Recent Advances of Design Optimization Techniques in Solid Rocket

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Abstract. A solid-propellant rocket or solid rocket refers to a rocket with an engine using solid propellants. The earliest solid rockets were powered by gunpowder. It is still used today in military armaments worldwide, model rockets, solid rocket boosters and on larger applications for their simplicity and reliability. With the fast development in the complexity of rockets, the importance of optimisation where the overall performance is maximised has been shown. Engineers are routinely given design tasks to find a design meeting the stringent constraints. For instance, researchers developed different optimisation techniques to maximise the overall performance while decreasing the economic and time requirements. This paper has reviewed four types of recent advances in design optimisation techniques used in solid rockets, with all the findings and analysis summarised. In conclusion, this study provides a useful reference to people who would like to know about different types of optimisation used in the current astronautical engineering field.

Keywords: Optimisation, Solid Rocket, Rocket Design.

1. Introduction

Modern Rocket development has developed after the concept of the three “fathers of rockery”. Konstantin E. Tsiolkovsky issued the Tsiolkovsky rocket equation, the equation defining the relationship between mass and speed; Robert H. Goddard’s practical experiment of a liquid-fuel rocket proved the concepts of modern rockery and Hermann Oberth’s novel of space vehicle and human travelling into outer space, and the realisation of the importance of multi-stage rockets all contribute to the development of modern rockery. The development of V2 saw Germans using liquid oxygen and alcohol to achieve a great thrust. With the end of World War Two, German Scientists went to either the United States or the Soviet Union to carry out their research on rockets. The first satellite named as Sputnik I, was launched by the Soviet Union on October 4, 1957. The US followed the Soviet Union and launched its first satellite of its own on January 31, 1958. Later in the same year, the National Aeronautics and Space Administration (NASA) was founded to organise all US space programs.

Since World War Two, the design of Space Launch Vehicle has become more complex. The design has interdependence of different variables and satisfies all different requirements, which makes designing the vehicle a complex problem. To maximise its overall performance, optimisation techniques are needed. Optimisation aims to produce the "best" design given several priority constraints or criteria. These include criteria such as maximising production, strength, dependability, durability, efficiency [1]. Engineers are frequently offered design assignments that need them to discover a design satisfies the specified criteria within the limits provided. Engineers are frequently required to determine which of several suitable design options best fits the client's requirements. This method of decision-making is known as optimisation [2].

In this paper, the issues of different optimisation techniques used in the modern advancement of solid rockets will be discussed from the aspects of the pros and cons of its approach. Four examples are selected to show their differences, with two focusing on Rocket Motors and two on Space Launch Vehicle design. Section 2 introduces 4 types of Optimisation approach; the Metaheuristic Optimization Approach, hybrid optimisation approach, hyper-heuristic optimisation and multidisciplinary design optimisation. Conclusion and prospects are presented in Section 3.

2. Main body

2.1. Metaheuristic Optimization Approach

Tola et al. [3] optimise the sectional shape of a slotted solid propellant based on hydroxyl-terminated polybutadiene (HTPB) utilising a connected internal ballistic-structural analysis and optimisation approach. Both structural integrity and internal ballistic performance have been maintained in this design. The structural integrity of the propellant has been examined using both the finite element approach and the linea viscoelastic analysis to simulate the heat transfer during cooling. Utilising coupled internal ballistic-structural investigations within a multidisciplinary optimisation framework, optimal specific impulse values for particular propellant mass, total impulse, and structural margin of safety are found.

