Artificial Intelligent Research Assistant for Aerospace Design Synthesis—Solution Logic

Thomas McCall,[1] Kiarash Seyed Alavi,[2] Loveneesh Rana,[3] and Bernd Chudoba.[4]
AVD Laboratory, UT Arlington Dept. of Mechanical and Aerospace Engineering, Arlington, Tx, 76019, USA

This paper has two objectives. First, the identification and communication of a research endeavor driving towards an aerospace artificial intelligence design and research assistant. The second objective is to present the evaluation of a proof of concept to employ a neural network to aerospace vehicle sizing. This test is part of the development effort to arrive at an intelligent assistant. The goal is to test the viability of a machine learning augmented synthesis tool with the intent to decrease the time to design convergence. The topic is approached from three avenues. First, a consideration of intelligence itself as best defined by humanity is considered, with the objective to identify key components to intelligence. The consideration of both natural and artificial intelligence provides direction into the definition of requirements for the system. This is the second avenue of approach. The second avenue leading to the overall objective, is the definition of a proposed artificial intelligence design environment. A key component to this system is identified as a readily modular synthesis approach that is both quick and computationally attractive. This requirement leads to the development and subsequent comparison of a neural network synthesis architecture compared to a standard synthesis software approach—the objective of this document. In order to test and demonstrate overall functionality, the case study chosen to be implemented is a hypervelocity lifting body reentry vehicle. The learning sets include five primary design parameters. The final outcome is the evaluation of a machine learning algorithmic approach to synthesis from a learned design data set versus the execution results of the subroutine developed synthesis code.

I. Nomenclature

AI	=	*Artificial Intelligence*
AVD	=	*Aerospace Vehicle Design*
AVD-DBMS	=	*Aerospace Vehicle Design Database Management System*
AVD_AI	=	*Aerospace Vehicle Design Artificial Intelligence*
S_{plan}	=	*Planform Area*
W	=	*load*
τ	=	*Slenderness ratio*
ΔV	=	*Velocity Required*

II. Introduction

FROM the early aerospace vehicle product gestation phase onwards, the future projects engineer is challenged to develop a level of assurance when committing resources towards a product aimed at achieving the envisioned impact on the future market years later. The success of a product is dependent on the quality of the underlying early forecasts. Consequently, the forecasting team or future projects environment is responsible to identify the available product solution space and risk topographies resulting in the correct choice of the facilitating technologies baseline design, architecture, or program.

---

[1] PhD Candidate, AVD Laboratory, UT Arlington, Student AIAA Member.
[2] PhD. Student, AVD Laboratory, UT Arlington, Student AIAA Member.
[3] Post Doc, AVD Laboratory, UT Arlington.
[4] Associate Professor, Director of AVD Laboratory, UT Arlington, AIAA Member

Envision the next-generation rocket scientist, a human aerospace design engineer, supported by an artificial intelligence (AI) assistant that correctly and comprehensively supports the design of aerospace vehicles or space transportation architectures with respect to highly multi-disciplinary domains stemming from the marketplace, the environment, politics, economics, and technology founded in an ever-changing real world. This is the overall objective of this research.

Presented in this document is a proposition for the development of a conceptual design phase artificial intelligence design and decision aid tool to augment and enhance the efficiency of the design engineer and decision-maker alike. This chapter presents the contextual background of the research and the research objective. This is followed by the discussion of intelligence and the identification of a research endeavor to develop an artificial intelligence (AI) solution concept to assist the conceptual technology forecasting or future projects team member. This paper concludes with the presentation of the current state of the research, specifically the test of aerospace reentry vehicle synthesis via a neural network.

III. Problem Identification

An aerospace vehicle is a product of a specific sequence of development and testing; this sequence of product development is referred to as the product life cycle (PLC). Classically, it can be broken down into six phases. The phases are: (1) Conceptual Design (CD), (2) Preliminary Design (PD), (3) Detailed Design (DD), (4) Flight Test, Certification, and Manufacturing (FT/C/M), (5) Operation, and (6) Incident/Accident Investigation (I/AI). The CD, PD, and DD phases are considered the general design phases. Each phase represents different inputs, tasks, and outputs—completion of which occurs with different toolsets and toolset fidelity. The design knowledge and freedom available, and the design change cost, those attributes characterize each phase. The result is that the CD phase is *the* initial critical phase responsible towards identifying the solution concept towards ensuring project success.

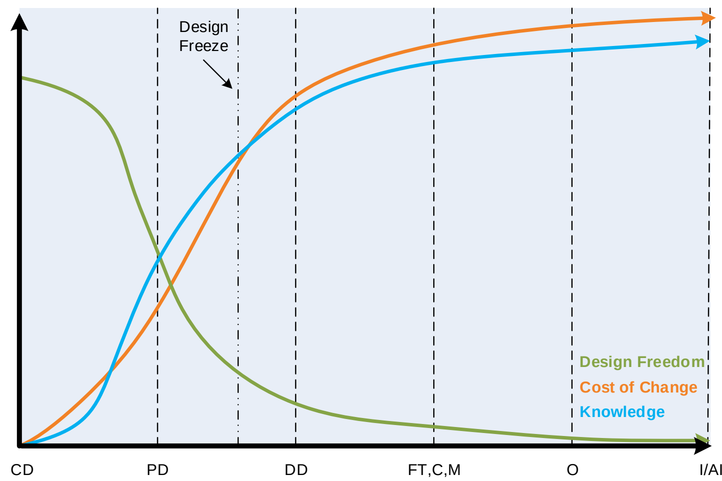

Figure 1. PLC with design freedom, knowledge, and cost of change represented

1. Knowledge & Design Freedom

Knowledge and design freedom during the PLC phases are not constant. Knowledge and design freedom are inversely related. As depicted in Figure 1, the knowledge available is minimal initially during the CD phase and increases nonlinearly through the PLC phases. The design freedom is exactly the opposite. The maximum design freedom available coincides with the point of minimum knowledge and decreases rapidly through the PLC phases.

2. Cost

The cost for significant design changes increases with the PLC phase. Nicolai states, "…the cost of making a design change is small during conceptual design but is extremely large during detail design." [1] This nature is reflected in Figure 1. In order to minimize potential cost, it is imperative that the correct design be selected early during the design process, which principally occurs during the CD phase

3. CD Phase

The CD phase is the phase in which the general design is selected. As postulated by Coleman, "… [t]he fundamental objective of this conceptual design phase is to satisfy the designer and decision maker that the selected concept is worthy of preliminary design continuation." [2] Similarly, Torenbeek reflects that "… [t]he object of this conceptual design phase is to investigate the viability of the project and to obtain a first impression of its most important characteristics." [3] The CD phase analysis results in the determination of the primary vehicle concept, configuration, and key design parameters. [4] By the end of the CD phase, approximately 80% of the vehicle configuration is established. [5] The inverse nature of the knowledge available and design freedom, the cost of major design change, and the purpose of the CD phase, makes it the critical phase of the overall design process.

