Applications of Optimization Techniques for Solid Rocket Design

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Abstract. Solid Rocket Motors (SRM) are rocket motors that use solid propellants (fuel/oxidizer). Optimization of the motor's design is the process to alter the schematics of the engine for higher engine efficiency and cost minimization. Solid Rocket Motor optimization is one of the key topics of aerospace engineering research today. Conventional methods for optimization have fallen obsolete due to the exceedingly large number of design variable in modern rocket engine optimization. This paper will summarize and review some of the related research carried out in this field. Modern methods of optimization are usually designed to be multidisciplinary using complex computerized hyper-heuristic algorithms like Genetic Algorithms, sequential quadratic programming, particle swarm optimization. In conclusion, this paper could be a useful reference for those who would like to acquire a scan of the field of modern SRM optimization, learn the core methodologies for the optimization process and understand the logic of related methods.

Keywords: Solid Rocket, Optimization Design, Hybrid Method.

1. Introduction

The Solid Rocket Motor is important in the modern field aerospace propulsion systems and will be a core part of it for the foreseeable future. Even with the advent of reusable rocket boosters, the SRM and its development will be essential in ballistic technology. Optimization of the SRM constitutes the core part of the research done in this field, the aim is to minimize cost and maximize engine efficiency for specific situations, payloads and vehicles. The modern era demands for increasingly complex optimization processes with new variable profiles that need to be monitored by new multidisciplinary optimization methodologies.

Kamran and Liang [1] developed a method of SRM optimization based off meta-heuristics, used a non-learning random function to control low level meta-heuristics to increase accuracy of global solution of the optimization. This yielded promising results of the optimization method. Wang et al. [2] investigated grain design optimization processes with genetic algorithms and sequential quadratic programming and used a hybrid optimization for the multidisciplinary grain design cycle which proved to improve the optimization efficiency. Wu et al. [3] developed a performance matching design framework which satisfies various thrust performance requirements, using a general design approach for general design parameters. Kamm and Gany [4] investigated a theoretical optimization process of a predetermined common vehicle and demonstrated the optimization principles of SRM optimization. Various parameters, connections of different variables and designs are discussed. Roy et al. [5] reviewed analytical optimization methods of SRMs. Acknowledging the recent shift away from analytical methods of optimization, it discusses how certain analytical optimizations could be more efficient for some specific grain designs. Mahjub et al. [6] provided a survey of recent advancements in SRM optimization including the logic of SRM optimization, its goals and aims with different methodologies and advancements in the field recently.

This paper aims to provide a summarization of the recent advances of SRM optimization. Section 2 provides summarizations for four articles in modern SRM optimization processes. Section 3 provides conclusions of the paper and prospects of future research.

2. Main body

In this section, applications of four typical optimization methods for SRM are discussed. The four methods include metaheuristic optimization approach, hybrid optimization method, hyper-heuristic optimization, multi-disciplinary design optimization.

2.1. Metaheuristic Optimization Approach

Tola and Nikbay [7] developed a method of Solid Rocket Motor Propellant Optimization with a coupled ballistic-structural interaction approach. This approach is necessary because the conventional method of analyzing the internal ballistic performance and viscoelastic structural strength disciplines is to use separate design groups, which leads to a need of many expensive iterations due to the lack of feedback between the design groups. This multidisciplinary design optimization approach couples the ballistic performance and the viscoelastic structural analyses for a more efficient methodology. The viscoelastic material properties, such as the young’s modulus, are used to produce a function of time-dependent temperature data of the propellant during the cool down process. (The viscoelastic material analysis has two steps: the cool down and the ignition process) a transient heat transfer is done to produce a time-dependent temperature data of the propellant grain finite element model during the cooldown. An ignition-related pressure data set will be produced by the internal ballistic analysis will then be applied to the viscoelastic propellant. This process illustrated by the authors in Figure 1.