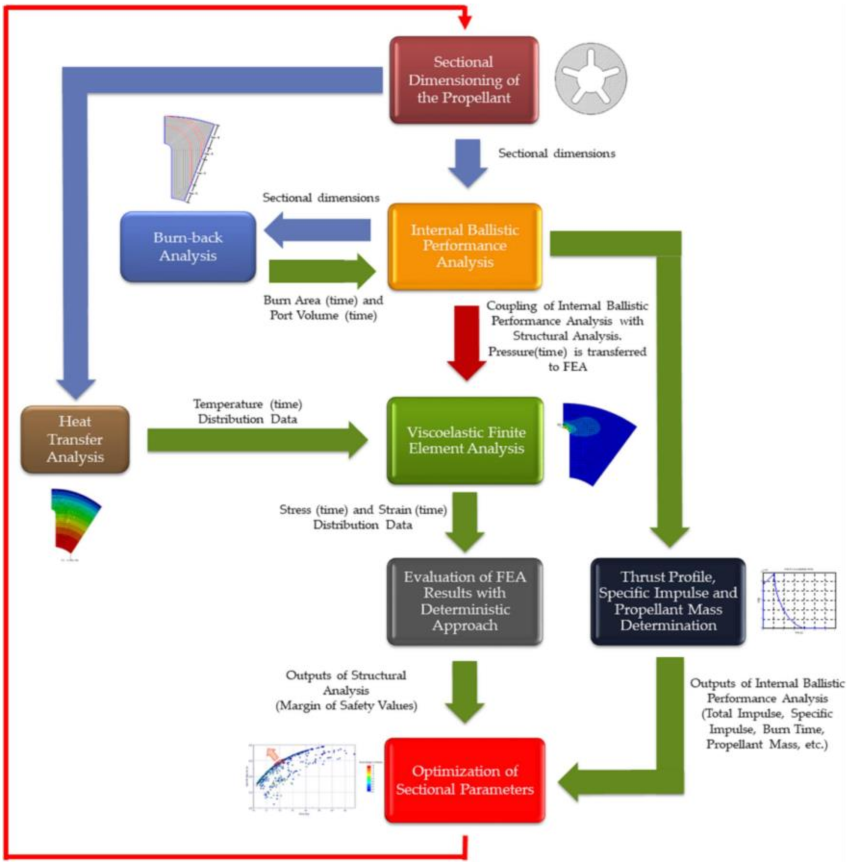

Figure 1. Optimisation approaches flow chart

In this research of the solid rocket motor, a multidisciplinary design optimisation strategy was employed to overcome the distinct design groups and costly iterations caused by the lack of a feedback system. It includes viscoelastic analysis and internal ballistic performance. The viscoelastic analysis includes both the cooling and igniting processes. Initially, a transient heat transfer analysis is carried out to determine the temperature data for the finite element model of the propellant grain during the cooling stage. Next, the viscoelastic propellant is exposed to ignition-related pressure data generated from the internal ballistics study. In this study, the approach represented in Figure 1 for paired analysis and optimisation has been adopted and proposed to increase the efficiency and accuracy of the optimisation operation. The first step involves calculating the sectional properties of the propellant grain. These geometric factors commence the internal ballistic performance analysis, which collaborates with the burn-back analysis to determine the relationship between the time and burn area and port volume. The output for the solid rocket motor includes the thrust profile, transient propellant mass, specific impulse, total impulse, and burning duration. Chamber pressure time data for the ignition stage of the viscoelastic finite element research is one of these findings. Due to the fact that the material properties in a viscoelastic model are temperature dependent, the cooldown step of the viscoelastic finite element analysis (FEA) model also need the results of the cooldown heat transfer analysis. The structural safety margin, incorporated in the optimisation criterion, is a deterministic approach for monitoring the strain and stress findings following the completion of the FEA. As the process of multidisciplinary optimisation converges, the ideal sectional parameters satisfying performance and structural requirements are established.

Internal ballistic-structural interaction is employed to undertake a multidisciplinary design optimisation study for a slotted solid rocket engine. For a rocket design with a constant outer radius, four continuous and one discrete parameters of the slotted cross-section of the grain are optimised to produce the greatest specific impulse with the least amount of mass while meets structural safety criteria. In this study's automated framework, modeFRONTIER optimisation software is adopted as a multidisciplinary optimizer, while Multi-Objective Genetic Method Solver II, a gradient-free based optimisation method, is utilized for optimisation with multiple goals. Figure 2 depicts the process of the interdisciplinary optimisation technique.