A. Difficulties Affecting the CD Phase

The criticality of the CD phase does not merit the exception of a tendency to difficulty mitigation or issue occurrence. The CD phase exhibits several design difficulty issues, two critical ones are: (1) design variable abundance and (2) design proficiency and multidisciplinary integration decrease. (Note however that these issues are not necessarily unique to the CD phase.) Each is addressed below.

1. Design Variable Option Abundance

The CD phase is characterized by a design freedom that translates directly into abundant design variable options and large datasets that require assistance in interpretation and handling. The synthesis-design process is at a "…stage of the design, [where] every parameter of design may correspond to a fairy large set of options." [6] Figure 2 illustrates the technical architecture level combination of mission-hardware-technology elements that come together to develop an aerospace system. As it can be seen from the figure, the total number of possible combinations (theoretically)—when only varying the mission and vehicle level options—increases rapidly to approximately two million distinct vehicle concepts. It must be noted here that this estimate does not even consider disciplinary specific parametric variations which if included would balloon the design options infinitely. Unsuspectingly, a large set of design parameters, each parameter corresponding to a large set of option combinations, translates to large datasets. The result is the daunting task to understand the significance of a variable among a multitude and make sense of massive quantities of data. This quantity is too significant for an individual to assess and comprehended all variables and subsequent combinations in this multidisciplinary cause-effect maze. Hence, it is critical that a physics-based AI capability be developed that can parametrically trace and evaluate parametric design combinations, learn to identify the best combinations, and ultimately augment the engineer through an AI-based learning environment. In short, the human designer needs AI assistance.

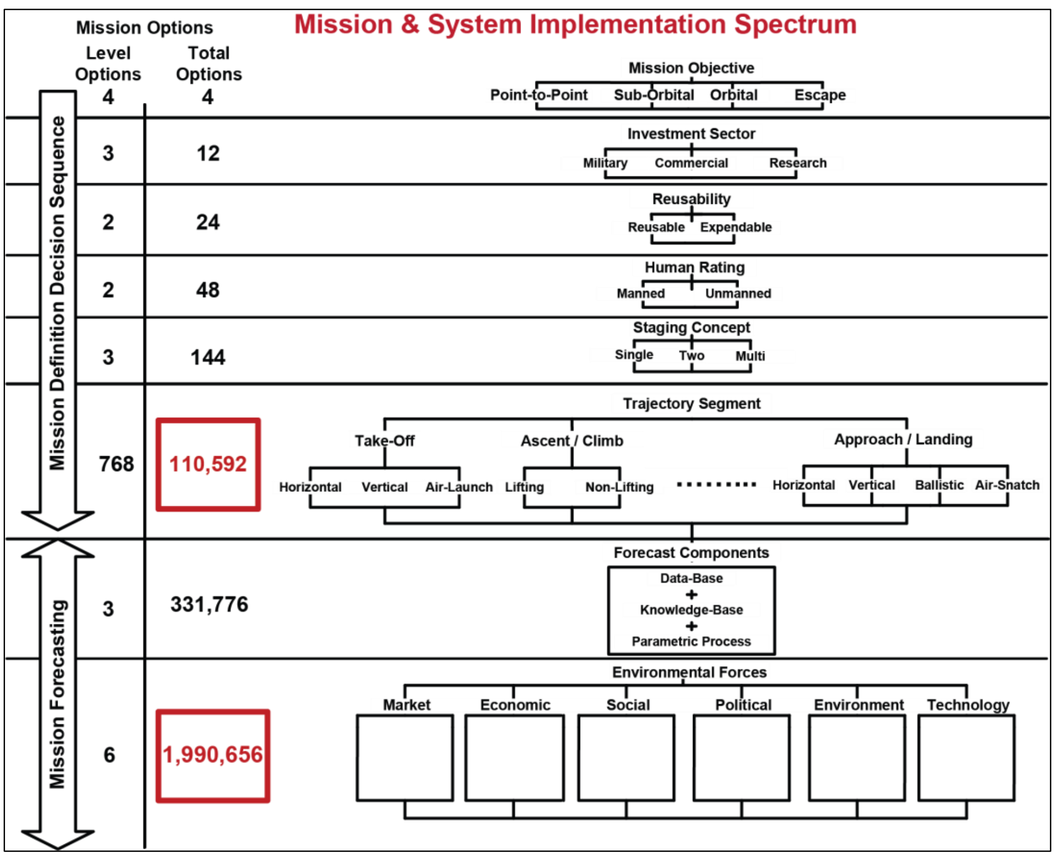

Figure 2. Illustration of orbital reentry vehicle design variables exponential increase to unsurmountable numbers

2. Design Proficiency

The CD phase is unique in the sense that it requires idea generation and therefore creativity and experience. However, an interesting trend has developed; the project exposure an engineer experiences is decreasing significantly.

Half a century ago, an engineer could expect to work on a dozen or more projects. Today, they may be lucky to see the completion of more than one. [7] The result of this phenomenon is the reduction in design exposure, design experience, and subsequently design knowledge. All of which are invaluable to a designer. This illustrates a situation necessitating a system of standardized knowledge retention, transfer, and expression.

Furthermore, there is evidence for a decreasing trend in tool integration while tool accuracy has simultaneously been increasing. Oza points out "…that qualitatively there is a noticeable change in product development vehicle sizing tool capability that spans the major eras of technology change." [8] He has observed that tool accuracy is outperforming the capture of multidisciplinary effects. This is illustrated in the figure below. Although accuracy is important, it is problematic if the toolsets and mindset of engineers and forecasters loses the ability or understanding of the significance of the design multivariate observability, testability, and understandability.

