Embracing the fourth Industrial Revolution - Challenges, Opportunities and Path Forward for Propulsion

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The aerospace industry is at a point where components are reaching design maturity and performance improvements are incremental. Other industries are competing for high skilled labor as barriers to entry are being lowered by technological developments with tech and phone companies making cars. Gaming and social media continue to become viable professions, further depleting the aerospace candidate pool. Workforce challenges and the looming threat of climate change necessitate a new paradigm. An artificial intelligence (AI) approach that enables revolutionary changes in system architecture, mission analysis and performance metrics is needed. The growing interest and development in the field of machine learning (ML) presents an opportunity to speed up by 10X or more the discovery, analysis and development of aerospace systems using artificial intelligence. Through Intelligent Design and Engineering of Aerospace Systems (IDEAS) we are embarking on a research and development effort that addresses this opportunity with a mindset to engage citizen scientists in aerospace. The objective of IDEAS is to enable design of systems based on requirements by leveraging citizen scientists, gamification, automation and artificial intelligence. We discuss possible approaches to generating data, training models and applying them to near term applications. Results of recent workshops with industry, academia and other agencies to identify challenges to adopting AI and machine learning are presented.

I. Nomenclature

α	=	angle of attack
N_{crit}	=	background disturbance level
Cl	=	lift coefficient
Cd	=	drag coefficient
Cm	=	moment coefficient

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Re	=	Reynold number based on chord
ss	=	suction side
ps	=	pressure side

II. Introduction

The human population, while still growing, is projected to plateau [1] toward the end of this century due to a drop in fertility rates driven by increased lifespans, reduced infant mortality and increased women's education levels. Fig. 1 shows the global population trend till 2100. The trends are nuanced though, as shown in Fig. 2 [2], with sub-Saharan Africa poised to continue growth while Central and Southern Asia see their peaks in the 2050s and Europe and North America show populations leveling off around 2025. This global plateauing is not as severe a crisis to the continuation of our species as the one our ancestors possibly faced while migrating out of Africa over the last 100 000 years [3]. However, locally, there are implications to our technological evolution. Our ancestors survived by being generalists, cooperating with each other and adapting to local conditions. It may well be that our technological survival requires such localization, cooperation, and adaptation with respect to technology development.