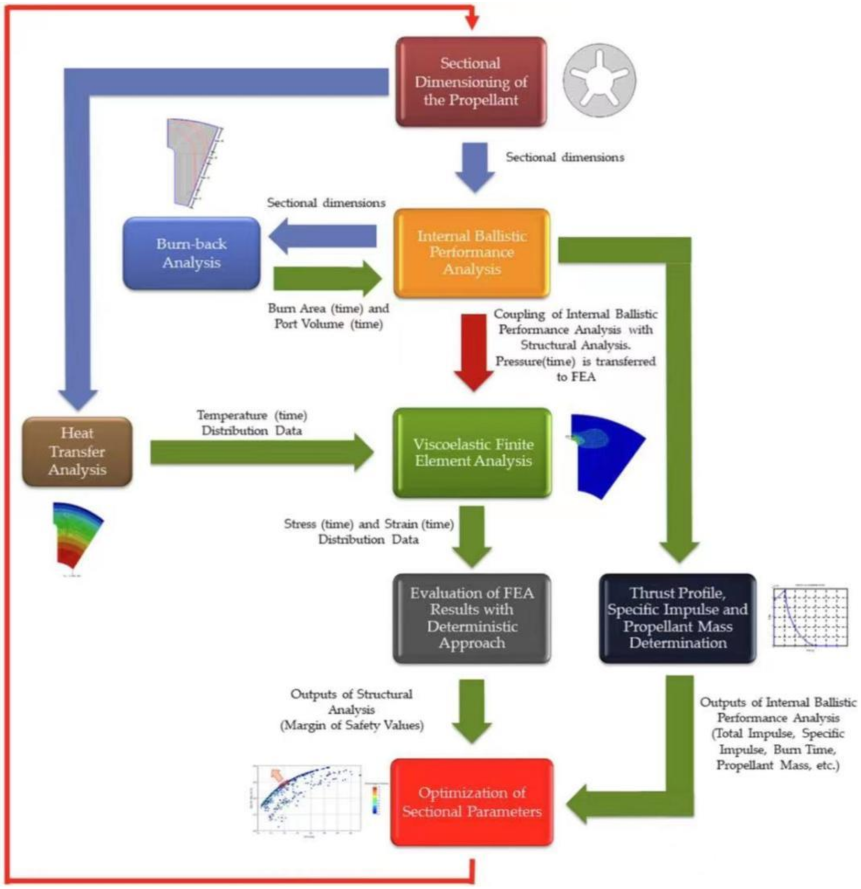


Figure 1. Flowchart of coupled analysis and optimization approach.

Zero-dimensional ballistic solvers and burnback analytical solvers were utilized to compute and predict the transient variation of camber pressure and rocket thrust. The process begins with determining the slotted propellant grain’s sectional parameters. The internal ballistic performance analysis couples with the burnback analysis to produce results of the burn area and port volume as a function of time by using the geometric parameters gathered. The output of this calculation process consists of the transient values of the propellant mass, the thrust profile, the total impulse, the specific impulse, and the burning time of the solid rocket motor (SRM). From this data set garnered, the results of the chamber pressure-time data are sent to the ignition step of the viscoelastic finite element analysis. Similarly, the cooldown step of the viscoelastic finite element analysis (FEA) model receives the cooldown heat transfer analysis, which is a time-dependent temperature distribution data set of the propellant, due to the physical properties of the material being a function of temperature in a viscoelastic model. After the FEA, the strain and stress results are produced and monitored by a deterministic approach called the structural margin of safety, which will also be considered in the overall optimization process.

Thus, the optimized geometric parameter for a slotted grain in consideration of both structural and internal ballistic performance criteria were produced.

The FEA process begins with determining the geometric parameters of the SRM as shown in Figure 2, for example the specific measurements and designs of the grain and the perforation.

