a bi-level optimization framework [8] developed for large scale and distributed MDO problems. The key concept in CO is the decomposition of the design problem into two levels, namely discipline level and system level optimization as shown in Fig. 1.

The transformation of the original coupled MDO problem into a CO framework is shown in Fig. 1. It can be seen that the problem is hierarchically decomposed along disciplinary analysis boundaries into N disciplinary optimization problems. The design variables and constraints of the original problem are partitioned as shown in Fig. 1. The system level optimizer is used to minimize the system level objective function (design objective function) while satisfying consistency requirements among the various disciplines by enforcing equality constraints at the system level ($g_i^* = 0$, $i=1,\ldots,N$). For example, $\boldsymbol{S}_i$ is a vector of subset of $\boldsymbol{S}$, composed of all variables which affect discipline i. The system level variables are treated as fixed parameters in disciplinary optimization runs. Thus, the role of each disciplinary optimizer is to minimize, in a least squares sense, the discrepancy between the disciplinary design variables and target values provided by the system level optimizer. The number of equality constraints N is related to the number of the disciplines. CO is posed in a hierarchical structure and, in comparison to a nonhierarchical system is advantageous because of its parallelization, lack of iteration requirements between disciplines and organizational characteristics. These features make CO well suited for use in a practical multidisciplinary design environment. However, due to complex interdisciplinary couplings, which are inherent in MDO problems, it results in a very high overall computational cost, limiting real-life applications of CO method. In addition, the equality constraints at the system level introduce some numerical features that hinder the direct application of gradient-based optimization algorithms at the system level within CO framework. To address these challenges, the remainder of this paper focuses on the implementation of a robust GA algorithm for solving optimization of remote sensing satellite mission using within distributed CO framework.

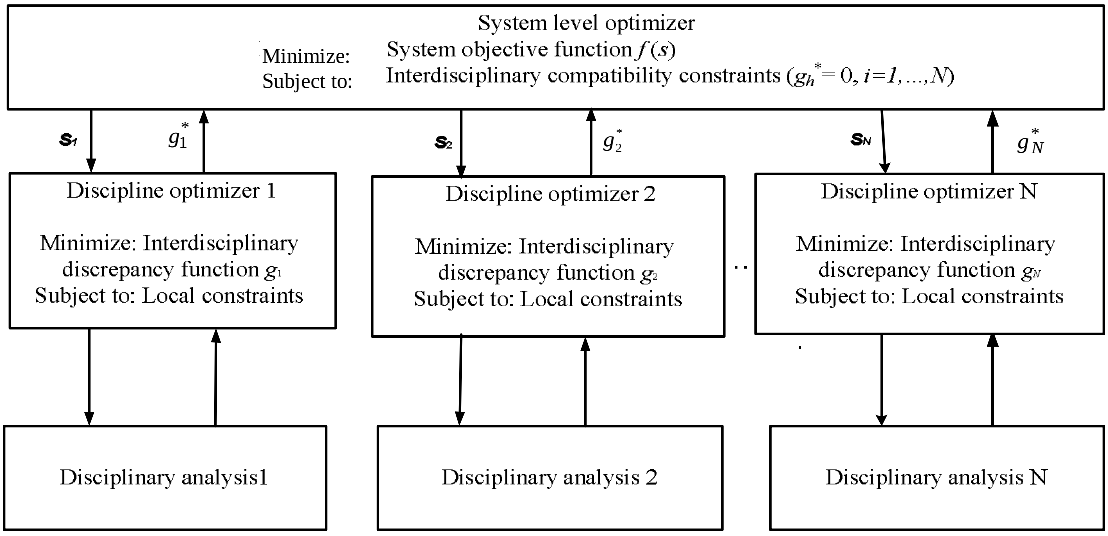


Fig. 1. Collaborative optimization framework

3. TEST PROBLEM

The satellite system design problem is divided into two levels namely, mission design block (MDB) and system design block (SDB) as shown in Fig. 2. The MDB block performs mission analysis and is a design based on mission and customer requirements. The SDB block is divided into various subsystems (disciplines) such as payload, electrical power supply (EPS), attitude determination and control system (ADCS), telemetry and tele-command (TT&C), thermal control system (TCS), structures, command and data handling (C&DH) as shown in Fig. 2. These disciplines are designed based on the analysis data provided by the MDB block and the design data interact with each other [17]. The design data communication between these disciplines and the MDB block is shown in Fig. 2.