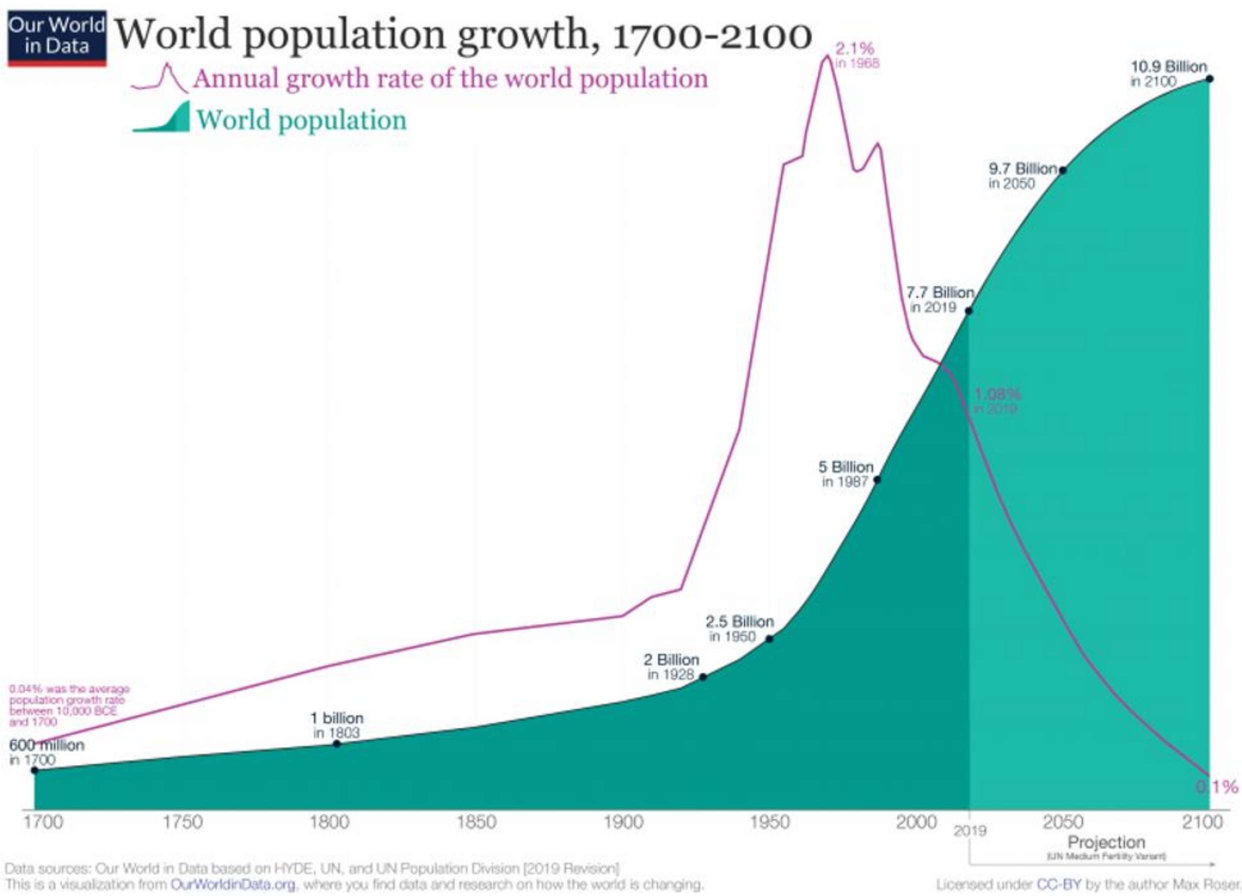


Fig. 1 Global population projection 2100 [1].

In the short term, urbanization is leading to a migration to cities as people look for opportunity and social mobility [2]. Remote work may drive a counter trend among certain demographics and segments of the workforce but emigration and inertia in the current socio-economic systems will likely see urbanization continue as a trend for at least a few decades. If our city planning, state and national infrastructure do not change, a majority of the ongoing population growth is set to be absorbed by urban centers. This presents challenges to sanitation, sustainability, congestion, safety and urban heat maps [4]. Sanitation includes people, processes and infrastructure related to ensuring clean drinking water, treatment and disposal of human excreta and sewage. Infrastructure may include transportation, buildings and trash cans. Processes may include filtration, recycling, moving waste or sewage from one location to another as relates to storm water, wastewater, solid waste. Congestion could lead to increased pollution, accidents and safety concerns. Considering that air transport related injuries are one of the lowest among transportation related injuries according to the U.S. Bureau of Labor Statistics [5], is there a role for the aerospace industry in tackling these challenges whether through technological or logistical means? Some potential paths forward might be integration of sanitation and power generation perhaps by using waste for power generation, intelligent routing, use of green aerial vehicles for sanitation to improve urban air quality by routing sanitation transport away from populated areas, the use of autonomous air vehicles to provide services and utilities to underserved populations and the integration of aviation with other local, state and national infrastructure. It might also be possible to leverage the growing access to space as a solution to some of these challenges.