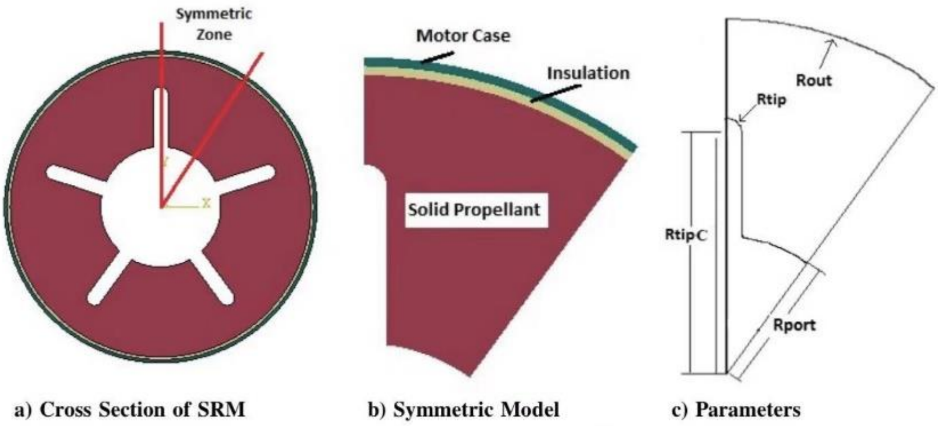


Figure 2. The process of modeling the geometric parameters

After the geometric parameters are determined, the physical properties of the material will be determined for later use in the different analyses. During the FEA the loading conditions are considered due to the different stages (cooldown and ignition) the structural environment changes, thus the maximum and minimum chamber pressures and the maximum strain and stress values will be monitored. Then the heat transfer analysis is applied gather results for the optimization, a surrogate model of the SRM is produced here to reduce expensive iterations of the optimization process. Finally, using the results of the internal ballistic solver, the heat transfer analysis for both the ignition and cooldown processes, the main finite element model performs the linear viscoelastic analyses of different grain designs. Figure 3 illustrates the FEA processes and analyses.

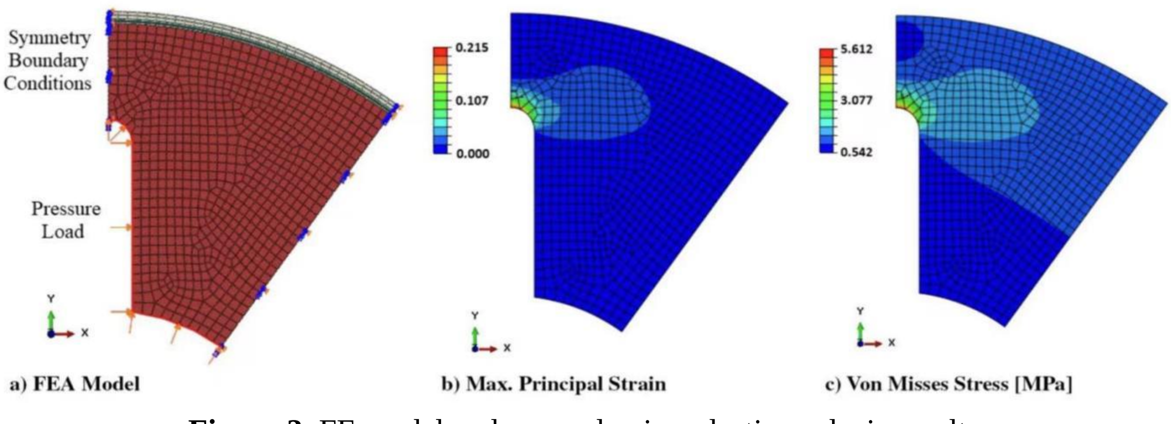


Figure 3. FE model and a sample viscoelastic analysis result

Then the FEA results are analyzed with the equation:

$$MS = \frac{Kt \cdot Za}{\mathrm{DF} \cdot \mathrm{Zc}} \tag{1}$$

Where Zc and Za represent data calculated from the FEA results, computed from the FEA; DF is a characteristic of the solid propellant between the values of 1 and 2; Kt is calculated from the effects of aging and variability of the propellant. The values of MS can be obtained. Negative MS values mean deficiencies in the design.