a) Subsystems design models of the test problem

In this test problem, four subsystems including: mission analysis, payload, EPS and launcher capability are used to demonstrate the proposed methodology. The test problem deals with the minimization of the resolution of the satellite imaging payload, subject to design constraints as well as the side constraints on the design variables. The design data for this problem is shown in Table 1. For other disciplines weight characteristics are obtained from parametric correlations [18]. The subsystems design models and formulation of the test problem is described in sections below.

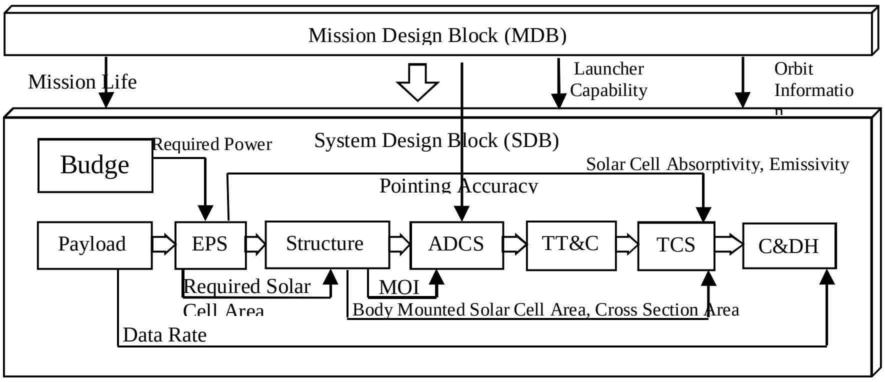


Fig. 2. Elements of a typical satellite system design

Table 1. Design data

Design objective function					
Minimize resolution (R)					
Design constraints					
Notation		*Description*	*Value*		*Unit*
			Minimum	*Maximum*	
DLD		Down link duration	5	15	min
* RT		Revisit time	90	150	Day
A_{sa}		Solar array area	≤ 1.2		m^2
M_{SAT}		Satellite mass	≤ 200		Kg
Design variables					
			Lower bound	Upper bound	
H		Orbital altitude	500	750	Km
D		Camera aperture	50	150	mm
Design parameters					
Subsystem	*Notation*	*Description*	*Value*		*Unit*
Ground station	ϵ	Minimum elevation angle	5		deg
Earth	μ	Earth gravitational parameter	3.986×10^5		Kgr^3/sec^2
	Re	Earth radius	6.378137×10^3		Km
	ω	Angular velocity of Earth	7.27E-5		Rad/sec
Payload	n_{pixel}	Instrument number of pixel	2048		---
	d_{pixel}	Instrument pixel size	10		μm
	$F_{\#}$	Optical parameter	8		---
	K	Constant parameter	1 or 2		---
	m_0	Camera mass	8		Kg
	d_0	Camera initial aperture	50		mm
EPS	Ω	Mass density of batteries	35		w.h/Kg
	DOD	Depth of discharge of batteries	0.25		---
	N_{batt}	Number of batteries	3		---
	t_n	Transition efficiency	0.09		---
	S_{pa}	Mass per unit area of solar array	5		Kg/m^2
	x_e	Power loss coefficient in eclipse time	0.6		---
	x_d	Power loss coefficient in day time	0.8		---

(**RT* is used as a constraint in the test problem and five different *RT* values ranging from 90 days (minimum value) and 150 days (maximum value) are used in five separate optimization runs and the results are shown in Tables 3 and 4).