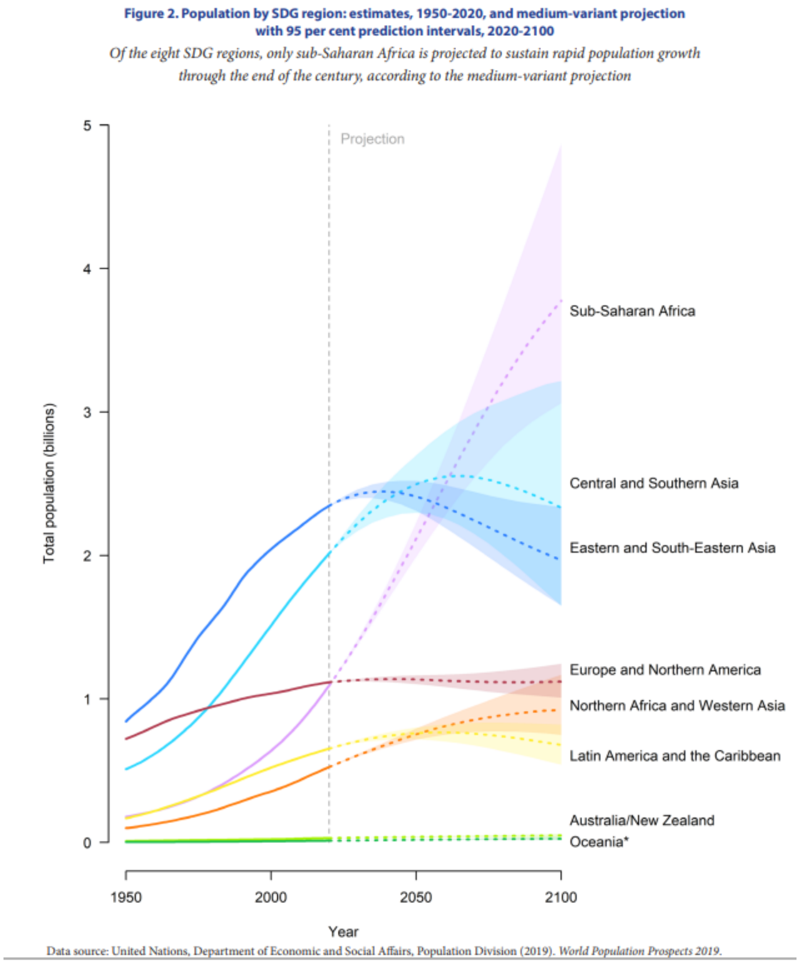


Fig. 2 Population projections by region [2].

While there are potentially several mitigating factors such as life extension and immortality projects [6][7][8] bearing fruit or a sudden reversal in fertility rates, it seems that the number of people available to perform work will decrease just as the rate at which technology advances and diversifies will increase at pace. Machine learning is coincidentally being used in many of these efforts to utilize large databases of human genotypes and phenotypes to develop approaches to combating diseases and promoting long life. Another controversial life extension practice is cryonics [9] that has been popularized for long duration human space travel. Ironically, easier access to space for human colonization might lead to yet another hominin exodus event, shrinking Earth's population. This leads to several challenges.

The first and most obvious challenge is a labor shortage. Highly skilled people entering the job market are being pulled into the commercial space sector [10][11], tech and information technology. We face the inevitable retirement of a large number of retirement-eligible workers [11] especially considering the higher proportion of baby boomers employed in aerospace. This was compounded by the recent COVID-19 pandemic that caused many to take a look at their life choices and reevaluate priorities, leading to retirements and career changes. Gaming and social media are becoming more profitable as a profession, attracting many new graduates. Some estimates show that there are approximately 2.69 billion gamers worldwide with $950 million in eSports revenue in 2020 [12]. The article in FinancesOnline [12] provides an excellent breakdown of gaming demographics by region, game type, rationale for gaming, and type of gaming platforms.

Second, more people are disconnected from the technology being developed. This includes not understanding more than the superficial minimum required to use technology, not being aware of how their data is being used by technology, not being aware of impacts to society from the use of technology and misuse of technology. A simple example of misuse can be seen with something as simple as gloves where even nurses and doctors may touch a trash can with gloves and then a patient or their face thus transferring germs. Perhaps technology needs to incorporate ways of showing impact in addition to performing a designated function. In the case of the glove, perhaps changing color when contacting germs or incorporating structural elements that prevent bio-films from forming, taking into account user behavior.

Another prescient challenge that is among the top 15 concerns of Americans [13] is growing income inequality and perceived lack of opportunity and social mobility. This is especially true of underserved communities and the bottom 95% of wage earners as seen in data from the U.S. Census Bureau [14]. This trend exists in many English-speaking nations while France, Japan and many other countries have closed the income inequality gap. While the causes have according to literature been linked to policy decisions in the past, future levers of income inequality might be technology development pace and the ability of regulations to keep pace with them. A related topic is tracing value added. If an organization uses publicly funded research from an institution such as a museum or a zoo to develop a product such as in the cases of biomimicry, does any recognition or remuneration go back to the publicly funded institution? May AI/ML play a role in tracing impacts of decisions? Can impact and value tracing/tracking be built into a product's or a process' lifecycle? Is it possible to be more inclusive of people in the design and development phases of products, processes and policy with a view toward equity?