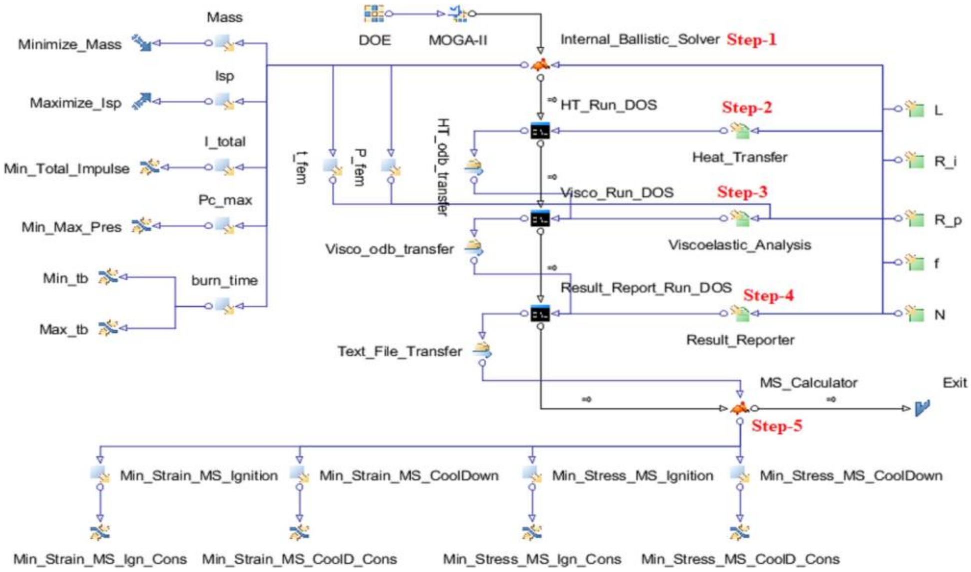

Figure 2. Process flow chart for multidisciplinary optimization [1]

Five steps make up the multidisciplinary optimisation process. Initially, the 0-D internal ballistic solution would be carried out using in-house Matlab code. During cooling, an investigation of heat transmission is conducted utilising in-house Python scripts. The propellant temperature-time data are then used to power a linear viscoelastic FEA. The FEA output are then written to text files using a third Python script, and a Matlab script uses these data to determine the structural margin of safety. Between the first and third phases of the optimisation process, the internal ballistic performance analysis and viscoelastic FEA model are connected. Here, the output of the 0-D solver, consisting of the pressure value at the first sharpest peak point and the rising time corresponding to that pressure, is sent to the ignition load phase of the viscoelastic FEM solver. The optimisation algorithm modifies the design space. The objective of the optimisation procedure is to determine an optimal combination of the geometric parameters generating the maximum specific impulse and the minimum propellant mass, subject to constraints on the total impulse, the burning time, the maximum pressure, and the margin of safety values.

The optimisation process is finished within 7 hours and 28 minutes, 454 feasible and 328 infeasible results construction and analysation have been accomplished. Figure 3 illustrates the plotted result, where each dot indicates a possible option. Figure 4 displays a Pareto-optimal solution with its frontier including the optimal solution. The result illustrates that the efficiency would be worse if the design were more cautious than the required value. Due to the fact that the Pareto-optimal set of design possibilities is given by the solution of a multi-objective optimisation problem, the designer must further refine the obtained designs based on previous work or other decision-making techniques. Consequently, industrial designers would prioritise their demands or incorporate new requirements into the design process. The optimal solution under consideration in this study would be the optimal design for a slotted solid rocket engine.

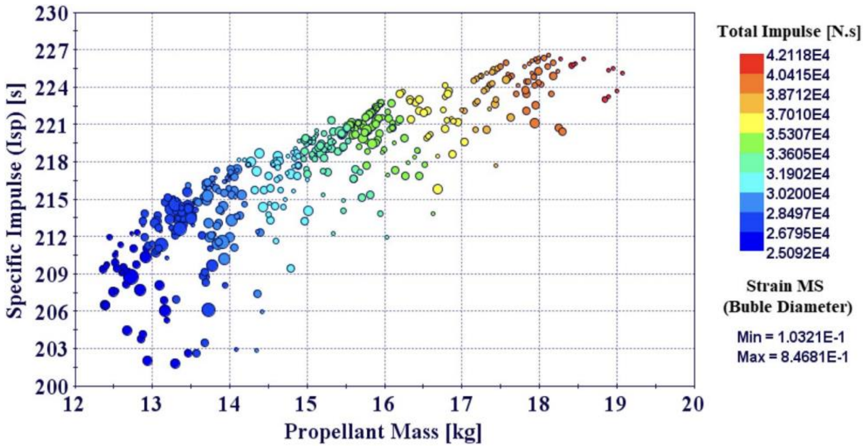

Figure 3. Distribution of viable propellant mass, specific impulse, total impulse, and MS chart configurations