Mission subsystem

The mission subsystem performs mission analysis and design according to space mission requirements. In this test problem, the main mission requirement is the duration in which the satellite can be viewed from the ground station for transmitting data (down-link data transmission (*DLD*)). Thus, the mission discipline has two important roles; firstly, the duration in which the satellite is able to simultaneously take images and send data to the ground station and secondly, the amount of information it can store in the storage mode. *DLD* can be expressed as follows:

$$DLD = \frac{T}{2\pi} \times 2\lambda \tag{1}$$

$$T = 2\pi\sqrt{\frac{(Re + H)^3}{\mu}} \tag{2}$$

$$\lambda = \frac{\pi}{2} - \left(\epsilon + \sin^{-1}\left(\frac{Re}{Re+H} \times \cos\epsilon\right)\right) \tag{3}$$

where T is the satellite period and λ is the Earth central angle, respectively.

Payload subsystem

Payload subsystem design model is constrained by the mission specifications, which must take requirements from MDB as shown in Fig. 2. The payload of the test problem is designed to capture Earth images and therefore, the main objective is to minimize the resolution of the satellite imaging payload, which is constrained by the satellite revisit time (*RT*) and can be expressed as follows:

$$RT = \frac{Re \times \omega \times T}{sw} \tag{4}$$

where sw is the swath width and can be expressed as:

$$\mathrm{sw} = 2H \times \tan^{-1}\{ \mathrm{n_{pixel}} \times tan^{-1}\left(\frac{d_{pixel}}{2000 \times F_{\#} \times D}\right) \} \tag{5}$$

$$M_{PL} = K \times m_0 \times \frac{D}{d_0} \tag{6}$$

where M_{PL} is the satellite payload weight, and other notations used in equations (4) – (6) are described in Table 1.

Electrical Power Supply (EPS) subsystem

The EPS subsystem is responsible for generating, regulating and distributing all electrical power to other subsystems. The EPS subsystem design has a significant impact on determination of overall design specifications of a satellite system. For example, the dimensions of solar panels are directly related to the installation methods of solar cells, geometrical dimensions and weight of the satellite. The solar cell and battery are the two main elements to the EPS subsystem design. In the test problem, the required surface area for solar panels can be calculated as follows:

$$A_{sa} = \frac{P_{sa}}{P_{Eol}} \tag{7}$$

$$P_{sa} = P_{av} \times \frac{\left(\frac{T_e}{x_e} + \frac{T - T_e}{x_d}\right)}{T - T_e} \tag{8}$$

$$P_{av} = 21e^{(0.006M_{SAT})} \tag{9}$$

$$T_e = T \times \sin^{-1}\left(\frac{Re}{Re+H}\right) \tag{10}$$

where A_{sa} is solar array area and other notations used in Eqs. (7)-(10) are described in Table 1.

Launcher subsystem

The available launcher capabilities including; fairing accessible space, allowable weight and orbit altitude must be taken into consideration in the design of the satellite. In this test problem, the maximum allowable weight of the satellite with respect to the required orbital altitude can be calculated as follows:

$$\frac{\text{calculated satellite launch mass } (M_{sat}) \text{ at altitude H}}{\text{allowable satellite launch mass}} \leq 1 \quad (11)$$

$$\text{Maximum allowable launch mass} = 750 - H \quad (12)$$

Therefore, as the maximum allowable launch mass decreases, the satellite orbital altitude (H) increases.

b) Conventional Optimization Problem Formulation

This section presents conventional optimization formulation and solution of the test problem described in Sections 3 and 3a. The objective function to be minimized is the resolution of the satellite imaging payload subject to mission, payload, launcher and power disciplinary constraints as well as the side constraints on the design variables. The design variables and constraints are shown in Table 2.

Table 2. Design variables

Description (notation)	Unit	Lower limit	Upper limit
Camera aperture (D),x_1	mm	50	150
Satellite orbital altitude(H),x_2	km	500	750

$$\text{Minimize:} \quad \boldsymbol{R} = \frac{d_{pixel} \times x_2}{F_{\#} \times x_1} \quad (13)$$

Subject to:

$$C_1 = \boldsymbol{DLD} \geq \boldsymbol{5} \quad (14)$$

$$C_2 = \boldsymbol{DLD} \leq \boldsymbol{15} \quad (15)$$

$$C_3 = RT \leq 150 \quad (16)$$

$$C_4 = A_{sa} \leq 1.2 \quad (17)$$

$$C_5 = \frac{M_{SAT}}{\text{allowable satellite launch mass}} \leq 1 \quad (18)$$

where $\boldsymbol{d_{pixel}}$ and $\boldsymbol{F_{\#}}$ are the instrument pixel size and optical parameter, respectively and $C_1(x)$ - $C_5(x)$ are inequality constraints involving mission, payload, power and launcher subsystems, respectively.