The ability to 3D print almost anything including weapons brings with it the possibility of printing armed drones that are weaponized adding to fear of terrorism. This is yet another concern among Americans and also identified in IATA's report on the future of the airline industry [15]. In-home print centers, community print centers and more personalized technology are inevitable. Microfactories [16] are a trend in this direction with localization, sustainability and automation as a focus. How might we ensure the safe deployment of this technology? How might we make the access to personalized technology more equitable and targeted toward social/public good? Undoubtedly, organizations such as the FAA may not be able to review and certify each piece of technology being developed. Is it possible to build an ontology of the real world such that we can use AI/ML to automate certifications and to ensure safety?

With the emergence of new propulsion markets and the gradual evolution of traditional markets, there is a broader design space that needs to be explored, by considering multiple functions while respecting new and emerging constraints. Traditional design methodology would take too long to discover, explore, and optimize this design space. The rapid product development cycle requires faster testing of integrated systems and designing the next test based on previous test data. Machine learning and artificial intelligence may provide a path forward.

All these trends point to the need to rethink the way we design, develop and deploy processes and technology. According to the World Economic Forum [17], "The real opportunity is to look beyond technology, and find ways to give the greatest number of people the ability to positively impact their families, organisations and communities." Is it possible for large organizations to establish a symbiotic relationship with the larger population by engaging them in the design and decision-making processes? Can we opensource codes and datasets to train common machine learning models? Can we gamify development to explore a larger design space and better engage the community? Can we track value added by the community and monetize the crowd's contributions to ensure equity?

With these challenges and opportunities in mind the authors seek to

1. identify NASA's role with respect to aeronautics (focus on propulsion) in the emerging digital ecosystem, given the sharp increase in the number of technology areas while budgets and workforce remain relatively constant.
2. establish a framework for rapidly developing concepts, evaluating ideas and analyzing systems to minimize cost and risk while increasing productivity, durability and operability in a complex ecosystem of sUAS (small unmanned air systems), UAS (unmanned air systems), PAVs (personal air vehicles) and other aircraft.
3. demonstrate or prototype the framework by designing from scratch a propulsion system that is part of an optimized overall system considering multiple interfaces, changing environmental conditions and mission points.

Note that while this effort focuses on propulsion in the near term, it is assumed that in the future, propulsion and other aspects of flight will be tightly integrated and thus we may talk of propulsive airframes or lifting engines. A framework that is able to tackle a multifunctional propulsion system design should be able to design other aspects of an aircraft and eventually multimodal transport.

III. Snapshot of Current Landscape

Here, we start with the current practice in various areas of propulsion system design.

A. Technical practice

Propulsion system design is currently carried out through a linear (iterative) process using systems analysis tools to assess and optimize design ideas. For instance, Numerical Propulsion System Simulation (NPSS) [18], NDARC [19], and Open Multidisciplinary Analysis and Optimization (OpenMDAO) [20] are based on independently designed components (compressor maps, material durability, cycle parameters) and legacy data or on low order analytic models primarily using gradient-based methods to optimize designs. Too many variables are involved in the design process to accommodate multi-functional component design that deviates from conventional architecture. Yet, new mission concepts require nonlinear interactions between components and the use of multi-functional architectures. Tong [21] used machine learning to predict core sizes for high efficiency turbofan engines. The study included a total of 200 engines, highlighting the lack of publicly available data for machine learning. One may do a more detailed analysis using computational tools. However, these are expensive with Large Eddy Simulation (LES), topology optimization and Direct Numerical Simulation (DNS) requiring large processing power and time not just to run simulations but also in preprocessing tasks such as model development and meshing [22]. These simulations are constrained by the fidelity of the models that are being meshed and the quality of the mesh. For multiphysics computations, this problem is exacerbated. Tallman et al. [23] state that AI surrogates provide improved productivity, robustness and accuracy while reducing cost and simplifying logistics and decision-making. In addition, AI surrogates may improve portability. For example, models trained at one university may be used directly by researchers everywhere without needing the original training set or the code used by the originators. A step forward in scalability and portability is the use of graph networks to simulate fluids and solids. Sanchez-Gonzalez et al. [24] represented particles in the domain as nodes in a graph network to simulate dynamic fluid and solid flows and their interactions through message passing. The authors claim that their method is extensible to finite element methods.

