

Liquid Rocket Propulsion Launcher Design System to Train AxSTREAM.AI. Reusability Aspects.

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Abstract

Utilization of Digital Engineering (DE) significantly enhances the lifecycle activities from concept through disposal, reducing required resources and time. DE of Liquid Rocket Propulsion (LRP) Launchers focuses on the application and integration of models and simulations to improve the process of their development. But what if you go further and use DE, assisted by experts, to train an Artificial Intelligence (AI). Afterward, the trained AI will minimize the human factor influence on DE of LRP launchers, and design them automatically for various missions and applications taking into account reusability aspects.

The authors of this paper applied model-based engineering (MBE) and developed the design system focused on the conceptual phase of launcher lifecycle. The comprehensive system integration of the complex hierarchical structure of the models with AI training in mind was considered in the paper. This system allows the launcher design based on the minimal number of requirements, like orbit and payload; determines the launcher's number of stages and their mass, thrust requirements and dimensions at the rocket level; and then performs a preliminary design of optimal LRE including turbopumps, taking into account lifetime as one of the criterions for the best configuration selection to maximize the reusability potential of the developed engine. The system is comprised of models of different scales and types, from 0D and 1D models at rocket and LRE cycle levels to a combination of 1D, 2D and 3D models at turbopump level. This structure of the system provides the capability to quantitatively evaluate and optimize a launcher and its subcomponents with a sufficient level of detail. The detailed structure of the engineering system, its levels, and integrated models are described in the paper. Also, the utilization of the developed system to train an AxSTREAM.AI is considered.

1. Introduction

In recent years, the Space Industry has become more and more attractive, and we are at the forefront of the New Space Race. For example, the financing of NASA in 2018 amounted to more than \$21 billion, ESA – \$6.5 billion, China - \$3 billion. With the increased attention to the Space Industry, the number of companies trying to develop their own launchers has skyrocketed. Therefore, the rocket launchers market is changing rapidly, with new companies establishing themselves in all segments of the industry. The market is in the state when the traditional approach to the technology development does not provide the commercial advantage and there is a need in the development of innovative concepts, technologies and approaches throughout the lifecycle of Liquid Rocket Propulsion launchers.

1.1 Competitiveness strategies

Players in this market are attempting to become more competitive by applying a variety of innovative tactics, such as:

- Additive Manufacturing (AM) [1]. This technology is being applied at different levels of launcher development. Some companies are using it for rapid prototyping of the components to speed up the process of new solutions

experimental validation. There is even an attempt to manufacture an LRE engine and entire rocket via 3D printing, minimizing the number of parts, and thus minimizing the lead time and cost [2].

- Reusable Launch System (RLS, or Reusable Launch Vehicle, RLV). This is a space launch system intended to allow for recovery of all or part of the system for later reuse. It is intended to reduce launch costs below those of Expendable Launch Systems (ELV). There are existing solutions with the reusable first stage [3] and boosters [4]. Despite these, the reusability draws a negative impact on the performance of the launcher, the cost per launch for SpaceX Falcon 9 with reusable first stage is \$50M [5] and with payload to LEO 13,150 kg it can be converted to \$3,800 per kg, which is significantly less than \$14,240 per kg to LEO of Atlas V 411 with comparable payload [6]. The alternative reusability approach, compared to the LEO of Atlas V 411 is a hybrid air-breathing rocket engine [7] propelling Horizontal Take-Off and Landing Vehicle (HOTOL) implementing Single-Stage-To-Orbit (SSTO) concept [8], which could potentially reduce the cost per launch.

1.2 LRE reusability aspects

Reusability requires an upfront investment and has to be part of the technical specification of the engine beginning from the conceptual design phase. It is important to note the performance is not the most important parameter for the reusable engine. Indeed, the reusable engine designed with performance as a primary design driver is neither operationally efficient nor simple. SSME is an example of such an approach. Making hardware reusable incorporates a new level of complexity, including the ability to repeatedly survive the re-entry environment, thermal protection, more robust structures, higher safety factors to minimize stress damage and extra propellant to perform deorbit maneuvers. Extensive and costly maintenance is the intrinsic by-product of placing the emphasis on performance. SSME after each flight required removal from the vehicle for maintenance resulting in more than 20,000 hours of direct and indirect labor and two months of calendar time [9]. In order to dramatically reduce the maintenance duration and cost, operability and supportability shall be the essential parts of the design process from the early beginning as it is impossible to implement them later to an existing design.