Conventional (All-At-Once) optimization using a robust GA algorithm (population size of 30, crossover 0.9 and mutation rate of 0.06) was used to solve the above optimization problem. The objective function (minimization of the resolution of the satellite imaging payload) as well as the satellite weight, altitude and swath width are obtained by varying *RT* between 90 and 150 days as shown in Table 3.

Table 3. Results of optimization (All-At-Once) using GA

Revisit Time Limit(day)	90	100	110	130	150
Satellite weight(Kg)	61.31	72.245	72.71	104.7	135.77
Satellite dimension(m)	0.402	0.432	0.4393	0.528	0.6391
Satellite altitude(km)	638.78	623.57	557.589	570.64	545.448
Satellite swath(Km)	30.138	27.036	24.23	20.56	17.72
Objective function: resolution (m)	14.71	13.2	11.833	10	8.654
Constraints: C_1- C_5	0	0	0	0	0

4. COLLABORATIVE OPTIMIZATION FORMULATION

The test problem described in Sections 3 and 3a is now implemented within a distributed CO framework. The test problem is decomposed into four disciplines (mission, payload, power and launcher) and a system level optimizer to coordinate the overall optimization procedure. The organization of the optimization process and the main components of mission optimization of spacecraft within a CO framework are shown in Fig. 3 and are described in the sections below:

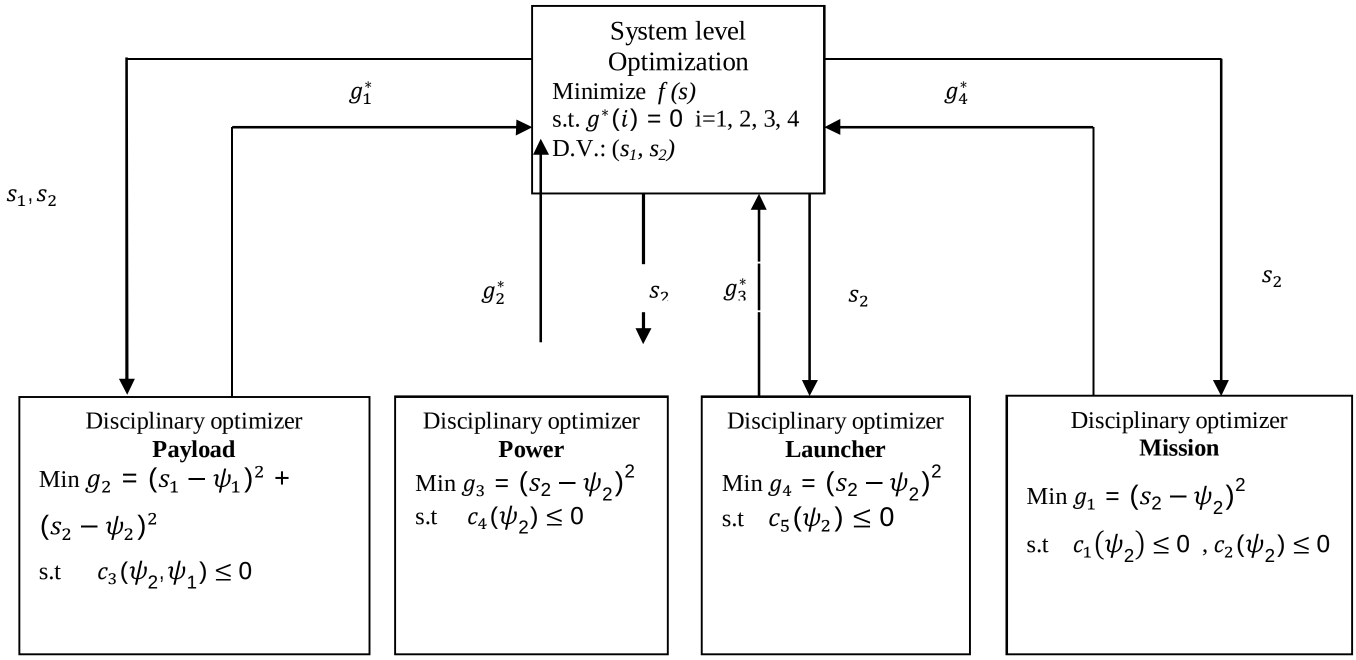


Fig. 3. Collaborative optimization of the test problem

a) System level optimization formulation

The formulation of the system level can be expressed as shown below [18]:

$$\text{Minimize: } f(x) = \frac{d_{pixel} \times s_2}{F_{\#} \times s_1} \tag{19}$$

$$\text{Subject to: } g_1^*=0,\ g_2^*=0,\ g_3^*=0 \text{ and } g_4^*=0 \tag{20}$$

$$50 \leq S_1 \leq 150 \text{ and } 500 \leq S_2 \leq 750 \tag{21}$$

The system level design variables s_1 and s_2 represent aperture of camera (D) and the orbital altitude (H), respectively. These are treated as system level target values (shared design variables) corresponding to discipline level design variables, ψ_1 and ψ_2, respectively. g_1^* – g_4^* are the system level equality compatibility constraints.

b) Discipline level optimization formulation

The discipline level optimization is free to satisfy its own constraints while minimizing its object functions, which is a discrepancy function and has to be minimized in a least square sense. The formulation of disciplinary optimization of mission, payload, power and launcher within the proposed CO are described below:

<u>Mission disciplinary design optimization formulation</u>

The discrepancy function to be minimized in the mission discipline is:

$$\text{Minimize: } g_1 = (s_2 - \psi_2)^2 \quad (22)$$

where s_2 and ψ_2 are the shared design variable (system level) and its local copy (discipline level), respectively. The constraints in mission discipline are:

$$C_1 = \boldsymbol{DLD} \geq \mathbf{5} \quad (23)$$
$$C_2 = \boldsymbol{DLD} \leq \mathbf{15} \quad (24)$$

In this disciplinary design optimization swath width is considered as the local design variable which is used to satisfy the constraints of the mission discipline.

Payload disciplinary design optimization formulation

The discrepancy function to be minimized in the payload discipline is:

$$\text{Minimize: } g_2 = (s_1 - \psi_1)^2 + (s_2 - \psi_2)^2 \quad (25)$$

where s_1 and s_2 are the shared design variable (system level), ψ_1 and ψ_2 are their local copies (discipline level) respectively. The constraint in payload discipline is:

$$C_3 = RT \leq C, C = \{90 - 150\} \quad (26)$$

where RT is the revisit time of the payload discipline.

Power disciplinary design optimization formulation

The discrepancy function to be minimized in the power discipline is:

$$\text{Minimize: } g_3 = (s_2 - \psi_2)^2 \quad (27)$$

where s_2 and ψ_2 are the shared design variable (system level) and its local copy (discipline level) respectively. The constraint in power discipline is:

$$C_4 = A_{sa} \leq 1.2 \quad (28)$$

where A_{sa} is the solar array area.

Launcher disciplinary design optimization formulation

The discrepancy function to be minimized in the launcher discipline is:

$$\text{Minimize: } g_4 = (s_2 - \psi_2)^2 \quad (29)$$

where s_2 and ψ_2 are the shared design variable (system level) and its local copy (discipline level), respectively. The constraint in launcher discipline is:

$$C_5 = \frac{M_{SAT}}{\text{allowable satellite launch mass}} \leq 1 \quad (30)$$

where M_{sat} is the satellite mass and allowable launch mass is obtained using launcher capability as described in section 3a.