There are obvious ethical implications to consider here regarding misuse of models, scientific rigor and explainability that need to be addressed. Some of these issues are elucidated in Mclarney et al [25]. The paper [25] provides a framework for NASA to address these ethical issues. A detailed list of areas where digital twins may add value to aerospace systems is presented in a position paper by AIAA and AIA[26].

Design optimization using a statistical approach coupled with CFD is still challenging [27]. With traditional statistical modeling techniques such as response surfaces using factorial designs, a very large number of data points may be necessary to model the non-linear response (e.g., turbulence, multi-phase flow interactions, etc.). However, the main issue in many cases is not even the large data requirement. The biggest pitfall in using traditional methods on highly non-linear problems is that the resulting models tend to have poor predictive accuracy even with the investment in collecting large data sets. This is because the input variables interact strongly in high dimensional non-linear systems. Thus, traditional Design-of-Experiments (DOE) based techniques cannot delineate the multitude of interacting effects. There have been several past studies related to design optimization using CFD or surrogate models validated by CFD (heat transfer, hydro turbines, air diffusers, airfoils, etc.).

Surrogate models based on data-driven techniques are used to approximate the expensive numerical models or experimental measurements. Building an accurate surrogate model for a practical turbomachinery application is often challenging due to a large number of input parameters, including boundary and initial conditions, system properties (e.g., material properties), model coefficients, geometry, and so forth. Moreover, generating dense data over a large domain by running numerical simulations and experimental measurements is not always practical. Hence, surrogate models are often constructed using limited samples that bring into question the surrogate model's accuracy at unsampled points. A wise sampling choice helps us reduce the prediction error. The next step toward construction of an efficient and accurate surrogate model is choosing and implementing a sampling technique. This can be performed by reducing the problem's dimensionality (e.g., by performing sensitivity analysis) so that only important input variables are used to build the surrogate model, choosing the best possible sampling technique for a given number of points, and by adding the most suitable next sample to improve the previous model prediction [28].

Using artificial intelligence and machine learning techniques also leverages the field of Uncertainty Quantification (UQ). UQ is one of the necessary elements to build confidence and credibility for a numerical simulation [29]. In an ideal scenario, UQ investigation requires a huge number of expensive CFD realizations since each variable, including model inputs and model parameters, has its range of uncertainty. AI and ML data-driven techniques can be applied to construct surrogate models to approximate CFD output as a function of input parameters. The constructed surrogate models often predict the output in a fraction of the time an expensive CFD run requires. Kriging is constructed based on Bayesian statistics. Gaussian Process (GP) [30] is among the popular surrogate models utilized by the UQ community. For example, Nili et al. [31] used this technique, replaced the CFD solution of a two-phase flow with a surrogate model, and performed a statistical global sensitivity analysis to rank and isolate the contribution of models' errors on the CFD model prediction. Park et al. [32] used Kriging to perform UQ on a two-phase flow CFD.

The design of a turbine or compressor can be broken into three sections, 1D, 2D, and 3D. The first step in designing an engine is the 1D analysis. A good 1D design can result in large efficiency gains for the engine compared to a 3D optimization of individual blade rows. Currently, designs of compressors and turbines begin with a meanline code [33] that solves for the velocity triangles using a fixed loss or by using a loss correlation [34][35][36] based on cascade data. This is the main weakness of the 1D code - it heavily depends on the quality of the loss data. Often these do not account for expansion or contraction of the channel, an optimized blade design, or varying channel radius. These loss correlations are based on early blade designs that start with a circular leading edge. A circular leading edge does not have a continuous second derivative and can result in more loss than conventional designs. Conventional blade designs also feature a flat suction side needed to operate efficiently in the transonic regime. Gathering loss data from more current blade designs into a database where a machine learning model can be trained can significantly speed up the development of modern gas turbine engines.