Reusable engine design paradigm is different from the expendable one. In particular, Bowcutt summarized, “Life cycle cost is driven more powerfully by operational parameters such as turnaround time, than by performance parameters such as engine Isp and dry weight. For example, it would take an approximate 30% change in engine Isp, or 100% change in vehicle dry weight, to equal a 15-day change in turnaround time” [10]. Therefore, the parameters that enhance reusability have more influence on cost than performance parameters. Some of these factors/parameters are [11]:

1. Minimization of post-flight inspections & servicing. The design should be made to minimize or even completely avoid the maintenance between flights. For example: apply integrated health monitoring system, which provides sufficient information to make a decision on whether servicing is required; select propellants which do not generate soot or use oxygen-rich cycle; etc.
2. Ease of access. The components with higher failure rates should be located to be easily accessed for maintenance. This will dramatically reduce disassembly and assembly time, reducing cost and human factor influence. Combination of this design approach with AM seems to be pretty promising.
3. Minimization of hardware recovery. It is obvious that the hardware shall be successfully recovered to be able to reuse it. Some examples of hardware recovery are barge landing, returning to land or mid-air recovery. It should be noted that the recoverable rocket is inevitably heavier than expendable one, due to the need for a safe landing. The engine must be more robust and be designed with higher safety margins to withstand harsh reentry conditions and landing loads. Higher safety margins inherently make the hardware heavier.
4. Increase service life. The service life of components requiring frequent maintenance must be improved in the first place. The high-pressure fuel turbopump and high-pressure oxidizer turbopump have a higher failure rate among SSME components [12], i.e. the turbopumps are the bottlenecks of the engine life. Therefore the maximization of turbopumps life will significantly improve the reliability of the entire engine enhancing its reusability potential.

1.3 Launch cost reduction

It is obvious that AM and reusability are focused on the reduction of manufacturing and mission cost which are considered recurring expenses. However, the nonrecurring costs are substantially higher (10-20 times) than recurring ones [13]. The nonrecurring expenses on the development of innovative reusable launcher technology, taking into account aforementioned aspects, are going to be much higher because every substantial advancement of technology requires more researchers to be involved [14] and time spent on hypotheses generation and their validation. Therefore, there is significant potential to further reduce cost per launch decreasing the nonrecurring costs.

Non-recurring costs have two major contributors [15]:

1. Design and development efforts amounting to the engineering work performed, which depends on the technical specifications of the system; and

2. Building and testing work performed on system and subsystem models.

The design and development technology efforts can be reduced improving the technology itself, which, in turn, can be achieved in at least 4 ways:

1. Improve the quality of the hypothesized solution to reduce the number of iterations between Reduced Order Modeling (ROM) level and detailed design level;
2. Reducing the time of the high-quality hypothesis generation;
3. Improving the fidelity of calculations performed with partial differential equation-based solvers without penalty on resources and time required, reducing the amount of testing and rework required to complete the design; and
4. Reducing the computational resources required to perform the calculations with differential equation-based solvers without a penalty on fidelity and robustness.

Unfortunately, the achievement of the design and development technology improvement in any of the previously mentioned approaches requires the involvement of a substantial number of researchers, resources and time.

Fortunately, rapidly emerging artificial intelligence (AI) technologies offer the potential to counteract this by accelerating certain design and development processes. An inevitable part of any AI technology is machine learning (ML), which requires relevant data to train the AI during the design and development process. The data can be obtained in different ways, depending on the specifics of the subject, objectives, parameters, etc. In the case of launcher design, the data to train AI can be obtained utilizing design systems developed by leveraging model-based engineering.

The authors of this paper have previously developed the system for the automatic preliminary design of a liquid rocket engine, which allows automatic & iterative execution of rocket engine cycle analysis and turbopump preliminary design, including fuel pump design, oxidizer pump design, turbine design, turbopump preliminary layout development, secondary flows simulation, bearings simulation, rotor dynamics, and stress analysis [15]. Taking into account the developed design system is easily extendable, the authors enhanced the system adding LRE layout preliminary design, making the system capable of a joint turbopump-engine layout preliminary geometry generation and selection of the best engine configuration taking into account multiple engine quality criteria [16].

The goal of the current study is to further enhance the design system to make it capable of determining the launcher's number of stages and their mass, thrust requirements and dimensions at the rocket level, and then perform a reusability oriented preliminary design of the optimal LRE including turbopumps for every stage, based on the minimal number of requirements such as orbit and payload, in the perspective of the utilization of the system as a source of data for AI training. Eventually, the trained AI will be capable of providing the same output as the engineering system does, almost instantaneously. It should be noted that system while in development [16] has already demonstrated engine preliminary design time reduction by a factor of 50, and the leveraging of the trained AI should further improve the design speed, making it possible to rapidly select the most suitable solution for the specific set of requirements. The proposed approach should significantly improve the first and second mentioned above ways of design and development technology and substantially decrease nonrecurring costs.

2. Hypothesis generation in LRP launcher design process

The very high-level representation of liquid rocket engine design process is presented in Figure 1.