c) Optimization algorithms

During the past decades genetic algorithms (GA) have received considerable attention and have experienced rapid development [19]. Their popularity lies in their ease of use and their ability to locate globally optimum designs. GA algorithms maintain large sets (populations) of potential solutions and apply re-combination operators on them to reach an optimum solution. Their ability to search an entire design space makes them more suitable for handling optimization problems with highly non-linear objective functions with many local optima. Moreover, they operate with coded sets of design variables as opposed to the design variables themselves, and they are more suited to optimization problems with discrete design variables. The main disadvantage of GA algorithms is the high computational costs. In addition, variations of the GA algorithms such as hybrid genetic algorithm and particle swarm optimization algorithm [20] have been introduced. In this study, both GA and sequential quadratic programming (SQP) optimization algorithms are studied for the system and discipline levels optimization of the test problem within a distributed CO framework. As discussed earlier in the paper, the constraints at the system level are equality (discrepancy function $g_i^*=0$, $i=1, 2.., 4$) and have a complex form as compared to constraints at the discipline levels. Their values correspond to a measure of disagreement between the targets given to a discipline by the system level optimizer. As described earlier in the paper, these values (system level constraints) are non-smooth at the transition from a plateau of zero values to a region of non-zero values (for more detail, see reference [21]). Therefore, derivative-based optimization algorithms such as sequential quadratic programming (SQP) cannot be used at the system level. In order to overcome these difficulties, a more robust optimization algorithm GA is used in this work, whilst SQP is utilized at the disciplinary (mission, launcher, payload and power) optimization process. GA operators used including selection, crossover and mutation as well as other parameters such as population size are tuned to enhance the convergence rate of the optimization. A population size of 30, crossover 0.9 and mutation rate of 0.06 were used together with the implementation of exterior penalty method to improve the convergence rate at the system level in the proposed CO framework.

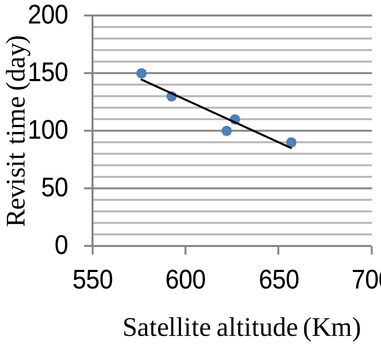
The sun synchronise orbit (SSO) is used and the allowable weight of the satellite is based on the orbital altitude where a launcher can position the satellite using the weight and altitude relationship as expressed in Eq. (11). In CO optimization process, the total weight of the satellite (payload, power, attitude control, structures, communication, harness, etc.) is used to compare with a specified range of weight limitation of the satellite as imposed by the launch vehicle during the optimization process. The optimization process is terminated based on the criteria that the difference of weight of the satellite between the previous and the current iteration must be less than 1 Kg. All disciplinary constraints are satisfied and the results are shown in Table 4.

Table 4. Results using the proposed CO framework

System level				Discipline level				
Design variable		Constraints	Objective function					
S_1	S_2		$F(x)$	Launcher	Mission		Power	Payload
Satellite Altitude (Km)	Camera aperture (cm)	g_1^* - g_4^*	Satellite resolution (m)	Satellite weight (Kg)	Satellite periodic time (Sec)	Satellite revisit time (*RT*) (day)	Solar panel area (m^2)	Satellite swath (*sw*) (Km)
656.38	5.55501	0	14.77	58.17	5871.68	90	0.392	30.25
621.87	5.889813	0.44e-6	13.198	67.37	5828.53	100	0.42	27.025
626.37	6.519798	0.11e-5	12.009	78.5	5834.15	110	0.446	24.59
592.119	7.33765	0.4e-6	10.087	101.774	5791.41	130	0.5167	20.656
576.2	8.269231	1e-7	8.71	136.28	5771.6	150	0.636	17.84

5. RESULTS

In the implementation of the proposed approach, *RT* is considered as a design constraint and five different values of the *RT* are evaluated in each optimization run as shown in the Table 4. The results (from Table 3 and Table 4) show that the technical features and satellite mission fully satisfy the requirements of the satellite mission. As it was expected, with the increase in altitude, the *RT* has also been decreased (Fig. 4). Although it is desirable to reduce resolution, this will increase the size and consequently the weight of the satellite, which is constrained by the requirements of the satellite launch vehicle. Figure 5 shows variation of the size of the satellite solar panel area with respect to the resolution.