One dimensional (1D) design gives velocity triangles (flow angles) and boundary conditions needed for 2D construction of the individual airfoil profiles and 2D/3D computational simulations. The losses can change depending on the thickness distribution and camber line, the losses can change [37]. It is important to keep track of these parameters. Often designers optimize the geometry but their database stays in a file. Aggregating optimization results into a large dataset and pairing it with a machine learning model can reduce the time to design 2D and 3D blade shapes by 40 to 50 times [38]. The data can also be fed back into the 1D tools where losses can be approximated using the best designs. One of the most challenging CFD applications is to optimize a two-phase flow system. Gas-liquid two-phase flows are encountered in a various application (e.g., automotive engines and aircraft engines). Designing systems to control such flows is enormously challenging due to the addition of new non-dimensional groups that characterize the two-phase flow system compared to a single-phase flow. Additionally, two-phase flows can exhibit nonlinear hydrodynamic instabilities that determine the system's overall behavior. It has been demonstrated by Miki et al. [39] that a systematic probabilistic approach could be a very powerful tool for designing, even for such a physically challenging system, and could significantly reduce the computational cost of design. Combining available experimental data, CFD (high-/low- fidelity CFD models) and a statistical approach within the framework of AI could open a new chapter of design optimization, which has been historically done solely by expensive experiments or CFD. Smaisim [40] trained an ANN (Artificial Neural Network) to model the thermophysical properties (conductivity, viscosity) of Cu-water nanofluids based on experimentally measured values at a range of Reynolds numbers and volume fractions. Zhao, N., & Li, Z. [41] demonstrated by comparing predictive values and experimental data that a neural network that they trained exhibited good modeling accuracy and could effectively extract the influences of nanoparticle volume fraction and temperature.

Currently, engine icing is predicted using modeling tools such as Glenn-ICE through break-up and sticking models [42]. Implementing these algorithms on-board an engine as part of a control system adds computational cost and weight. It may be that neuromorphic circuits [43] or pretrained models would reduce weight, processing time or both. Health monitoring within engines is primarily limited to bulk measurements such as a thermocouple at a stage exit or flow rate somewhere along the flow path. This reduces the ability of the control system to maintain the engine at optimal conditions. Some applications of ML/AI for fault detection, diagnostics and maintenance are provided by Michelassi et al. [44].

Traditionally, material discovery is expensive and takes a significant amount of time. Material design and discovery have been accelerated by applying machine learning. By leveraging data science and machine learning approaches, researchers have guided the understanding and design of various new materials with tailored properties, functions, and behavior. Industry and academia are utilizing large material databases to aid the design and discovery of materials targeted for optimization of specific properties [45][46][47]. Arnold et al. [48] used surrogate modeling for multiscale analysis of composites. Researchers are now attempting to predict the microstructure and material selection based on structural requirements at a macro level. This is being extended to include aerodynamic, thermal and other considerations. Looking forward, there is the promise of being able to model structures under deformation given work such as that of Sperl et al. [49] who demonstrated the ability to simulate fabric movements and deformations. In combination with work such as that of Sanchez-Gonzalez et al. [24] it may be possible in the future to model and analyze dynamic fluid structure interactions in real time. An example is shown in Shen et al. [50]. Most of these futuristic applications of AI/ML are being used for gaming physics and thus do not need the same accuracy or resolution that engineering applications might require. However, such low-resolution applications could be used to inform topology optimization or for design of experiments.

Aircraft inlets are designed to maximize net thrust, and this requires a compromise between drag, pressure recovery, and mass flow. The engine inlets of aircraft that are highly maneuverable or operate in a transonic regime require designs capable of handling a wide range of angles of attack [51]. The design of intakes has a significant impact on aircraft's engine operations. With the availability of computing power, designers have optimized the intake design to minimize flow distortion, pressure loss, and outlet area. Vyas et al. [52] used a multi-objective optimizer to explore a range of intake designs for transonic flight. They used the same design tools as Juangphanich et al. [37]. After these optimizations are performed and the report is written, the database is consigned to storage. NASA and the broader community can leverage these design tools and the associated data to train surrogate models and to design inlets to multi-objective requirements. The model and the optimization tool can be made publicly available such that students participating in design competitions may use them. The results and data generated can be used to retrain surrogate models.