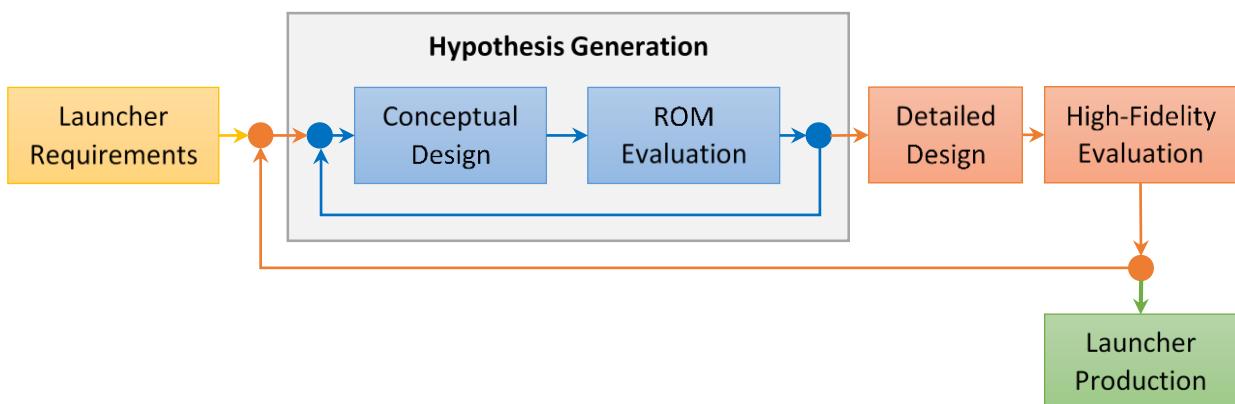


Figure 1: High-level representation of LRP launcher design process framework

It is obvious that any design process is iterative and for LRP launcher design, this also holds true. The iterations take place at different steps and levels of the design process. In particular, it is very common for some iterations to take

place at Hypothesis Generation step, where Conceptual Design and ROM Evaluation sub-processes are being repeated until Launchers Requirements are met. The other iterative process happens if the High-Fidelity Evaluation of the Launcher Requirements are not met and it is required to return to the Hypothesis Generation process to generate a new conceptual design. It should be noted that High-Fidelity Evaluation typically means calculations performed with partial differential equation-based solvers (e.g. computational fluid dynamics simulations, finite element analyses) and/or experiments (e.g. component tests). The second iterative process often takes place due to an insufficient level of details taken into account during the Hypothesis Generation process, which leads to significant discrepancies between actual parameters determined at High-Fidelity Evaluation step and requirements for the launcher. Thus, it is required to either increase the number of factors taken into account during the Hypothesis Generation or generate new concept taking into account High-Fidelity Evaluation findings.

For such complex devices as an LRP launcher or just an engine, even at the Hypothesis Generation step, it is required to take into account the vast number of factors influencing engine reusability, weight, dimensions, configuration, and performance. Taking this into account during the Hypothesis Generation step of LRP launcher design would be very resource intensive and still oversimplified without leveraging a DE. Fortunately, in 2019, by leveraging DE, we can reduce the time consumption of the Hypothesis Generation steps which makes it possible to integrate reduced order physics-based models, and avoid excessive oversimplification thus reducing the number of iteration with the Detailed Design and High-Fidelity evaluation.

The current study is focused on Hypothesis Generation step of LRP launcher design process. The high-level representation of the Hypothesis generation process considered in this study is presented in Figure 2. As it can be seen, the Launcher Conceptual Design (Hypothesis Generation) itself consists of the multiple iterative sub-processes at the cycle, engine and components levels. In turn, at the components level, the iterations are being performed for all the components of the stage and engine, such as turbopump, thrust chamber, tanks, etc.