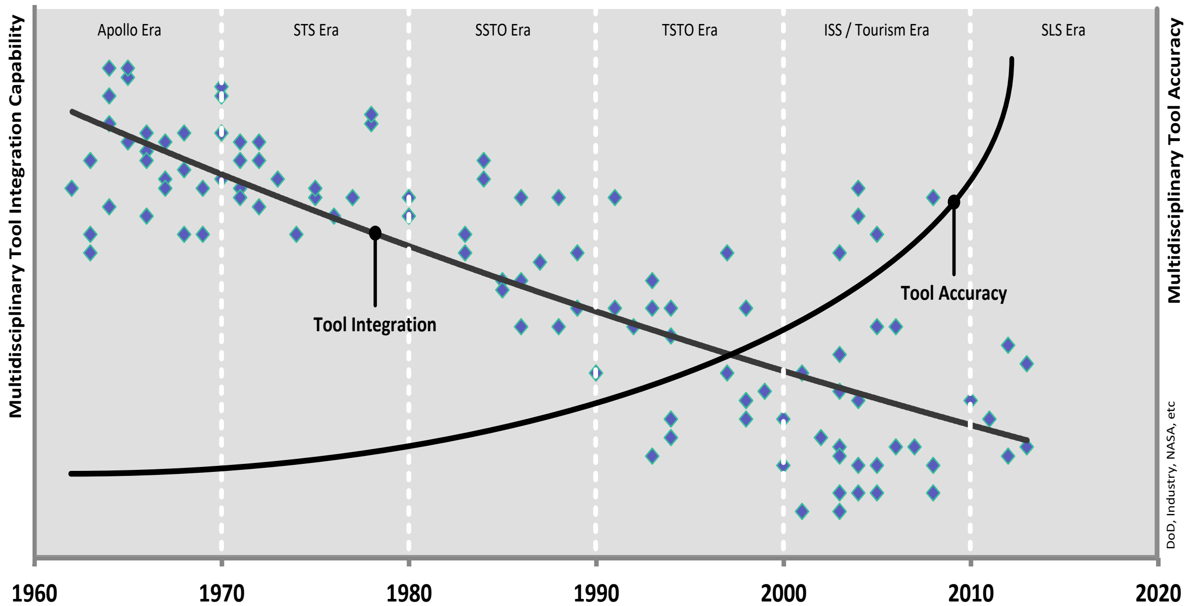

Figure 3. Forecasting capability: tool integration vs. tool accuracy [8]

B. Synthesis in Aerospace

Recalling that the objective is to arrive at the next generation toolset for and to enhance the engineer and forecaster, a consideration of the progression to the current synthesis toolsets is considered. It is necessary to first understand current approaches and evaluate how they can be improved and advanced into an intelligent frame work. Furthermore, a new classification scheme is established. A summary of the synthesis review is illustrated in Figure 4.

Chudoba [4] provides a historical review of flight vehicle design synthesis systems and tracks the evolution in design methodologies from the legacy textbook synthesis processes to the modern-day computerized synthesis systems. A hierarchy of five generations of synthesis systems is defined based on the level of increasing proficiency at integrating multi-disciplinary effects, see Table 1. The classification scheme selected distinguishes the multitude of vehicle analysis and synthesis approaches according to their modeling complexity, thereby expressing their limitations and potential. The first four generations of synthesis systems address modeling-complexity evolution of design approaches from 1905 to present day capability, highlighting primary characteristics of each class.

The transition from Class II to Class III represents the first use of computer automation in the design environment. These early design methodologies are found to focus on the selected discipline-specific analysis but lack the multidisciplinary integration that is later implemented manually. Lovell comments that, "…*initial computer applications were confined to aspects of structural analysis and wing design. There was some resistance to the use of computers in initial project design because of the complex decision-making process involved. However, they enabled more detailed analyses to be made and hence allowed a greater range of carpet plots with additional overlays to be prepared to show the effects of configuration variables on performance"* [9]

Class IV synthesis systems are identified to involve multidisciplinary integration of disciplinary analysis but are limited in application to a single-point design optimization and mostly applicable to one specific vehicle configuration. The majority of synthesis systems up to Class IV are applicable only for subsonic and supersonic aircrafts while only a select few address the hypersonic vehicle class. Synthesis systems like Czysz's Hypersonic Convergence [10] and PrADO Hy. [11] are identified as significant methodology implementations of Class IV type systems.

Table 1. Five generations of evolution of CD Synthesis approach by Chudoba [4]

Class	Design Definition	Develop Time	Characteristics
Class I	Early Dawn	Until 1905	Trial and error approach, experimental, no systematic methodology
Class II	Manual Design Sequence	1905-1955	Physical design transparency, parameter studies, standard aircraft design handbooks
Class III	Computer Automation	1955-Today	Computerization of methods, reduced design cycles, detailed exploration of the design space, discipline-specific software
Class IV	Multidisciplinary Integration	1960-Today	Computerized design system, MDO, data sharing, centralized design
Class V	Generic Design	Future Generation	Configuration independent, sophisticated design, true inverse design capability, Knowledgebase systems

The assessment leads Chudoba to define the requirements for the next generation of *Class V - Generic Synthesis Capability*, which is identified as a design process rather than a design tool. In this regard, the focus here is on developing the capability over its application. The primary emphasis in this class is on the development of modular and dedicated disciplinary methods libraries and their integration into a central multi-disciplinary synthesis architecture.

In continuation of Chudoba's review of synthesis approaches, Huang [12], Coleman [13], Gonzalez [14], Omoragbon [15] and Oza [16] have conducted additional surveys of existing aerospace vehicle synthesis approaches. These reviews cover a total of 126 synthesis approaches which include legacy textbook design synthesis methodologies and modern-day computerized synthesis systems.

Based on these reviews, the following conclusions provide an overview summary of the existing capability and major drawbacks of the traditional and current design methodologies (these methodologies fall under Class IV according to Chudoba's classification, see Table-1):

1. The majority of the existing synthesis systems have been developed for aircraft design application. Only selected few design synthesis systems exist that address hypersonic vehicle systems. Particularly, an efficient and dedicated design synthesis systems for highly integrated hypersonic vehicles is still missing that has to quantifiably forecast the mission-configuration-technology scenarios.
2. Synthesis is the primary integration capability that is the key to close (converge) the design through iterations.
3. Synthesis system are not able to efficiently define the design solution space topography; optimization is a preferred approach not the total picture.
4. Many design synthesis systems tend to have a common structure with different computational procedures. However, the design methodologies of synthesis systems are not transparent. There is a lack of efficient computerized synthesis systems and multi-disciplinary interaction at the conceptual design level.
5. Existing synthesis systems have been developed specifically for a particular type of application (e.g. subsonic, supersonic, airbreather, rocket propulsion, wing body, lifting body etc.). This implies that the many initial assumptions and methods that are hard-coded at the development stages of the synthesis system and limit its application to only that specific. As the system is applied over time, it becomes hindered and stagnated, limited by the initial application boundaries. There is no generic synthesis system for the flight vehicle conceptual design that can be consistently applied to several applications and produce a fair non-partial assessment. This inability impedes the system's ability to assess all available design options and provide the best design solution independent of hardware, configuration, and technology specifications.

The final outcome of the Gonzalez [14] endeavor was the successful development of a state-of-the-art Class-V capability, AVD-DBMS (Aerospace Vehicle Design Database Management System). The AVD-DBMS is a proven (see examples [17] [18] [19]) Class-V platform that is an instrument to generate unique user-specified problem-specific sizing code (traditionally represented by Class-IV) with complete method and process transparency. The AVD-DBMS is shown to provide the flexibility to rapidly create a new sizing code specifically tailored for independent trade execution as required by the design problem at hand. Furthermore, this allows for parallel sizing studies, thus enabling designers to generate a vast number of converged solutions and identify the wider solution space. This capability and approach allows the designer to explore the complete design solution space and parametrically compare distinct design options consistently.