The development of a zero-dimensional internal ballistic solver was applied in this method using an in-house code which serves as the 0-D performance solver. This procedure is prepared because the performance of a SRM can be determined by the pressure-time and thrust-time data sets, whereas the efficiency of the system is produced by the specific impulse. The algorithm of the solver is mainly based off the conservation of mass. Grain Burn back Analysis is done to ascertain the profiles of burn area and port volume necessary for the internal ballistic solver.

Finally, the optimization begins with the multidisciplinary process composed of five steps. Firstly, the 0-D internal ballistic solution is performed with in-house Matlab code. Secondly, two python codes solve the heat transfer analysis during the cooldown phase, thus deriving the FEA process based on the temperature-time profile of the propellant. A python code is then derived to store the FEA data in the form of text files. Using these results, the structural margin of safety values is calculated with an in-house Matlab code. The coupling of the internal ballistic performance analysis with the viscoelastic FEA model is done between the first and third steps of the optimization process.

A complete and detailed overview of a multi-disciplinary optimization process for SRMs is presented. It describes a complete multilayered coupled analysis with full explanations and logic processes which provide the researcher with ample information on the topic. Overall, this article is of high quality and includes extensive details of a complex optimization of the SRM.

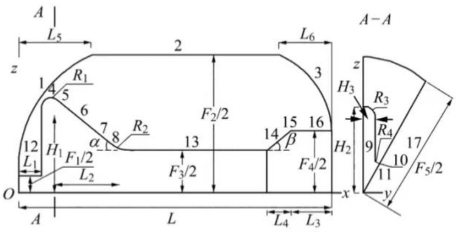
2.2. Hybrid Optimization Method

Nisar et al. [8] presented a method to design and optimize the 3D FINOCYL grain (FCG). A series of computations were adopted for the optimization of the grain configuration. The algorithm analyzed various grain shapes that are combinations of key shapes like the ellipsoid, cone, cylinder, sphere, torus, and inclined plane. The hybrid optimization process includes a mesh of genetic algorithm for global solution convergence and sequential quadratic programming for further local convergence of the solution. The derivation of the hybrid method was detailed from the component methods and results of optimized grain parameters for the SRM using this technique are discussed.

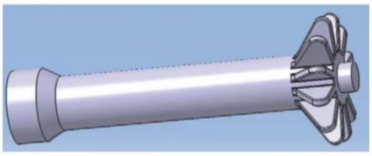
The FINOCYL is a 3D grain configuration which stands for “fin in cylinder”, a design that is usually applied to low fineness ratios (L/D) requiring internal grains. This type of heuristic optimization for grain engineering is lacking in the field, though the same sort of technique has had ample contributions in other mathematical problems. By using a genetic algorithm (GA) and sequential quadratic programming (SQP), where the GA performs a preliminary search in the solution space for a general direction in optimization research, then the SQP refines the solution found by the GA. This sort of optimization technique is essential because the 3-D optimization process of the FCG is very complex, including seventeen independent variables in the model, and with this method the convergence region will be located more efficiently.

Table. 1. List of Performance Optimizations

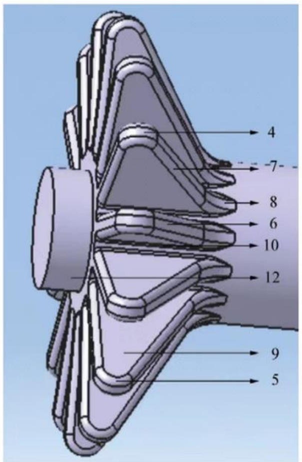
Parameter	SQP	GA	HO
Fav/kN	153.80	150.10	157.30
mp/kg	4875.2	4857.50	4832.40
tb/s	71.80	72.27	71.85
Abi/m2	6.72	6.35	7.59
BR/(mm·s-1)	6.55	6.47	6.61
Pav/MPa	6.88	6.69	7.01