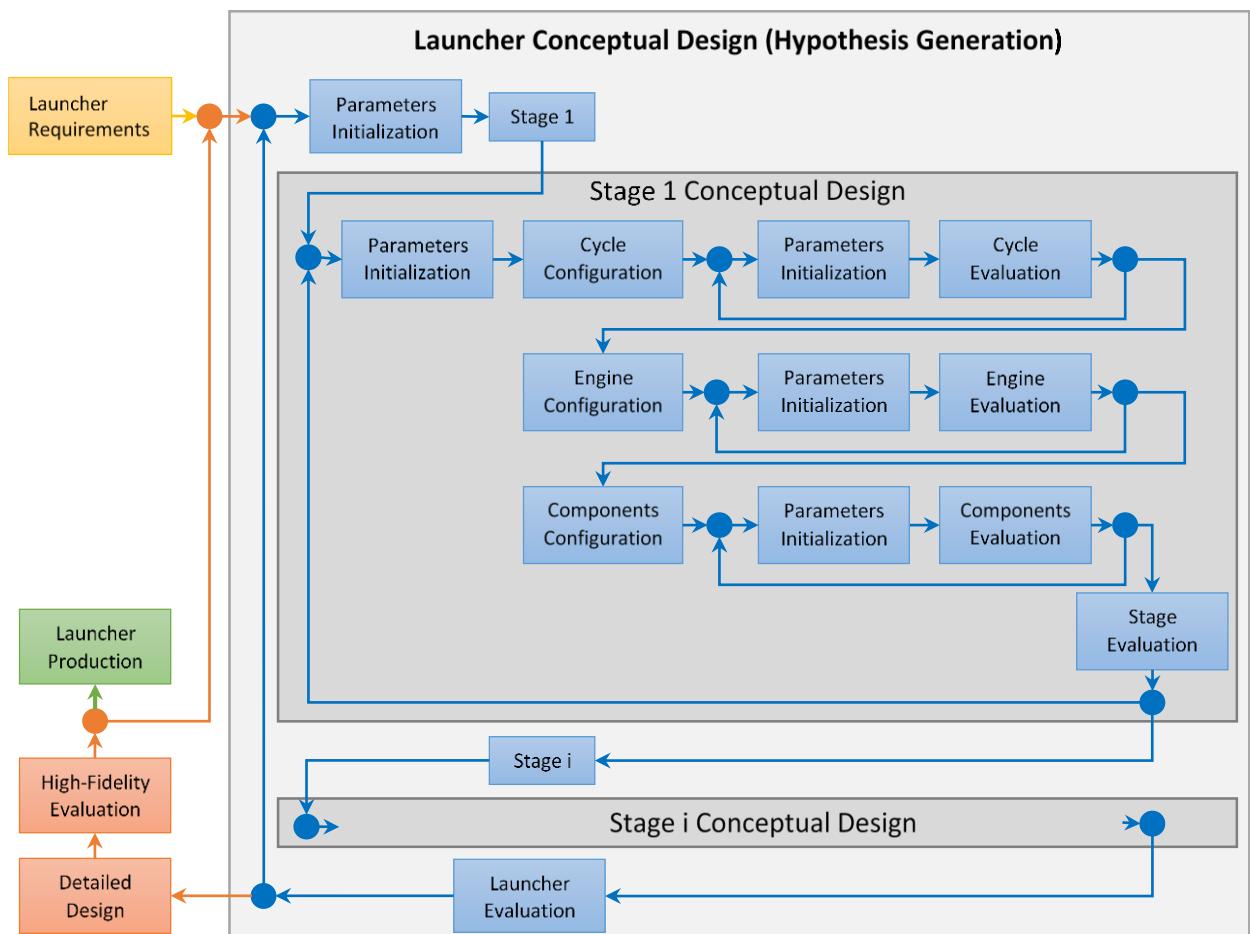


Figure 2: Hypothesis-centric view of LRP launcher design process framework

One of the crucial LRP engine components is a turbopump, which itself is a complex unit, and consists of a pump(s) and a turbine. Conceptual design of a turbopump requires consideration of secondary flows system, which in turn

requires rotor configuration evaluation, forces evaluation, and bearings evaluation taking into account structural and other constraints, and propellant separation requirement. In order to be able to perform conceptual design of pump(s) and a turbine, it is necessary to make certain assumptions with regards to the secondary flow system and other relevant turbopump parts, then do ROM evaluation of all the parts and subsystems and return to pump(s) and the turbine for reevaluation. The similar conceptual design process takes place for the other LRP rocket components: parameters initialization, then evaluation and return to parameters initialization taking into account evaluation results as shown in Figure 2. Taking this fact into account and that the multiple iterative processes take place for multiple components at different levels of the conceptual design of LRP launcher which includes multiple iterations, the entire process might take a significant amount of time, especially if the initial assumptions are far from target values to be found.

3. Artificial intelligence in the conceptual design of LRP launcher

From the perspective of the application of AI in the conceptual design of LRP launcher, it would be desired to eventually be able to select system components from an existing database and determine how they can be connected to satisfy the constraints while improving upon the objective.

From a mathematical standpoint, the type of problem to be solved during the hypothesis generation of LRP launcher is a Mixed-Integer Problem (MIP) in that the solution vector contains both integer (components and connections) and continuous (design parameters) variables. Depending on the type of component level ROMs employed, the mixed integer problem may be a mixed integer linear programming problem or a mixed integer non-linear programming problem, which is meant to signify that, when all integer variables are fixed to potential integer solution, the resulting mathematical program is either a linear optimization problem or a nonlinear optimization problem.

It is apparent that AI can be applied at different steps and levels of the conceptual design process presented in Figure 2 and even for the entire launcher. In order to do that, it is required to complete corresponding ML process(es). Taking into account the MIP nature of the task, ML should be performed for multiple configurations (integer parameters combinations) of the components to determine dependencies of continuous output variables from input variables. Having an AI tool, taught according to the described above approach, it will be possible to eventually get the best solution of the conceptual design of LRP launcher.

In this study supervised ML was applied at the engine design level. However, reinforcement learning could be applied also, especially for the initialization of the parameters of the time-consuming processes.

In the current study, three input parameters were used: payload, orbit and propellants pair. These parameters were common for the design system and ML. The output of the design system is actually a complete set of parameters for engine components and for engine overall, including geometry, mass, performance, stress and life parameters, thermodynamic and kinematics, etc. However, for the purpose of this study, the only performance and life parameters were used as source data for ML.