F ig. 4. Revisit time variation to altitude

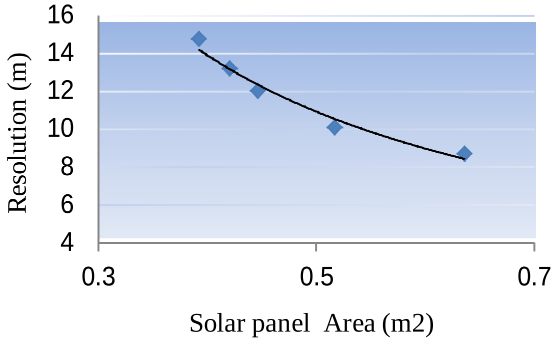
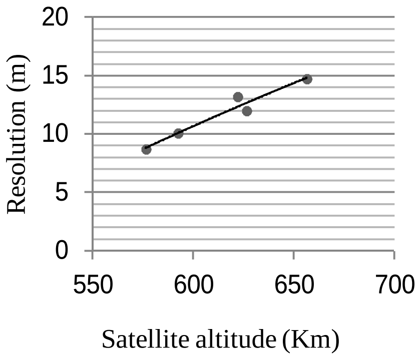


Fig. 5. Solar panel area variation to resolution



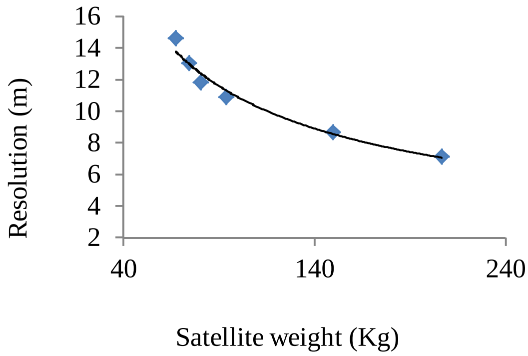


Fig. 5. Resolution variations to satellite altitude and weight

The variation of resolution with respect to the orbital altitude and weight of the satellite is shown in Fig. 5. The design space of the weight and resolution can be used as a decision making tool to help the designer make a balanced design decision among competing design objectives such as cost and performance.

6. CONCLUSION

This paper described distributed collaborative multidisciplinary optimization for remote sensing small satellite mission in LEO. In this approach, the design optimization problem of the satellite is divided into system and discipline levels. The disciplinary optimization involves subsystems such as payload, power, mission and launch. The overall design objective function was the minimization of the resolution of imaging payload of the satellite. Due to the peculiar characteristics of the equality constraints at the system level a robust GA algorithm is utilized at the system level, whereas at the discipline levels computationally efficient algorithm SQP is used. Several important design parameters and their inter-relationships in the design of the satellite mission were also investigated, for example, variations of the solar panel area and weight with resolution of the satellite (Figs. 4-5).

The results obtained show that distributed CO using the GA adopted in this paper has the same level of accuracy as with the conventional all at once approaches (Tables 3, 4), however, the proposed approach provides potential for solving complex multidisciplinary design problems such as the design of satellite systems where it would be difficult or very time consuming using conventional all at once approaches.

REFERENCES

1. AIAA white paper: Current state of the art on multidisciplinary design optimization (MDO) - An AIAA white paper. AIAA, Washington, D.C. (1991). An Integrated Evaluation System for the Conceptual Design of Space Systems.