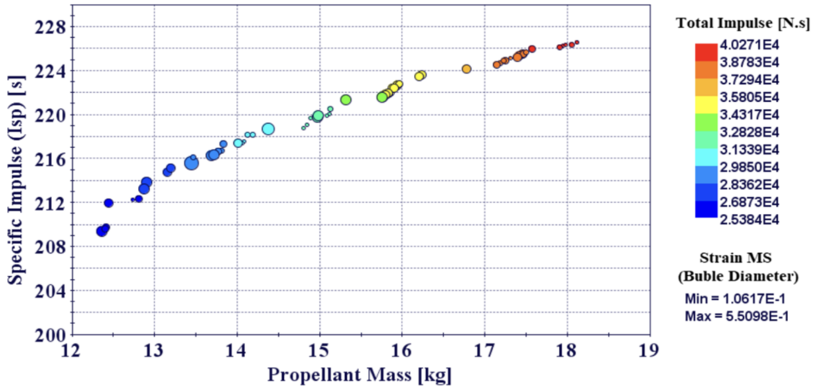

Figure 4. Pareto-optimal set distribution for propellant mass, specific impulse, total impulse, and MS chart

Overall, a coupled internal ballistic-structural interaction technique was used to optimise the interdisciplinary design of a slotted solid-propellant rocket engine. This system's key components are an internal ballistic solver, burnback analytics of the propellant geometry, a parametric cooldown heat transfer analysis based on finite elements, and a parametric linear viscoelastic analysis of the propellant. In addition, a replacement heat transfer method forecasting the time necessary for the propellant system to cool down was created and verified for autonomous and effective heat transfer analysis. For each element of the propellant geometry, the viscoelastic FEM model is given with time-dependent temperature data. Maximum specific impulse and minimal propellant mass were the goals of the optimisation technique, which was affected by internal ballistic performance restrictions including the margin of safety, burning duration, and total impulse in addition to structural strength. Numerical and graphical findings highlight the gain of the linked analysis and multidisciplinary optimisation strategy for the design of the solid rocket motor. This study's technique is particularly significant since it offers a tiny, automated, and trustworthy framework that is easily transferrable and adaptable, allowing for the efficient construction of a myriad of other solid rocket systems.

2.2. Hybrid optimisation

In order to optimise the FINOCYL grain (FCG) design for solid rocket motors, Krirram et al. [4] proposed using a hybrid optimisation approach that combines a genetic algorithm with sequential quadratic programming. There are around seventeen independent variables that must be optimised in 3D FCG geometry, making the optimisation exceedingly complex. Due to the difficulties in discovering local convergence areas and establishing a fair starting approximation when using a local optimizer, the hybrid optimisation approach would consider both the global and local viable regions.

Global and local searching are the two main methods used to solve continuous constraint problems. Global searching requires a great focus on global searching space, the local searching, on the other hand, focuses on convergence to a locally optimal solution. In their hybrid optimisation model, Krirram et al. try to integrate both existing local and global searching methods into a joint solver.

Krirram et al. intend to merge local and global searching strategies into a single solution using their hybrid optimisation model. HO connects GA and SQP, whereas GA connects FCG design and performance code. GA provides many design benefits, such as the capacity to integrate discrete and continuous variables, the availability of population-based searching without the requirement for an initial solution [5-6]. The initial parameters are supplied to the design analysis code before being sent to the performance code. The leading solution from GA is then sent to SQP as a nearly optical estimate and becomes SQP's beginning guess for solution convergence. SQP discovers a local solution via exact analysis, resulting in the optimal solution to the issue. The sources [7–8] provide a more comprehensive description of SQP. Figure 5 displays the algorithms of the HO.