The current best practice approach to synthesis is modularity as represented by the AVD-DBMS, the next step in synthesis is AI integration. Many approaches to incorporate a type of AI or machine learning techniques has been done. Common uses include expert systems, evolutionary algorithm optimization, and knowledge based systems. However, as in the case of the Class IV and earlier approaches, the systems are still problem specific. The next generational system is a AI assistant that can augment the engineer and employee dynamically the systems describe in this section.

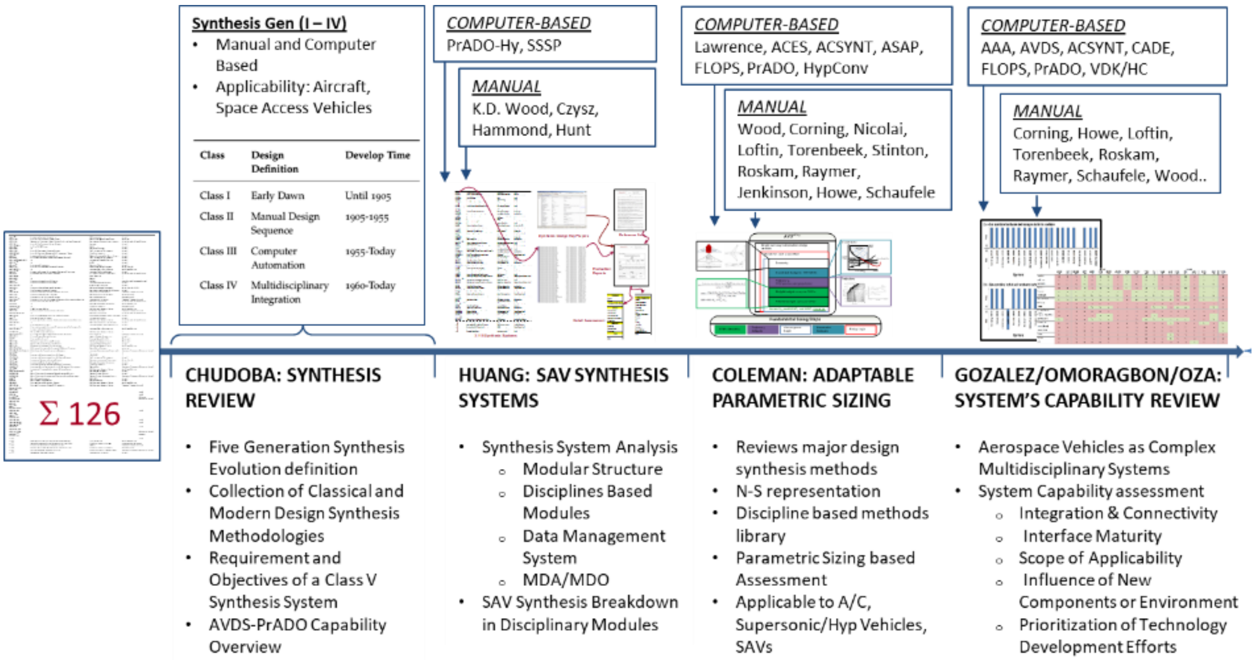

Figure 4. Synthesis System's Reviews by AVD

C. Summary and Outlook

Up to this point, a consideration of the product design cycle, the CD phase significance and inherent difficulties, and a synthesis summary review have been discussed. From this discussion, is evident that the early phase engineer and forecaster require adequate assistance and augmentation through their toolsets. The current state of toolsets shows the need for adaptability, transparency, and modularity. The solution to which is a composable multidisciplinary synthesis design fabricator as found in the AVD-DBMS. The next evolution in synthesis is the full integration and development of AI. This brings forward the next issue, defining intelligence and laying out a next generation AI assistant framework.

IV. Intelligent Assistant

In the current chapter there are three points of discussion. First, a consideration of intelligence, both human and artificial intelligence, is provided. This is followed by the general solution concept for the AI assistant where system capability and criteria requirements are identified. The chapter ends with a development roadmap to arrive at an AI assistant.

A. Intelligence

In the following section, we address two primary questions. What is intelligence? What is artificial intelligence? The intent is to establish a working definition of intelligence to guide and support the definition of an artificial intelligence design environment and subsequent solution concept.

1. Human Intelligence

The subject of human intelligence and identifying (let alone quantifying) it is a large topic unto itself and as such only a brief discussion is given here. The discussion of intelligence is ancient, going back thousands of years. For the purposes of this document, consider only the last century. A common interpretation of intelligence is the notion of multiple intelligences. In the late 1930s, Thurstone [20] correlated intelligence to multiple abilities, identifying nine (verbal comprehension, reasoning, perceptual, speed, numerical ability, word fluency, associative memory, spatial visualization). Gardner [21] similarly identified intelligence as multiple intelligences working together (Visual-Spatial, Verbal-Linguistic, Bodily-Kinesthetic, Logical-Mathematical, Interpersonal, Musical, Intrapersonal, Naturalistic). Many of these categories such as computer vision and natural language processing are currently reflected in the field of AI. Intelligence has also been classified as attributes. Sternber [22] identifies three attributes of intelligence: (1) analytical intelligence, (2) creative intelligence, (3) practical intelligence. These attributes translate to applicable aspects as problem solving, application of past knowledge to new situations, and adaptability to a new environment respectively. With these considerations regarding the discussed various attributes of the human intelligence, the next section discusses artificial intelligence.

2. Artificial Intelligence

The definition of AI depends on the individual asked. In its broadest state, artificial intelligence is the mimicking of human intelligence by a computational means. As stated by Munakata, AI is "…the study of making computers do things that the human needs intelligence to do." [23] Russel further breaks the definition down based upon thought process and reasoning, and behavior arriving at four distinct definition categories. [24] The four definition categories are (1) systems that think like humans, (2) systems that act like humans, (3) systems that think rationally, and (4) systems that act rationally. Given that the CD phase is the arena of the proposed research and synthesis system development is the objective, the broad working definition of AI, is a system that acts rationally where a "…system is rational if it does the 'right thing,' given what it knows." [24] For the purposes of engineering it is logical to arrive at Russel's definition. However, the definition needs to be expanded into an even more usable sense. Human intelligence is a multidimensional ability to apply past knowledge and experience to adapt to a new situation and solve a problem. If this notion of human intelligence is correlated to rational acting as described by Russel and combined with a best practice approach to engineering (see Figure 5), a working definition of artificial intelligence for engineering design application is arrived at. Translating this to the engineering and computer domain, artificial intelligence is the self-utilization of a connected database, knowledge base, parametric process, and logic base to arrive at and adapt to a new situation to solve a problem and derive new understanding of a topic following the rational application of an integrated, converging, and self-assessing process.