Artificial Neural Network (ANN) has the following structure: 3 neurons in the input layer, 2 hidden layers with 136 neurons each and 136 neurons in the output layer. All layers are fully-connected. Activation function – sigmoid. 136 neurons in output layer correspond to 2 continuous output parameters (life and performance) for 68 configurations of LRE (the description of the configurations is provided below). Each pair of output neurons corresponds to one specific layout configuration, representing 68 different combinations of integers, i.e. components and their specific connections. Organized in that way, ANN will predict the performance and life of each layout modification. Thus, it is possible to adjust the criterion for best configuration selection, whether on performance, or life or combination of both. The gradient descent method with backpropagation was used to train the ANN. Error function:

$$RSS(w) = \frac{1}{2} \sum_{i=1}^N (f(x_i, w) - y_i)^2 + \frac{\lambda}{2} \|w\|^2 \quad (1)$$

where

W - the matrix of weights of the neural network,

x_i - vectors of input parameters;

y_i - vectors of predicted parameters;

λ - the parameter of regularization;

$f(x, w)$ - the activation function;

N - a number of dataset items.

4. Implementation of the conceptual design of the LRP engine

Utilizing the developments performed during authors' previous studies [15] and [16], the authors developed an extended integrated system, which requires only three major input parameters: orbit, payload and propellants pair. The system finds the best configuration of the engine, including different turbopump configurations, number of thrust chambers and number of turbopumps. The integrated system scheme is presented in Figure 3. The system performs cycle evaluation, turbopump conceptual design, including its different configurations and thrust chamber design. The expanded view of the turbopump conceptual design is presented in the right part of Figure 3. As it can be seen, the turbopump itself envisages conceptual design of multiple components and subsystems:

- Oxidizer pump preliminary design
- Fuel pump preliminary design
- Turbine preliminary design
- Turbopump preliminary layout development
- Rotor mass/inertia parameters preliminary determination
- Estimation of axial and radial forces on bearings, bearings simulation and rotor dynamics analysis
- Secondary flows (leakages) system analysis and determination of the required amount of propellant for each bearing branch
- Preliminary stress analysis of turbomachinery components

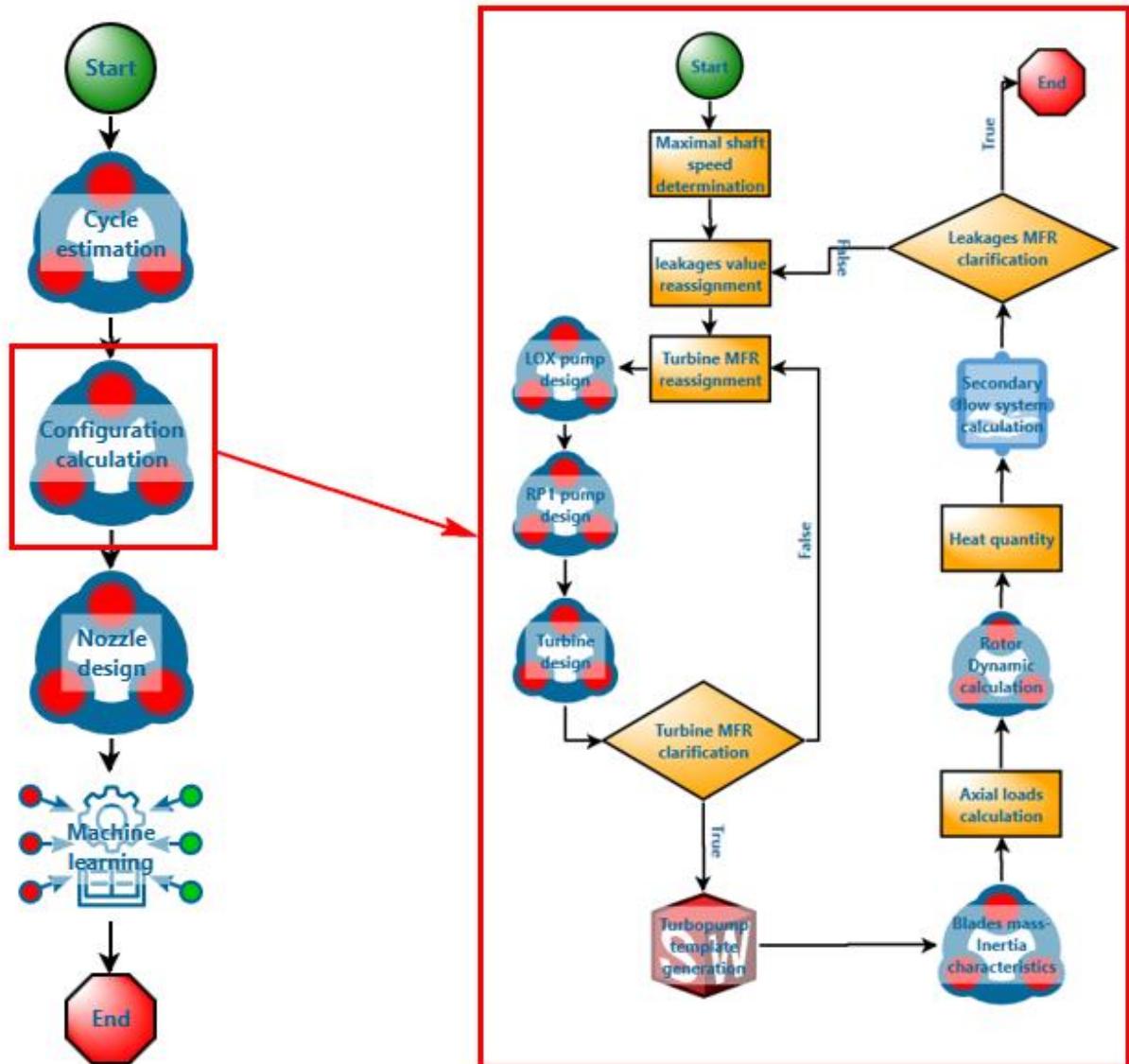


Figure 3: LRP engine conceptual design system

The gas-generator cycle was considered during this study.