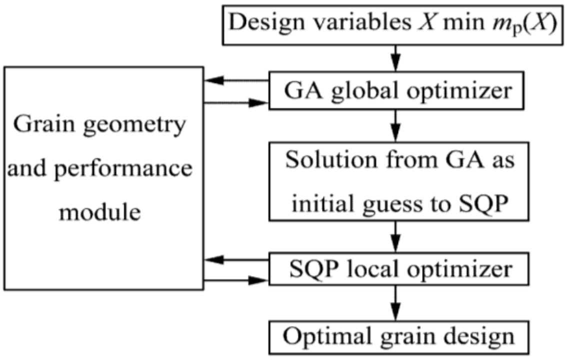

Figure 5. Hybrid Optimisation Algorithms

With the usage of the HO method, it has been a success for the complicated 3D FCG grain to be designed and optimised. The results are evidence that it has met all constraints. With m_p required to be <=5 040kg, SQP and GA have achieved a better result of 4 875.2kg and 4 857.5kg, respectively. The HO technique has improved further, with the m_p reduced to 4 832.4kg. With properties of FCG design and optimisation influenced by each design variable, although the SQP and GA methods both reached m_p within constraints, the HO still has advantages in reaching the optimal solution, especially for problems with large numbers of design variables.

The utilisation of both GA and SQP approaches is crucial to the optimisations. It also eliminates the potential of falling prey to incorrect local convergence, which has successfully optimised the propellant mass and reduced it to the bare minimum while taking into account all constraints..

2.3. Hyper-heuristic optimization

Currently, the need for variable scale design necessitates problem-domain independent algorithms. As the number of the design parameters expands exponentially, the inclusion of inter-disciplinary design aspects in the preliminary design phase of launch vehicles becomes an increasingly crucial aspect of the optimisation approach. [9] Rafique et al. assert that the Hyper heuristic approach (HHA) is the way forwards.

HHA utilises a non-leaning random function which is sequentially applied to low-level meta-heuristics (LLMHs). As LLHMs, this work utilises the Genetic algorithm. This technique achieved the desired objective by diversifying the population and steering the search with feasible solutions injections.

The free lunch theorem [10] stated that no algorithm could outperform every other algorithm across all problem classes. Even if one algorithm surpasses another in a certain class of issues or another class of problems, this method's performance would be poorer to others. Applying multiple heuristics at different phases of the search is a great method for enhancing the generalizability of heuristics [11]. To that end, a hyper-heuristics is proposed [12], which essentially describes the process of picking heuristics to solve problems [13-14].

The HHA outlines the process of selecting problem-solving heuristics utilising heuristics. The main objective of HHA is to output good estimations in a variety of settings without or with minimal adjustment of the algorithm, as opposed to optimal results. With HHA, a complicated, interdisciplinary problem may be solved regardless of the problem circumstance. In addition to being exhaustive, of high quality, and repeatable, it conducts an exhaustive search for global optima with being trapped at local minima.

The HHA begins by configuring the function of control. It is crucial that the control function is not biased, since this might have a negative impact on performance quality and cost. Random sampling increases generalizability and eliminates bias in the control function by providing an estimate of the mean and uncertainty of the output variables that is free of bias.

```
Optimization routine
Initialize (NLRF)

        • Set population size for each LLMH
        • Set total number of outer loop iterations
        • Set total number of inner loop iterations
        • Set convergence criteria

While (convergence NOT achieved)

        • Create public-board to store information
        • Generate sub populations for LLMH (random)

    For   i = 1 to outer loop iteration      OUTER LOOP
---------------------------------------------------------
    For l = 1 to sub iteration

        For  j = 1 to sub population size

            Call   INDIVIDUAL  HEURISTICS

                    Evaluate Constraints
                    Evaluate Fitness
                    Store Global Best
                    Store Local Best
        End

CALL OFF-SPRINGS FUNCTIONS

    Create new off-springs
    Send information to public-board

    End
INNER LOOP ----------------------------------------------
CALL POPULATION HANDLING

        Shuffle m% of new population given to n optimizers
        Generate new sub population (NLRF)
        Generate new sub iterations (NLRF)

CALL   POPULATION DIVERSIFICATION (NLRF)

IF  ( outer loop iteration ≤ ε)
    Insert local best to sub population (random )
End

IF (outer loop iteration ≥ λ)
    Insert global best to sub population (random )

End

    End
End
MAIN LOOP
```

Figure 6. Pseudocode for the Python program

The working algorithms have been developed, and the pseudocode shown in Figure 6 follows. It starts with a set of inputs that establish many criteria, including the goal, constraint function, and design space specification. Then, the total number of outer and inner loop interactions, the total number of potential LLMHs, and the limitations of operators in LLMHs are calculated. The random operator then slices the number of inner iterations and total population into three portions for each of the three LLMH used in the research, and records the local and global best and worst solutions discovered by each LLMH. It would continue until one outer loop iteration is complete, at which time a new population with random values would be generated. To diversify the solution, the random function redistributes the new population and inner iterations to each LLMH at random, and the local and global best solutions are injected into the new population after a predetermined number of inner and outer iterations.