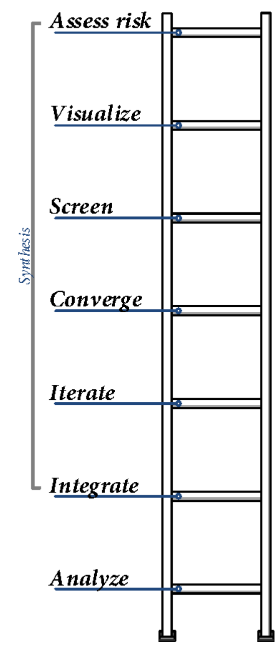

Figure 5. Design ladder

B. System Concept

Based on the consideration of the CD phase, it has been established that the CD phase is grossly hindered by the problem of knowledge and proficiency degradation and retention. Based on the synthesis system review, the resulting conclusion is that most computational toolsets are highly developed high-fidelity thus high-inertia tools that generally require excessive source code familiarity and user time input to produce any significant modification to allow the system to address unique applications and configurations not originally considered in the tool development. With these conditions, a next-generation system is not only logical but urgently required. This is best stated by the following:

> *Currently, any design synthesis or design update depends on the designer's ideas and experience base on an ad hoc basis. Possible approaches to technology leaps in this area include idea stimulus approaches; use of artificial intelligence and knowledge-based systems to convert designer's judgments and rules of thumb into algorithms; techniques for visualization of the design space; multidisciplinary optimization; and automated synthesis or inverse engineering* [25]

To that end, the objective is to develop a Class VI system.

The AI solution concept is now outlined and discussed in this section. The fundamental criteria requirements for a best-practice conceptual design toolset have been deduced through the synthesis system's review. These criteria act as the merit of measure for the fundamental solution logic and define the primary characteristic attributes of the system. We begin by identifying several key system criteria requirements and follow with a general definition and explanation of the solution concept. The requirements of the system's capability are determined by the now identified character of intelligence and the necessities of the highly fluid and non-static nature of the conceptual design phase.

1. System Criteria Requirements

Based on the synthesis system review, a necessity of a toolset is identified that is capable of rapid turnaround with a modular structure to adapt to new concepts and configurations, thus providing the designer with an advanced synthesis capability to develop comprehensive solution design topographies. Such a tool would require minimal user knowledge of the system and minimum user time investment for the output of a useable synthesis or sizing code with awareness of the developing world of artificial intelligence and potential future application.

The system criteria requirements are determined by the now identified shortfalls of current synthesis systems and the necessities of the highly fluid and non-static nature of the conceptual design phase. The following are identified as the primary requirements criteria for a best-practice next-generation synthesis capability:

- *Flexibility*: modularity to handle any fidelity and unique concept or configuration.
- *Adaptability*: ability to adapt to new problems, vehicles, or configurations while maintaining applicability and usability.
- *Expandability*: ability to expand the underlying framework and capability when new data, knowledge, and processes are added
- *Transparency*: transparent to the user and customer (if desired) of the operation of processes and systems, the methods, underlying knowledge and data.
- *Rapidity*: quick turnaround, able to adapt and keep up with a rapid environment and quick turnaround deliverable times
- *Automation*: key pre-requisite to arrive at an efficient assistant.

2. System Capability Requirements

The above requirements translate into a CD phase capability (where synthesis occurs) that is critical to design success. This next generation AI environment is tasked to provide the individuals involved access to the best tools available. Since modern synthesis methods the aerospace industry is experiencing will continue to grow in complexity, the AI implementation has a primary focus on time to market and cost. Since the environment will continue to become even more computationally rich in the data-knowledge-process domains, beyond the reasoning abilities of humans, automated AI synthesis is the primer with the following system requirements:

- knowledge generation and retention through dynamic knowledge base & data base;
- scenario based multi-disciplinary analysis (MDA) design and integration;
- self-composing architecture capability with configuration, hardware, and mission independence;
- visualization and interpretation of design space topography;
- natural language interfacing;
- rational action without human oversight;

The objective is to create a unique system not bound by a fixed analysis structure that can self-educate, self-act, and do so with the best critical thinking process available.

3. Concept

The topic of the AI research assistant aimed at augmenting hypersonic vehicle and technology forecasting are both areas of high impact. They necessitate advancement due to several decades of stagnation and neglect in the aerospace domain. The current approach to design and decision support is plagued with problems, including (a) dependency on disciplinary optimization to convince and assure without offering a multi-disciplinary guarantee of total system convergence, (b) non-standardized approach to synthesis system assembly, and (c) machine learning and AI being inadequately applied, frequently relegated to optimization and parameter approximation. Upon successful completion, this study advances the standard for design through three avenues: (1) transparency (2) design approach standardization and consistency (3) knowledge and data retention and derivation. This platform will enable organizations to innovate rapidly but more importantly experiment at lower cost and build shorter fail-cycles. It is the cost of experimentation that affects the frequency to experiment and it is the lack of experimentation that hinders knowledge expansion.

The objective is the development of an Aerospace Vehicle Design AI assistant (AVD-AI) that represents a best practice implementation of an AI augmented multi-disciplinary vehicle synthesis framework that integrates a dynamic Data Base System (DBS), Knowledge Base System (KBS) and Parametric Process System (PPS). The AVD-AI system is envisioned to support the decision-making process by providing an intelligent, adaptive, and parametric framework for systems design, strategic planning, and technology forecasting. AVD-AI is an evolution of the currently existing best practice aerospace design synthesis capability residing in the AVD Laboratory, the AVD-DBMS platform.

The DBS, KBS, and PPS implementation is analogous to and emulates the human domains of memory, experience, and logic that enables dynamic feedback learning and decision-making capabilities of organic intelligence, see Figure 6. The symbiosis of these modules uniquely allows this first-generation artificial design intelligence synthesis system to correctly solve multi-disciplinary aerospace-related problems. This next-generation artificial-design-intelligence assistant correctly and comprehensively supports the human decision-maker and designer of aerospace vehicles. The resulting system's overall aim is at reducing cost, risk, and development time spans by accelerating the design process by augmenting the person with an intelligent computer assistant.