5. Teaching AI

In order to generate the set of data to use for ML, a series of runs of the integrated system was performed. The set of input parameters is the following:

- Orbit: LEO
- Payload, kg: 500, 1500, 5000, 10000
- Propellants: RP1 and LOX

For each payload listed above, the following configurations were considered:

1. One turbopump and one thrust chamber
2. One turbopump and two thrust chambers
3. One turbopump and three thrust chambers
4. One turbopump and four thrust chambers
5. One turbopump and five thrust chambers
6. One turbopump and six thrust chambers
7. One turbopump and seven thrust chambers
8. One turbopump and eight thrust chambers
9. One turbopump and nine thrust chambers
10. Two turbopumps and two thrust chambers
11. Three turbopumps and three thrust chambers
12. Four turbopumps and four thrust chambers
13. Five turbopumps and five thrust chambers
14. Six turbopumps and six thrust chambers
15. Seven turbopumps and seven thrust chambers
16. Eight turbopumps and eight thrust chambers
17. Nine turbopumps and nine thrust chambers

It should be noted that four different configurations of turbopump (Figure 4) were considered for each of the configurations of the engine listed above, i.e. 68 mentioned earlier configurations (integer combinations) of the engine were generated for each of four specified above payloads and this data were used to teach AI.

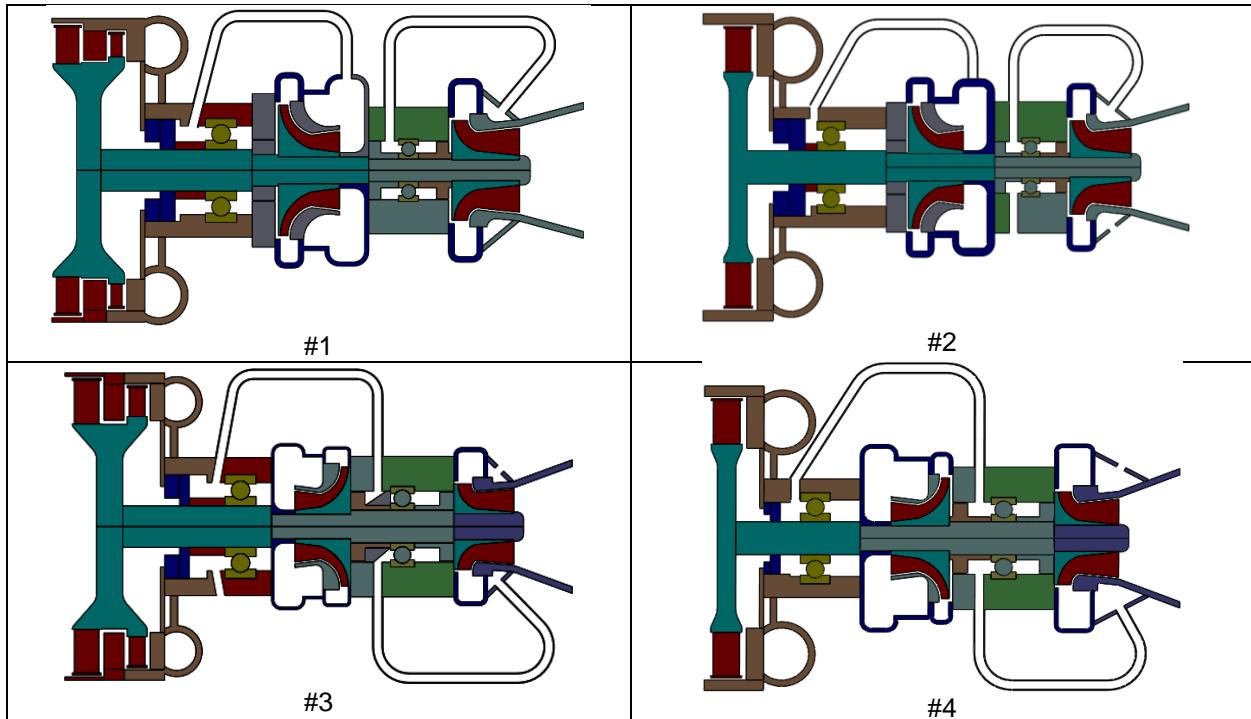


Figure 4: Considered turbopump configurations

The continuous output parameters were the following:

- Performance parameter. Which was calculated based on the following parameters:
 - Engine mass including turbopump - M_engine
 - Mass of the propellants required to drive turbopump during the stage operation - M_(TPU_drive)
- Life parameter.