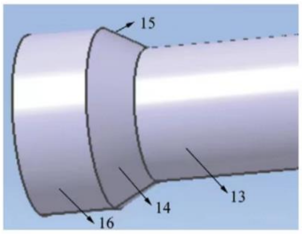
(a) 3D parametric view



(b) Inner void of 3D FINOCYL grain



(c) Fins enlarged view



(d) Cone enlarged view

Figure 4. Illustration of 3-D FINOCYL grain

After the variables and parameters needed for the algorithm are calculated using computer codes, the optimization process of minimizing a function denoted M, with 18 variables. The optimization model is then solved through the GA and SQP, after which the hybrid optimization (HO) will link the GA with the SQP. The GA will pass on the optimal guess to the SQP process, where the local convergence is determined.

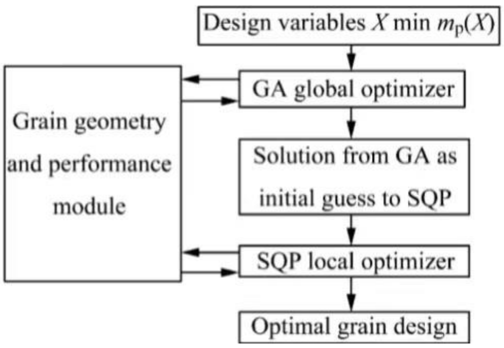


Figure 5. Flowchart of the HO algorithm

Overall, a detailed optimization process of a specific grain design and an adequately detailed process of its optimization procedure and logic are presented. The contributions will be useful for those searching for specific SRM grain designs and optimization processes for them.

2.3. Hyper-Heuristic Optimization

Rafique et al. [9] emphasized the demand of multidisciplinary designs and optimization processes for satellite launch vehicles. A Hyper Heuristic approach was presented, which integrates genetic algorithm, particle swarm optimization and simulated annealing through a random function. The results yielded through this method of optimization for the air launched satellite launch vehicle proved to be effective in multiple facets.