2. Santhanakrishnan, D., Parks, G. T., Jarrett, J. P. & Clarkson, J. P. (2009). An integrated evaluation system for the conceptual design of space systems. *7th Annual Conference on Systems Engineering Research (CSER 2009), Loughborough University* – 20th- 23rd April 2009.
3. Byoungsoo, K. (2002). Conceptual space systems design using meta-heuristic algorithms. Ph.D. thesis, University of Colorado.
4. Hassan, R. A. (2004). Genetic algorithm approaches for conceptual design of spacecraft systems including multi-objective optimization and design under uncertainty. PhD thesis, Purdue University.
5. Magnin, M. (2008). Multi-Objective Optimization under Uncertainty of Satellite System via Simulated Annealing. *12thAIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*.
6. Kodiyalam, S. & Sobieszczanski-Sobieski, J. (2001). Multidisciplinary design optimization: some formal methods, framework requirements, and application to vehicle design. *Int. J. Vehicle Design*, (Special Issue) Vol. 25, pp. 3-32.
7. Cramer, E. J., Frank, P. D., Shubin, G. R., Dennis, J. E. & Lewis, R. M. (1992). On Alternative Problem Formulation for Multidisciplinary Optimization. *4th AIAA/USAF/NASA/OAI Symposium on Multidisciplinary Analysis and Optimization.* Cleveland, OH, AIAA 92 – 4752.
8. Kroo, I. (1995). Decomposition and collaborative optimization for large scale aerospace design. *ICAS/LaRC / SIAM Workshop on Multidisciplinary Optimization, Hampton, VA.*
9. Sobieszczanski-Sobieski, J., Agte, J. & Sandusky, Jr. R. (1998) Bi-level integrated system synthesis (BLISS). *Proceedings 7th AIAA/USAF/NASA/ISSMO Symposium Multidisciplinary Analysis and Optimization (St. Louis, Mo)*, AIAA 98 – 4916.
10. Sobieszczanski-Sobieski, J. (1988). Optimization by decomposition: A step from hierarchic to non-hierarchic systems. *Second NASA / Air Force Symposium on Recent Advances in Multidisciplinary Analysis and Optimization.* Hampton, VA, NASA – CP – 3031.
11. Kim, H. M., Rideout, D. G., Papalambros, P. Y. & Stein, J. L. (2003). Analytical target cascading in automotive vehicle design. *J. Mech. Des.*, Vol. 125, pp. 481-489.
12. Broun, R. D., Moore, A. A. & Kroo, I. M. (1997). Collaborative architecture for launch vehicle design. *Journal of Spacecraft and Rockets*, Vol. 39, No. 4, pp. 478-486.
13. Sobieski, I. P. & Kroo, I. M. (1996). Collaborative optimization applied to an aircraft design problem. *AIAA paper 96-0715, the 34th AIAA Aerospace Science Meeting and Exhibit* , Reno, Nevada , January 15-18.
14. McAlister, C. D., Simpson, T. W., Kurtz, P. H. & Yukish, M. (2002). Multidisciplinary design optimization test based on autonomous underwater vehicle design. *The* 9th *AIAA/ISSOM Symposium on Multidisciplinary Analysis and Optimization Atlanta*, Georgia, Sept. 4-6.
15. Lon, K., Khatri, A., Thunnissen, D. & Au, S. K. (2007). Conceptual design of the Ship Tracking and Environmental Protection Satellite (STEPS). *Proceedings of the 2007 Asian Space Conference*, Paper 116.
16. Alexandrov, N. M. & Lewis, R. M. (2000) Analytical and Computational Properties of Distributed Approaches to MDO. *AIAA – 2000 – 4718, 8th AIAA / NASA / USAF / ISSMO Symposium on Multidisciplinary Analysis and Optimization*, Long Beach, California.
17. Hwang, K. L., Lee, B. R. & Kim, S. J. (2004) Development of system engineering design tool for small satellite conceptual design. *Journal of KSAS*, Vol. 32, No. 9, 93-103.
18. Wertz, J. R. & Larson, W. J. (1999). *Space Mission Analysis and Design.* 3rd ed., Microcosm, Torrance, California, USA.
19. Goldberg, D. E., (1989). Genetic *algorithms in search, optimization and machine learning.* Addison – Wesley, Reading, Massachusetts.

20. Kaveh, A. & Malakouti Rad, S., (2010). Hybrid genetic algorithm and particle swarm optimization for the force method-based simultaneous analysis and design. *Iranian Journal of Science & Technology, Transaction B: Engineering*, Vol. 34, No. B1, pp. 15-34.
21. Zadeh, P. M., Toropov, V. V. & Wood, A. (2008). Metamodel – based collaborative optimization. *Journal of Structures and Multidisciplinary Optimization*, Vol. 32, No. 2, pp. 103-115.