In this research, test function-based benchmarks were also constructed to examine the performance of HHA. This section contrasts HHA with various non-gradient-based optimisation strategies. HHA performs exceptionally well in solving these classical test functions. With the success rate of all functions being over 98%, this demonstrates that HHA is a stable function with high accuracy and robustness in its result. By comparing HHA with other methods, it indicates the HHA advantages over GA, PSO and SA during the search for the global optimum. The capacity of HHA to solve complex numbers is better than the widely applied heuristic optimisation method. In the study, the HHA was evaluated on the air satellite launch vehicle's design (ASLV). The outcome of this study demonstrates that it has been effectively utilised to solve the challenging design challenge for ASLV.

Overall, HHA tackles complex and multidisciplinary problems with an independent problem scenario extremely well. It undertakes an extraordinary search for global optimal solutions while avoiding local minimums. The high computational cost is one disadvantage of using HHA. However, it can be decreased with further improvement on computation resources.

2.4. Multidisciplinary design optimization

To accomplish mission objectives, a Space Launch Vehicle (SLV) is needed, which requires tight integration between several disciplines and robust interactions between its constituent subsystems. Due to the interdependence of disciplines, subsystems, and performance, the analysis of the final SLV design and performance optimisation becomes complex.

Generally, an iterative design process begins with an analytical method that determines the optimal mass distribution for a multistage rocket based on a delta-V calculation. However, this simpler technique has resulted in suboptimal solutions since. The multidisciplinary challenge in the design of a SLV includes several physical phenomena, groups of variables, complex interconnections, and high system-subsystem interaction. Using Multidisciplinary Design Optimisation (MDO) approaches, this research by Dupont et al. [15] would concurrently take into account all technical disciplines and economic aspects. In addition, it allows for rapid exploration of several design concepts while reducing design iterations. This results in an optimised end product as well as major cost savings and risk migration.

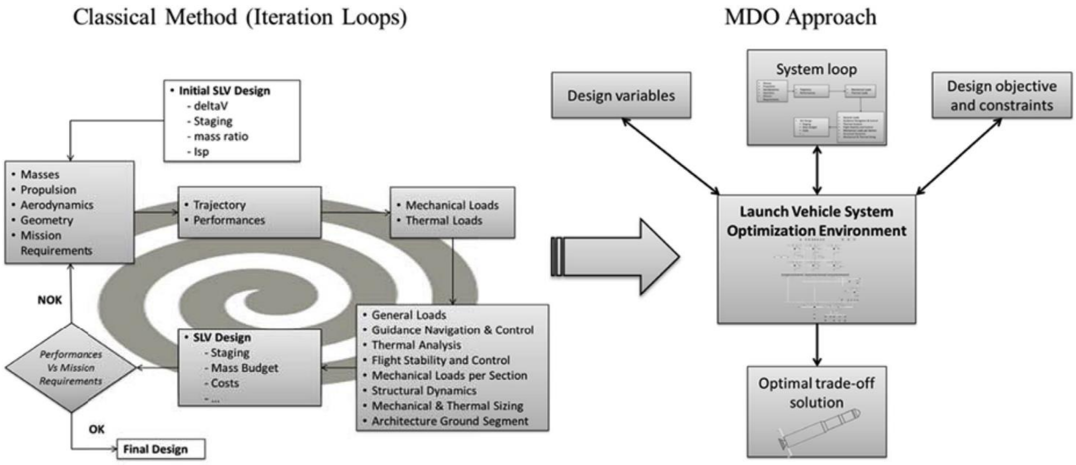

Figure 7. Classical Method vs MDO Approach

In a conventional iterative procedure, a starting, random design is "checked" on several criteria as frequently as necessary, altered, and then the checking loop is repeated. In contrast, the MDO technique allows for customised and perhaps numerous objectives and makes use of automated computing. By minimising human participation and design time, hundreds of ideas and a large number of design variable combinations may be investigated, and all assessed designs can be recorded. The optimisation algorithm also manages all parameters at the outset, which reduces the complexity of initialisation problems and reduces the risk of missioning the global optimal solutions. As illustrated in Figure 7, adding constraint to the MDO is achievable.