The performance parameter or quality criterion of the engine conceptual design was determined as:

$$\text{Quality criterion} = \frac{M_{\text{engine}} + M_{\text{TPU_drive}}}{\text{Payload}} \quad (2)$$

It is important to notice that all parameters of all the components and subsystems included in the LRP engine conceptual design system are available as output and can be further utilized as a specification or initial state of the components and subsystems at the detailed design step.

Life parameter was estimated for turbopump as for the most critical component of the engine in terms of failure. The loads that the turbopump is exposed to can be divided into static (pressure, heat loads, centrifugal forces, torsional momentum, etc.) and dynamic (alternating gas forces in turbine blades, hydraulic forces, etc.). The blades of the turbine first stage are typically the most loaded elements of the turbopump.

The lifetime of the turbine blades is determined by many operational factors, such as operating temperature and stresses, operating time at different modes, rotational speed, and amplitude of temperature differences, number of starts, and level of dynamic loads.

In the current study, lifetime was predicted based on the static strength and temperature conditions of the turbine blades, taking into account the mechanisms of creep failure and long-term strength.

To calculate the lifetime, the Larson-Miller curve was used. The Larson-Miller curve represents the dependence of the long-term strength from the Larson-Miller parameter. Larson-Miller parameter can be presented as:

$$P_{L-M} = T(\lg(\tau) + 20), \quad (3)$$

where

T – operating temperature, K;

τ – estimated lifetime, hours.

Lifetime is estimated based on maximum allowable stresses in the hub section of the turbine blades that were compared to stress rupture. Static stresses were calculated in AxSTREAM® where the beam model strength calculation method is used.

Utilization of the above method allows estimation of the lifetime at the preliminary design level. The future detailed design level should include the clarification of lifetime taking into account high and low cycle fatigue

Total of 136 hours was required to obtain the results for all 68 configurations for four payloads, i.e. 272 runs of the integrated system. The calculation results were used for ML. The trained data discrepancy does not exceed 0.2%.

6. AI-assisted design

The trained ANN was used to determine the best engine configuration as a part of the LRP stage conceptual design process. The integrated system is presented in Figure 5.

It is important to note the execution of the process presented in Figure 5 requires less than a second of time, comparing to 30 minutes of the execution time of LRP Rocket engine conceptual design system presented in Figure 3. It is obvious that the completion of the iterative process of engine conceptual design, including thrust chamber and turbopump preliminary design, would require a minimum of 5-6 weeks of experienced engineer labor time for a single configuration.

In order to evaluate the accuracy, the AI-assisted integrated system was run for four payloads (different from payloads used for training): 800, 1800, 4000, and 8000 kg. The determination of the best configuration was made in two ways:

1. Maximizing the quality criterion and neglecting the life of the turbopump. It should be noted that stresses evaluation was still performed and both pumps and turbine were tuned to have stresses below the maximum allowable, taking into account certain safety margins. However, life estimation was not taken into account. This approach represents the extreme case of expendable launcher design.
2. Maximizing the life of the turbopump and neglecting the quality criterion. The main difference of this approach from the previous one is that the life estimation was put on top of the priorities, i.e. the best configuration was selected based on maximum life of the turbopump, i.e. the quality criterion was not taken into account. This approach represents the extreme case of reusable launcher design.

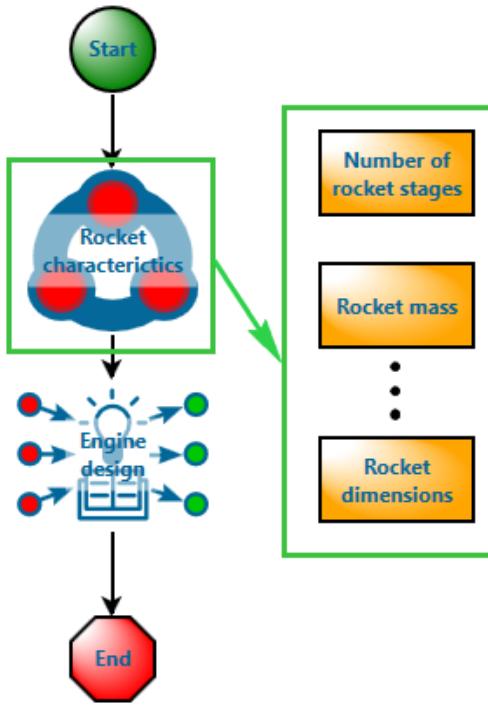


Figure 5: AI-assisted LRP launcher stage conceptual design system

It was also possible to implement the third approach utilizing weights for the quality criterion and life criterion and receive some compromise solutions. However, the selection of the weights requires a separate discussion and was not considered in this study. Nevertheless, it is obvious that the third approach being implemented would provide some solution between the two extreme cases considered. The results for the first approach are summarized in Table 1. As the table shows, the error does not exceed 5.0 %. The accuracy could be improved with the addition of more points to the ML data. The AI predicted that for the given values of payload the turbopump configuration #3 for payloads 800, 4000 and 8000 provides better performance. Turbopump configuration #4 was determined as the best one for payload 1800. However, numbers of turbopumps and thrust chambers were different for different payloads. For the considered parameters AI demonstrates that it is better to have a number of turbopumps equal to the number of thrust chambers. Table 1 also contains the number of stages of preliminary dimensions and mass for each stage.