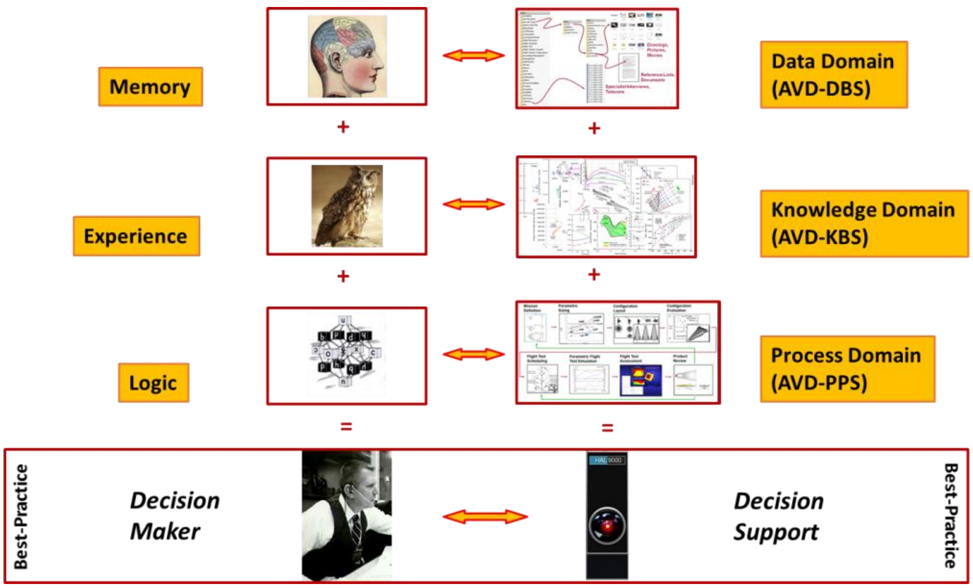

Figure 6. Correlation of biologic intelligence foundation blocks to computer domain

To create such a unique entity requires four critical elements. The elements are: (1) Database (DB), (2) Knowledge Base (KB), (3) Process Base (PB), and (4) a Great Intelligence (GI). The DB, KB, and PB provide the foundation of which the GI acts and are the common elements to many current synthesis tools. However, the implementation and process of integration and utilization of these three elements will be unique. Elements 1-3 have been the work of five different PhD projects within the AVD Laboratory over the last decade. Those research efforts focused on the first three elements. The following outlines the conjunction with the fourth element.

The GI is comprised of four fundamental elements. The elements are expert system, multi-variable multi-disciplinary optimization, Pareto Analysis, and data mining. Each element will be a different independent module. The expert system requires the data mining and Pareto Analysis to feed the inference system for knowledge deduction and induction. The Pareto Analysis is a logic element for the system to identify relevant design variables to execute logic algorithms. The GI will result in a capability to retain design knowledge, identify key design variables, provide an independent design capability without human logic input, provide a solution space identification capability, and derive new knowledge of the system studied all while acting independently and rationally.

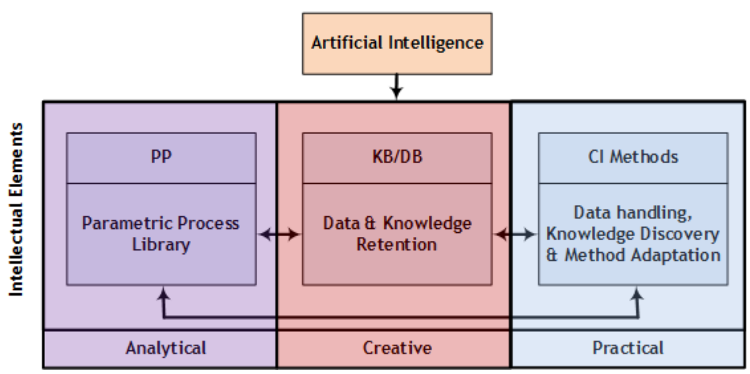

Figure 7. General AI solution concept blocks

C. Development Outlook

The drive towards an intelligent assistant has been organized into a. five sequence approach. Each sequence is composed of individual tasks.

Figure **8** shows an overview of the approach. The sequence's five sub-phases with primary objectives are defined below.

I.1) Preparation: Establish *Situational Awareness* of the current state-of-the-art in the selected AI domain through a dedicated literature review. Identify, test, and evaluate approaches for system use and integration. Identify and formulate solution concept.

I.2) Experiment Setup: System Conditioning tasks are performed by preparing training data; fundamental system building blocks are populated, trained, and formulated (such systems are database, knowledgebase, methods library, and evaluation metrics).

I.3) Experiment Execution: System Development occurs here through integration of fundamental building blocks (defined in previous step) in the AVD-DBMS platform.

I.4) Prototype Evaluation: System Execution takes place in this sub-phase where the AVD-AI capability is validated through a synthesis case-study demonstrating impact of inclusion of prior knowledge on enhanced performance.

At this point, research activities are in sequence 1.1. The remaining elements of this paper presents the results of an exploratory study to evaluate the potential for neural network application to sizing approximation.

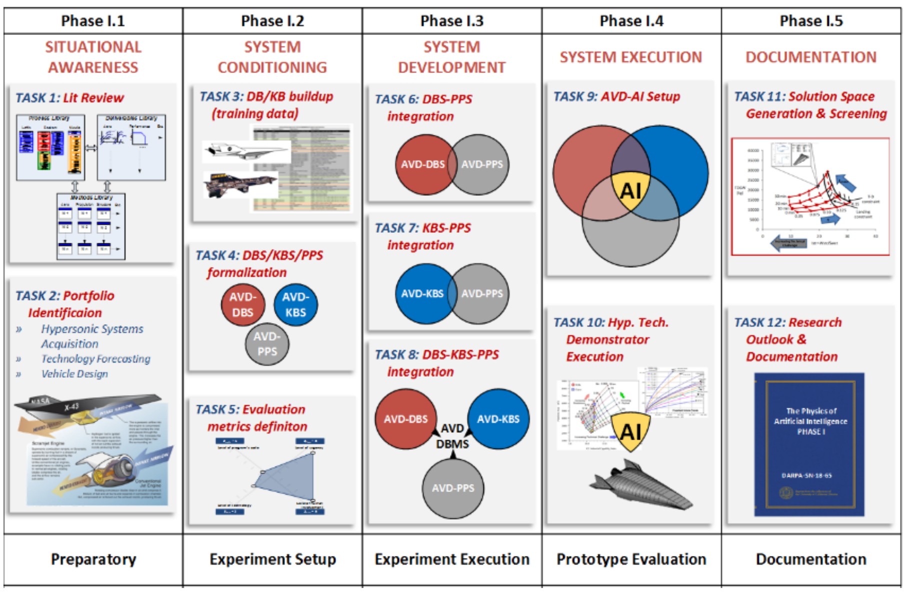

Figure 8. Phase I tasks, schedule, and milestones overview

V. Synthesis Augmentation

In the current section, the experiment setup for the machine learning approach is provided followed by the execution results.

A. Purpose

The purpose of this experiment is to test the viability of using machine learning, specifically a neural network, to predict sizing outputs. The objective is to identify if the approach delivers sufficiently accurate results to provide a first estimate to a sizing routine. It is expected that such a system could be used to provide a sufficiently accurate first guess of the independent convergence variables in order to accelerate the convergence process. Additionally, a secondary purpose is to evaluate the accuracy of a machine learning augmentation in the sizing application. In regards to the execution of the machine learning process, a frequent issue is that the results are obtained without a physical understanding of how or why the results are correct or arrived at exists. The opposite is true for this situation. The underlying physical models are sufficiently known, however, the execution process is time expensive. The goal is to skip the known physics to arrive at a suitably accurate result.