This project's purpose is to construct an SLV capable of delivering a specified payload to a destination orbit with the lowest cost. A two-stage, integrated, layered optimisation method is adopted. This leads in a system-wide optimisation at the global level that seeks to achieve the goal by determining, in particular, the optimal propellant mass distribution throughout the different stages while adhering to design constraints. Important because it requires optimising control law and has its own algorithms for layered optimisation is the trajectory of the vehicle. The major response is the actual mass of the payload sent to the target orbit. This unique issue, which is presented as an optimization problem, demands careful optimisation. Because of the complexity of SLV's design, this optimisation was handled as part of the overall process, as opposed to using a specialised trajectory optimisation tool integrated into the optimisation process. This modelling ensures a more reliable procedure.

A Multiple Discipline Feasible (MDF) technique utilising MultiDisciplinary Analysis is used to write the overall issue (MDA). Engineering issues like SLV lend themselves very well to MDF. In contrast to the launch vehicle design problem's inherent sensitivity, MDF enables the prolonged monitoring of the process by managing and fine-tuning the design parameters.A feasible zone can be quickly found using a GA and then utilise local optimisation to fine-tune the parameters. As a result, our approach entails running a number of concurrent optimisations while incrementally improving the design variables and restrictions.

Fig. 8 illustrates the logic behind the MDF technique used with the HADES V15.0 platform. The platform includes interconnected modules with a system optimisation loop exchanging input and output. Each module denotes a stand-alone "black box" instrument that may determine a particular physical or economic parameter or offer an initial estimate of the size of a subsystem. A launch vehicle design is created for each simulation (or MDA), and true performances are computed using the trajectory tool, which has a specific optimisation procedure built in. The modular design of HADES V15.0 makes it a versatile platform that can adapt to the demands of individual projects and include new features or updated models.

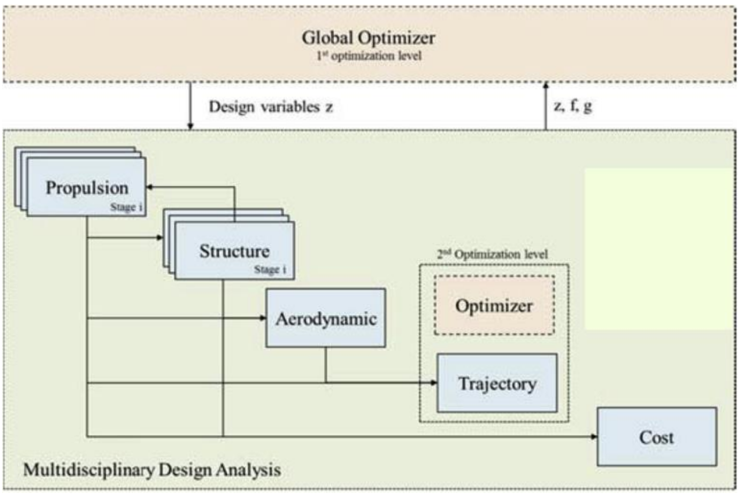

Figure 8. Launch vehicle design's MDF approach

Technical and economic modules are integrated into HADES V15.0 in a library. These modules are quick, reliable, and adaptable to the MDO process. It guarantees a full system loop in a matter of seconds. If necessary, they may be swapped out for more intricate programmes (such as CFD and CAD/CAE nodes).