Table 1: Results of AI-assisted LRP launcher conceptual design (Approach #1)

Payload, kg	800	1800	4000	8000
Predicted configuration	Turbopump configuration #3, 2 turbopumps, 2 nozzles	Turbopump configuration #4, 4 turbopumps, 4 nozzles	Turbopump configuration #3, 5 turbopumps, 5 nozzles	Turbopump configuration #3, 8 turbopumps, 8 nozzles
AI-predicted <i>Quality criterion</i>	1.202	1.364	1.258	1.313
Calculated <i>Quality criterion</i>	1.232	1.430	1.290	1.322
Error, %	2.5	4.7	2.5	0.7
#stages	2	2	2	2
Rocket mass, ton	55.51	100.58	180.61	300.19
1 st stage diameter	2.12	2.58	3.14	3.72
1 st stage length	21.18	25.82	31.38	37.17
2 nd stage diameter	1.16	1.41	1.71	2.03
2 nd stage length	11.55	14.09	17.12	20.28

The results for the second approach are presented in Table 2, comparing them with the results of the first approach. As it can be seen the ANN provided different turbopump (TPU) configurations, their number, and a number of nozzles for the considered approaches. Also, the mass of the engines selected by the second approach is higher regardless of

the payload. The mass increment varies from 1.46 % to 8.24 %. The higher mass increment takes place at smaller payloads. This is the price for the better life of the TPU.

Table 2: Comparison of the approaches to LRP launcher conceptual design

Payload, kg	800		1800		4000		8000	
	1	2	1	2	1	2	1	2
Predicted configuration	TPU #3, 2xTPU, 2 nozzles	TPU #1, 3xTPU, 3 nozzles	TPU #4, 4xTPU, 4 nozzles	TPU #4, 9xTPU, 9 nozzles	TPU #3, 5xTPU, 5 nozzles	TPU #4, 9xTPU, 9 nozzles	TPU #3, 8xTPU, 8 nozzles	TPU #4, 9xTPU, 9 nozzles
AI-predicted <i>Quality criterion</i>	1.202	1.285	1.364	1.481	1.258	1.277	1.313	1.338
Mass increment, %	6.764		8.236		1.464		1.909	

Off-the-shelf software tools utilized in the study

The AxSTREAM® Platform was used in the design system, including:

- The AxSTREAM® Preliminary design for turbomachinery preliminary design
- The AxSTREAM NET™ 1D hydraulic networks analysis tool was used for leakage flows simulation
- The AxSTREAM Rotor Dynamics™ and AxSTREAM Bearings™ were used for rotor dynamics and bearings simulation
- The AxSTRESS™ was used for preliminary stress analysis of turbomachinery components
- The AxSTREAM ION™ was utilized for the development of the turbopump preliminary design system, including operation flowchart design, optimization, integration of the off-the-shelf and custom software tools, and execution.
- AxSTREAM AI™ was used in AI-assisted LRP launcher stage conceptual design system

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Conclusions

1. Reusable engine design paradigm is different from the expendable one. In other words, the reusable engine design shall be designed not with performance maximization strategy, but with minimization of turnaround; reducing post-flight inspections and servicing; implementing ease of access design; minimizing hardware recovery; and increasing service life. Reusability oriented design actions shall be initiated from the early conceptual design phase of LRP launcher development.
2. The integrated system of LRP rocket engine conceptual design suitable to teach AI was developed. The system takes orbit, payload, and propellants as an input and provides the best configuration of the engine for different combinations of the input parameters with the capability to adjust the criterion of best configuration selection, whether on performance, or life, or combination of both.
3. From a mathematical standpoint, the type of problem being solved during the hypothesis generation of LRP launcher is a Mixed-Integer Problem in that the solution vector contains both integer (components and connections) and continuous (design parameters) variables. Fully-connected ANN with two hidden layers and sigmoid activation function were developed and trained to implement AI-assisted LRP launcher conceptual design.
4. ML was performed based on 68 different configurations of the engine for different payload levels. The AI-assisted conceptual design of LRP stage was developed and tested. The error in prediction of mass does not exceed 5.0 % and for some payloads is less than 1.0 %. The execution of the developed AI-assisted LRP stage conceptual design is less than 1 sec, i.e. almost instantaneous. Which allows performing launcher conceptual

design in record-breaking time, dramatically reducing the design part of nonrecurring costs, providing a substantial commercial advantage in such a dynamic market.

5. Trained ANN provided different turbopump (TPU) configurations, their number, and a number of nozzles for the considered approaches. Also, the mass of the engines selected by the second approach is higher regardless of the payload and varies from 1.46 % to 8.24 %. At that, the higher mass increment takes place at smaller payloads. This is the price for the better life of the TPU.

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