B. Approach

1. Process

After generation of the test data two sets of matrices of a) input, and b) target are needed. With the help of a built-in Fitting App within the Neural Network toolbox, the data will be ready for the training phase. Figure 9 shows the process flow of the method implement.

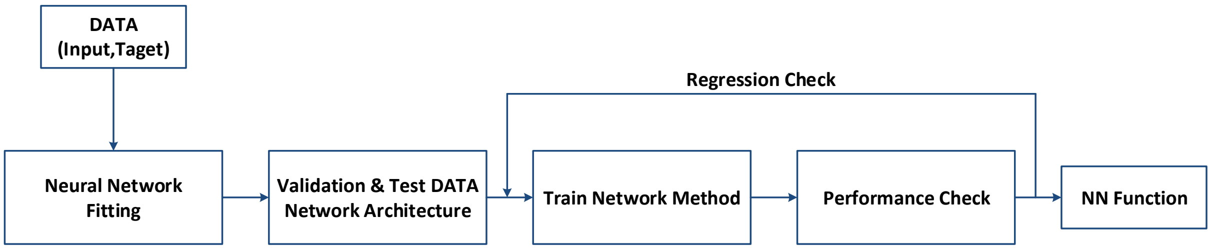

Figure 9. Data training flow diagram

The following steps define the process to develop a neural network function which is utilized for this study:

1) Pick the sample data from workspace.
2) Define Input and Target values.
3) Assigning Validation and Test data as fraction of the whole.
4) Assigning the number of the desired networks.
5) Choose a training method and train the data correspondingly.
6) Check the performance and the regression of the data.
7) If the desired analysis achieved, export the function code for usage.

2. Data Generation

With the help of AVD-DBMS, a total of 1200 lifting body vehicle cases have been sized for this experiment. The overall study is broken down into three phases, a) Gather the neural network function for all the 1200 cases, b) Randomly select 240 cases and re-train the network, c) Randomly select 60 cases and re-train the network. The inputs to the training system consist of slenderness ratio (τ), cross-section base area shape, cargo weight, and ΔV.

Decreasing the number of training cases at each time will allow to check for the accuracy of the network study and the final differences. If less data proves that the system keeps it accuracy at a desired range, the run time can decrease drastically. The training methods used throughout this study are a) Levenberg-Marquardt b) Bayesian Regularization c) Scaled Conjugate Gradient.

C. Results

Table 2 shows the comparison results of trained data of 1200 different lifting body vehicles versus the DBMS calculated value. The purpose of this table is to check the accuracy of the method and check even if this approach is applicable. By analyzing the data, it is calculated that Bayesian Regularization Method (b) provided the higher accuracy for this study. Next step of this study is to reduce and eliminate the initial training data. This means, by training the neural network system with less number of sample data, the system can generate same accuracy in it's results.

Table 3 shows the results using only 240 points to train the system and input five random points outside of the trained data boundary to assess the accuracy of the trained system. It is visible that the %Error increased in comparison to Table 2 but is still within the desirable range. Again, the Method (b) shows a better accuracy for this study. Lastly the same study has been conducted but only with 60 points to train. Based on presented results in Table 4, it is clear that the less training point will decrease the accuracy of the system when the input outside the training boundaries are used. These results can now be used as initial guess into the DBMS system to help forecaster/designer to arrive at their desired converged vehicles is faster manner.

Table 2. Comparison between three neural network training methods

Method		Actual		Experimental		% Error	
		S_{plan}	W/S_{plan}	S_{plan}	W/S_{plan}	S_{plan}	W/S_{plan}
a	P1	28.49	8750	31.33	8754	9.06	0.04
	P2	24.04	9672	28.93	9664	16.90	-0.08
	P3	51.41	6840	44.24	6842	-16.19	0.04
	P4	89.76	4202	90.40	4206	0.70	0.08
	P5	28.37	11424	29.61	11446	4.19	0.19
b	P1	28.49	8750	28.57	8750	0.28	0.00
	P2	24.04	9672	24.28	9672	1.00	0.00
	P3	51.41	6840	50.40	6839	-2.00	-0.01
	P4	89.76	4202	89.41	4202	-0.40	0.00
	P5	28.37	11424	28.59	11424	0.78	0.00
c	P1	28.49	8750	-119.69	8613	123.81	-1.59
	P2	24.04	9672	164.46	9847	85.38	1.78
	P3	51.41	6840	136.74	6238	62.41	-9.64
	P4	89.76	4202	96.98	3785	7.44	-11.02
	P5	28.37	11424	57.49	11834	50.65	3.46

Table 3. Accuracy comparison of 240 points with random inputs

Method		Actual		Experimental		% Error	
		S_{plan}	W/S_{plan}	S_{plan}	W/S_{plan}	S_{plan}	W/S_{plan}
a	P1	53.31	3550	52.53	3553	-1.49	0.09
	P2	31.86	8223	30.15	8238	-5.68	0.19
	P3	24.04	9672	24.13	9659	0.36	-0.14
	P4	59.38	1812	61.09	1805	2.80	-0.43
	P5	34.64	5418	34.92	5420	0.80	0.03
b	P1	53.31	3550	53.92	3558	1.13	0.24
	P2	31.86	8223	30.80	8203	-3.44	-0.25
	P3	24.04	9672	24.59	9623	2.24	-0.51
	P4	59.38	1812	58.39	1805	-1.69	-0.40
	P5	34.64	5418	35.90	5461	3.52	0.78
c	P1	53.31	3550	67.51	3778	21.03	6.04
	P2	31.86	8223	-18.21	9321	274.96	11.78
	P3	24.04	9672	-2.40	9630	1100.14	-0.44
	P4	59.38	1812	67.04	1909	11.42	5.06
	P5	34.64	5418	112.29	4844	69.15	-11.84

Table 4. Accuracy comparison of 60 points with random inputs

		Actual		Experimental		% Error	
Method		S_{plan}	W/S_{plan}	S_{plan}	W/S_{plan}	S_{plan}	W/S_{plan}
a	P1	53.31	3550	50.88	2960	-4.79	-19.93
	P2	31.86	8223	20.58	4193	-54.79	-96.11
	P3	24.04	9672	21.18	6859	-13.50	-41.02
	P4	59.38	1812	59.66	1810	0.46	-0.13
	P5	34.64	5418	29	3816	-20.18	-41.99
b	P1	53.31	3550	51.08	2959	-4.37	-19.97
	P2	31.86	8223	22.24	4210	-43.25	-95.34
	P3	24.04	9672	19.59	6805	-22.74	-42.14
	P4	59.38	1812	60.77	1804	2.28	-0.44
	P5	34.64	5418	27	3799	-30.33	-42.62
c	P1	53.31	3550	-213.36	2979	124.99	-19.15
	P2	31.86	8223	367.52	3576	91.33	-129.91
	P3	24.04	9672	46.97	7150	48.82	-35.28
	P4	59.38	1812	39.96	1798	-48.59	-0.81
	P5	34.64	5418	-20.44	4154	269.47	-30.44