With the drastic increase in computing power, multi-disciplinary optimization has evolved from classical methods to modern heuristic methods, these meta heuristic methods prove to be superior to the traditional methods. But with the increasing demand for the scale of variables and profiles in consideration of the optimization process. New hyper-heuristic approaches have demonstrated the direction of evolution in the field. The HHA presented here utilizes a non-learning random function (NLRF) applied to a low-level-meta-heuristic (LLMHs). Genetic algorithm, particle swarm optimization (PSO) and simulated annealing (SA) are the LLMHs.

```
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. Pseudo code of the HHA program

Key reasons and benefits of the necessity of the HHA approach explained by the article detail the increasingly complex and vast amount of variable profiling in modern day SRM optimization requires the processing power of the HHA approaches. The conventional methods used to optimize the process may run into many local minimizations the obsolete methodologies cannot oversee. The HHA will prevent these mistakes from happening. The schematics of SRM designs include a vast number of non-linear limitations, which may prompt researchers using conventional optimization techniques to run into local minimums. Old heuristic models of optimization will need extensive tuning in the modern era of frequently changing premises and demands for optimization. The HHA's goal is to derive a method which is easy to utilize and understand conceptually, while also being accurate and diverse. The HHA is an algorithm that is aimed to solve complex and multidisciplinary problems with high efficiency and quality in finding the global minimization and avoids local minimums.

Information of specific optimization calculations and processes along with simulations of applying this methodology into real SRMs are included. The details of optimization processes considering the modern era are demonstrated. Moreover, methods and considerations are important in modern era SRM optimization processes.

2.4. Muti-disciplinary Design Optimization

Dupont et al. [10] presented the methodology in space launch vehicle design along with the optimization processes. The process is done using the property software platform HADES V15.0. The goal is to design and optimize a vehicle schematic that minimizes costs while sufficing for mission demands like payload mass, number of stages and propulsive technologies. The methodologies involved incorporated a Multidisciplinary Design Feasible (MDF) approach coupled with GA calculations for Global optimization and Gradient-Based Algorithms for finetuning of results. It explains the benefits of MDF processes compared with conventional methods when applied to modern situations and demands of increasingly multifaceted optimization processes. It argues that using an integrated platform for multi-objective and multi-disciplinary optimization offers a time and cost-efficient way to optimize profiles of small space launch vehicles. Real life examples are adopted that have utilized this methodology like the ROXANE and the H2020 ALTAIR project.