At NASA GRC, the UIUC (University of Illinois at Urbana Champagne) airfoil database [53] was used to train a neural network [54] to predict lift and drag of an airfoil for a range of angles of attack, Reynolds numbers and Mach numbers. This is shown in Fig. 3 and Fig. 4. This was a proof of concept to determine if it is possible to develop airfoil shapes based on required performance parameters. Before attempting this, the inverse was implemented with a model trained to output performance based on a range of input parameters.

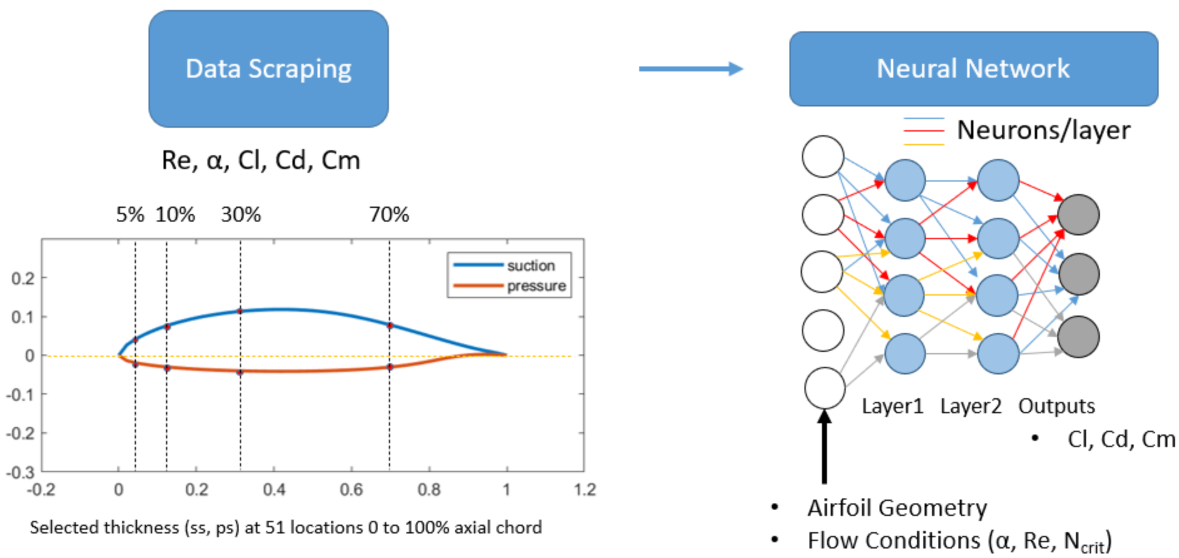


Fig. 3 Input data and architecture of neural network trained on UIUC database.