VI. Conclusion

This document communicates the research and development of an intelligent research assistant for the engineer and decision maker endeavor at the AVD Laboratory at the University of Texas. The objective is to derive, construct, and test a prototype AI research design assistant for technology forecasting applied to hypervelocity systems. The proposed system will incorporate (1) best standard approaches for synthesis (2) data and physics driven high-dimensional systems modeling and (3) knowledge derivation and retention. Fundamentally, the system proposed is an AI-human collaborative development, discovery, and exploratory conceptual-design synthesis system approach and execution. The objective is to push the bounds of the current state-of-the-art to illustrate a total system technique in which conceptual design synthesis of a product is done consistently, correctly, and with the assistance of an AI computer assistant. This assistant will be able to retain, derive, and present solution concepts, data, and new knowledge at the benefit of the current and future human operator. The result would be a better-informed workforce allowing for better decisions and reduction in errors and therefore costs.

The hypersonic or hypervelocity vehicle was selected for the topic for the development of the AI assistant. Today, a key contributor aiding the development of hypersonic flight test vehicles is effective preservation and constructive application of the available past-to-present hypersonic knowledge-base. The AI system is needed to accelerate and leapfrog the industry to identify disruptive vehicle configurations not identified with techniques used previously. The hypersonic vehicle drive for fruition has been slow and arduous, hampered by cyclic interest and funding. The result has been a slow configuration evolution over the past half-century.

This document additionally communicated the results of an exploratory study into sizing augmentation by neural networks. The objective is to investigate the applicability of a neural network trained to predict sizing architectures converging variable output with the goal to accelerate the convergence process through improved first guess values. The results showed a satisfactory accurate capability. The next step in this exploratory study is to expand the study to include incomplete data sets, randomness, and convergence time improvement.

VII. References

[1] L. M. Nicolai and G. Carichner, Fundamentals of Aircraft and Airship Design, vol. 1, AIAA, 2010.

[2] G. Coleman, "Aircraft Conceptual Design - An Adaptable Parametric Sizing Methodology," 2010.

[3] E. Torenbeek, "Synthesis of Subsonic Airplane Design, 1982," *Delft: Springer.*

[4] B. Chudoba, Stability and Control of conventional and Unconventional Aircraft Configurations: a Generic Approach, BoD--Books on Demand, 2001.

[5] B. Chudoba and W. Heinze, "Evolution of Generic Flight Vehicle Design Synthesis," *The Aeronautical Journal,* vol. 114, no. 1159, pp. 549-567, 2010.

[6] C. Krishnamoorthy and S. Rajeev, Artificial Intelligence and Expert Systems for Engineers, vol. 11, CRC press, 1996.

[7] B. Chudoba, "Managerial Implications of Generic Flight Vehicle Design Synthesis," in *AIAA Paper, AIAA-2006-1178, 44th AIAA Aerospace Sciences Meeting and Exhibit, Reno, Nevada*, 2006.

[8] A. Oza, "A Portfolio-based Approach to Evaluate Aerospace R&D Problem Formulation Towards Parametric Synthesis Tool Design," 2016.

[9] D. Lovell, "Some Experiences with Numerical Optimisation in Aircraft Specification and Preliminary Design Studies," in *International Congress of the Aerospace Sciences*, Munich, 1980.

[10] McDonnell-Douglas, "Hypersonic Research Facilities Study. Volume II Part 2 Phase I Preliminary Studies Flight Vehicle Synthesis," NASA-CR-114324, NASA, 1970.

[11] W. Heinze, "Ein Beitrag Zur Quantitativen Analyse Der Technischen Und Wirtschaftlichen Auslegungsgrenzen Verschiedener Flugzeugkonzepte Fur Den Transport Grosser Nutzlasten," Ph.D. Dissertation, 1994.

[12] X. Huang, "A Prototype Computerized Synthesis Methodology for Generic Space Access Vehicle (SAV) Conceptual Design," Ph.D. Dissertation, The University of Texas at Arlington, Arlington, TX, 2005.

[13] G. Coleman, "Aircraft Conceptual Design-an Adaptable Parametric Sizing Methodology," Ph.D. Dissertation, The University of Texas at Arlington, Arlington, TX, 2010.

[14] L. Gonzalez, "Complex Multidisciplinary System Composition for Aerospace Vehicle Conceptual Design," Ph.D. Dissertation, The University of Texas at Arlington, Alrington, TX, 2016.

[15] A. Omoragbon, "Complex Multidisciplinary Systems Decomposition for Aerospace Vehicle Conceptual Design and Technology Acquisition," Ph.D. Dissertation, The University of Texas at Arlington, Arlington, TX, 2016.

[16] A. Oza, "Integration of a Portfolio-based Approach to Evaluate Aerospace R and D Problem Formulation Into a Parametric Synthesis Tool," Ph.D. Dissertation, The University of Texas at Arlington, Arlington, TX, 2016.

[17] L. Rana, T. McCall and B. Chudoba, "Parametric Sizing Boeing X-20 DynaSoar to Gain Program Architectural Understanding of Sierra Nevada Corporation’s Dream Chaser (AIAA 2017-5355)," in *AIAA SPACE and Astronautics Forum and Exposition*, Orlando, FL, 2017.

[18] L. Rana, T. McCall, J. Haley and B. Chudoba, "Conceptual Design Solution Space Identification and Evaluation of Orbital Lifting Reentry Vehicles based on Generic Wing-Body Configuration (AIAA 2017-5127)," in *AIAA SPACE and Astronautics Forum and Exposition*, Orlando, FL, 2017.

[19] L. Rana, T. McCall, J. Haley and B. Chudoba, "Parametric Sizing Implementation for Generic Lifting-Body Configuration Executing a Low Earth Orbit Mission (AIAA 2017-5356)," in *AIAA SPACE and Astronautics Forum and Exposition*, Orlando, FL, 2017.

[20] L. L. Thurstone, Primary mental abilities., Chicago, 1938.

[21] H. Gardner, Frames of Mind: The Theory of Multiple Intelligences, Basic Books, 1993.

[22] R. J. Sternberg, Beyond IQ: A Triarchic Theory Of Human Intelligence, Cambridge University Press, 1985.

[23] T. Munakata, Fundamentals of The New Artificial Intelligence: Neural, Evolutionary, Fuzzy and More, Springer Science & Business Media, 2008.

[24] S. Russell, P. Norvig and A. Intelligence, Artificial Intelligence A Modern Approach, 2 ed., Pearson Education Inc, 2003, p. 27.

[25] J. Blair, R. Ryan, L. Schutzenhofer and W. Humphries, "Launch Vehicle Design Process: Characterization, Technical Integration, and Lessons Learned," 2001.