A comparison between conventional methods and MDOs are presented to emphasize and explain why a MDO is much more useful and efficient in solving calculations, making it necessary for modern SRM projects to adopt this method.

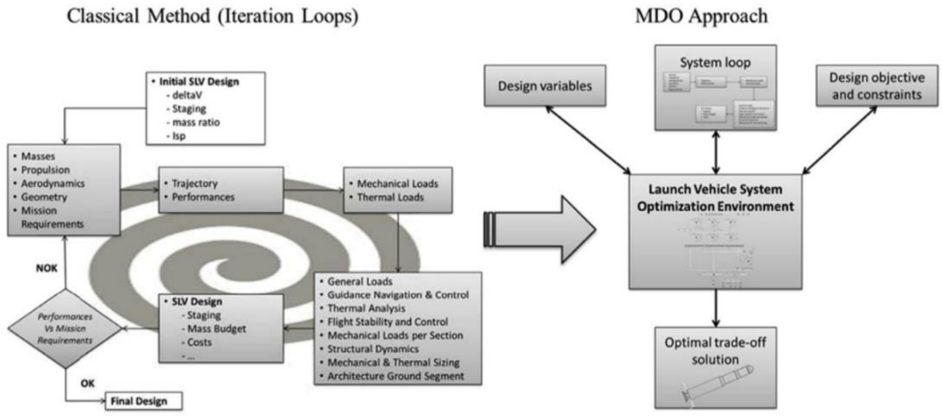


Figure. 7 Comparison diagram of the classical method with iteration loops and the MDO approach

The research approaches the optimization process with a global system level optimization, with the primary aim to find the repartition of propellant masses between the different stages while satisfying the design constraints. The approach relies on the general problem being considered as a Multiple Discipline Feasible (MDF) approach, which is bases on MDA processes. With the MDA processes the approach then utilizes a GA for a feasibility zone, then it will use the local optimization to refine parameters. A real-world example of the rationale of the MDF approach applied to the HADES V15.0 platform is shown in Figure.12.ws

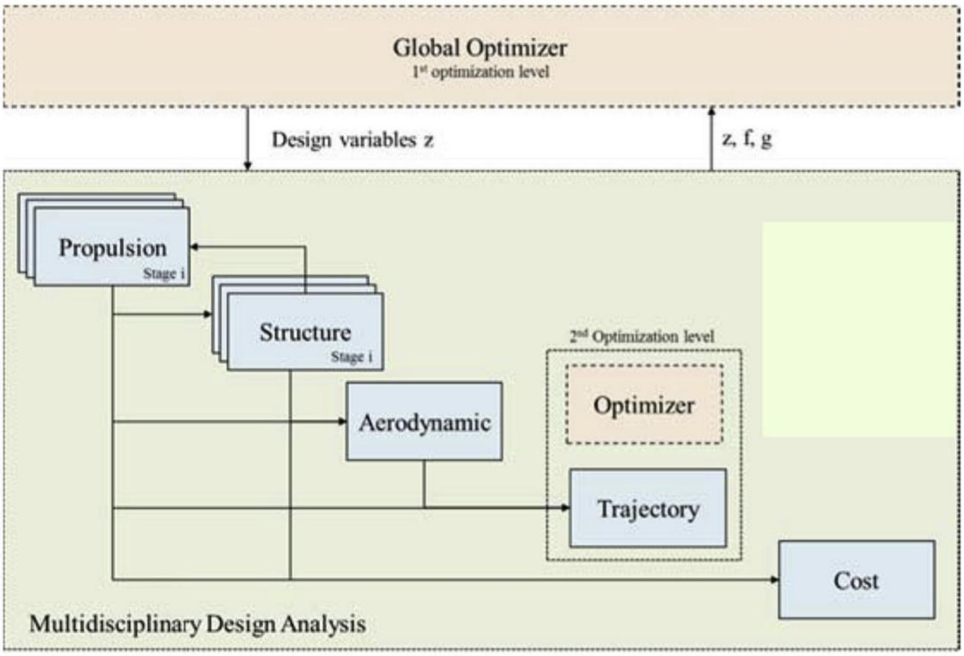


Figure. 8 MDF approach for launch vehicle design (HADES V15.0)

The research emphasizes the benefits of a MDO environment, the powerful pre and post processing of the SLV design environment like the GA, Broyden-Fletcher-Goldfarb-Shanno algorithm, (BFGS) yield a good process for more and more refined results of optimization in the MDO process. Figure.13 shows the work flow an SLV design.

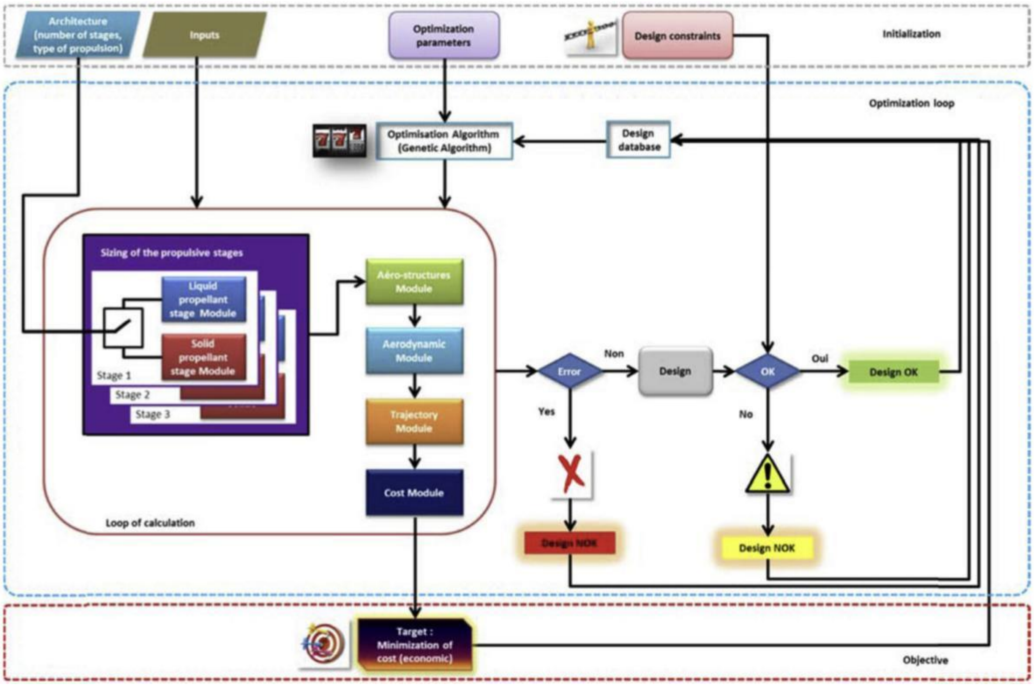


Figure 9. SLV design process and logistics

The results presented in this research process contributes to the field of SRM optimization by using real applications and experiences dealing with real-world projects. This grounds the paper in good credibility, the discussion of these real-world projects can be especially useful to confirm or judge popular optimization methodologies and techniques prevalent in recent research.

3. Conclusions

This paper presents of survey of recent advancements on SRM optimizations. The conclusions can be summarized as follows. The modern demands in SRM optimizations demonstrate a trend that necessitates a multidisciplinary approach to optimization and uses hyper-heuristic algorithms for global and local optimizations. Prospects for further research should include more real-world applications and results for these proposed methods of optimization. Many grain design optimization theories have been published in the field, an evaluation and combination of these theories should be done in the future.

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