This research evaluated the suitability of several launch vehicle propulsion systems to varied mission types using three market goals. The nominal orbit analysed for all missions is a 600km Sun-Synchronized Earth Orbit (SSO), and three payload classes and four launch vehicle types have been assessed. Figure 9 illustrates the outputs of the optimisation cycle by depicting the relationship between launch cost and global lift-off mass (GLOM). The results of optimising the KKK design for a 400kg payload are shown in Figure 9. It displays, as coloured dots, each feasible alternative in terms of actual performance, the optimisation target, and technical restrictions. Specifically, the graph illustrates the payload mass as a function of cost, with dot sizes and colours reflecting, respectively, the GLOM and maximum diameter of each candidate design. This figure is helpful for discovering designs with the required performance and the lowest launch cost. The "least costly" concepts are organised along a Pareto front, which covers all of the fesible designs. Then, to allow for some departure from the nominal payload aim, an acceptability area (green rectangle) is constructed around the 400-kilogram objective. The ideal design should be determined inside the green zone and near to the Pareto front, since solutions outside of these regions may be less expensive but less effective at achieving the desired result. As the "best" design, the proposal with the lowest launch cost within the accessible zone was selected.

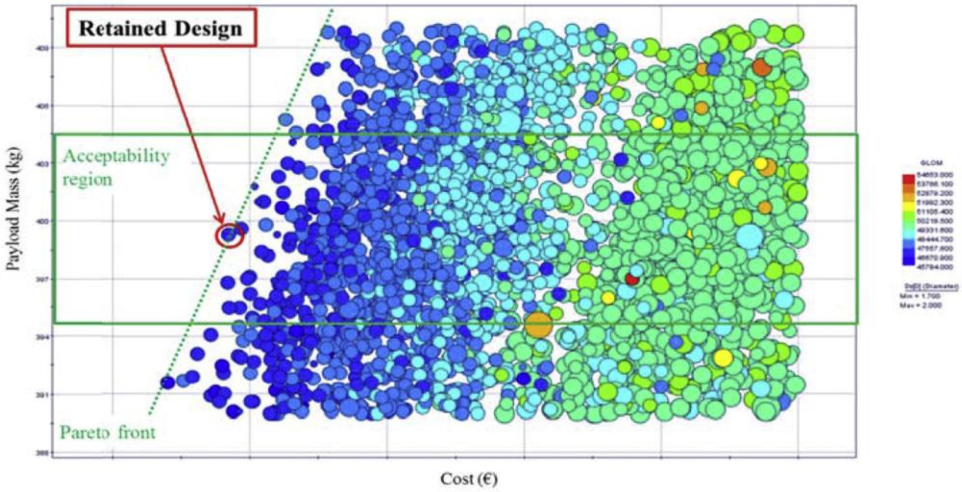

Figure 9. Examples of solutions obtained for the KKK architecture

From this synthesis, we could conclude that the best architecture is the same in GLOM and cost. It highlights the interest in the MDO approach. These findings emphasise the value of applying an MDO strategy that takes into account both technical and economic factors right away during the design process of a new SLV. This investigation demonstrates how an approach that is just focused on technical criteria can result in quite different findings than an approach that also takes into account economic factors. The time for performing the entire study and finalising the trade-off only took a few weeks, which significantly reduced the time for an optimised concept. The use of an integrated platform for multi-objective and multidisciplinary optimisation makes it efficient while ensuring a quick, precise final output. Future enhancements, presently under development, are focused on an optimisation technique that minimises the need for human input by promoting automated parameter adjustment inside a single optimisation cycle. Other expansions of this technology to more applications and the incorporation of sophisticated CAD/CAE and CFD tools are other areas that need refinement in order to give continuous effective computation time.

3. Conclusion

In this paper, the recent advances in the Design optimisation technique are summarised. The main conclusions can be drawn as follows: (1) The Metaheuristic Optimization approach developed by Tola et al. on a solid-propellant rocket motor has achieved an efficient, automatic and practical process with graphical and numerical output explaining the approach; (2) Khurram Nisar et al.

accomplished 3D FCG grain using the Hybrid Optimisation method which well satisfies the mass of propellant and reduces the minimum while acknowledging all parameter; (3) Rafique et al.'s paper demonstrates that the hyper-heuristic optimisation is effective and search for global optima and avoid local minima extremely well; (4) The study of Dupont et al. demonstrate the effectiveness of Multidisciplinary design optimisation in the space vehicle design phrase with the high performance and low cost it demonstrates. In addition, further application of these optimisation approaches and new ways of improvement of all optimisation techniques might prove an important area for future research.

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