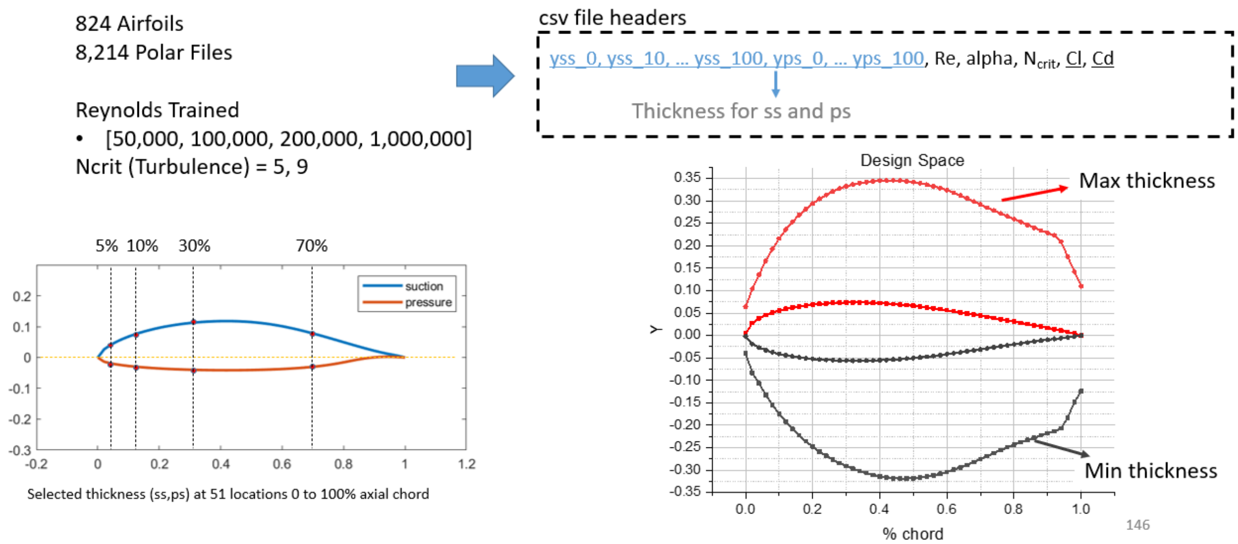


Fig. 4 Airfoil 2D Design space that neural network can explore.

Fig. 4 shows the parameter space within which the neural network was trained and Fig. 5 shows preliminary results. When properly normalized across the dataset the model provides excellent predictions (purple line). Further results are to be published and the data set and models intended for public release.

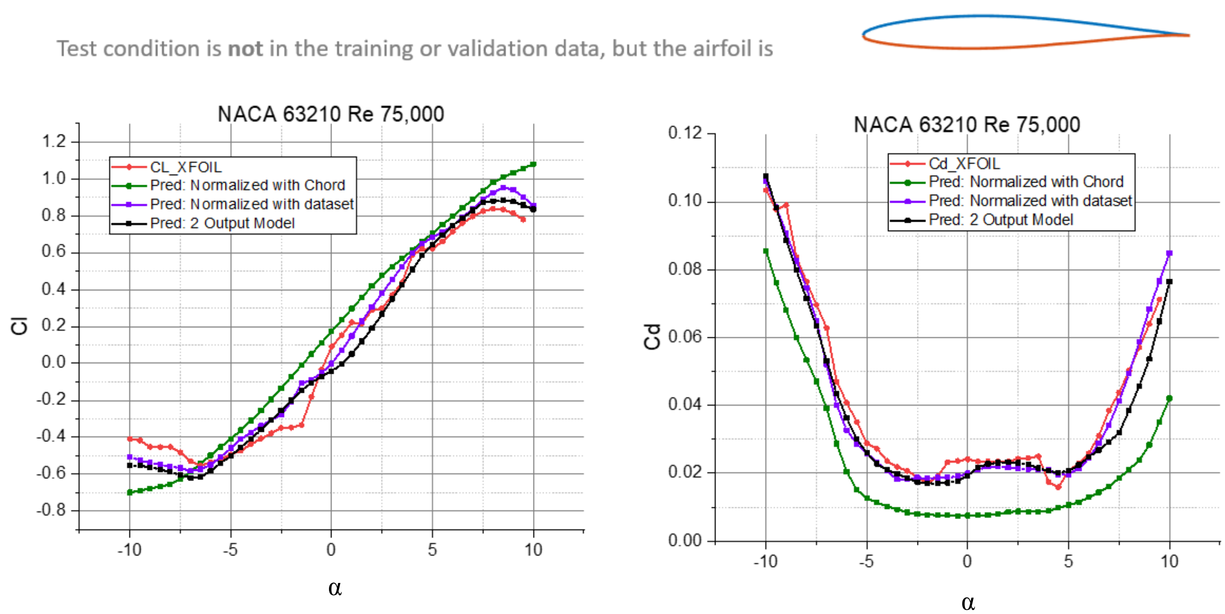


Fig. 5 Prediction of lift and drag coefficient using neural network for various structure of input.

Among commercial vendors, Autodesk [55] and Altair [56] utilize topology optimization and AI to incorporate multifunctionality and to explore a larger design space given constraints. ANSYS [57] uses machine learning to choose an appropriate solver for a given problem from a choice of sparse direct solution, preconditioned conjugate gradient solution, Jacobi conjugate gradient solution, Incomplete Cholesky conjugate gradient solution, and Quasi-Minimal Residual solution.

The Department of Defense (DoD) Propulsion Digital Enterprise is an effort to incorporate emerging technology into their standard design practices. Fig. 6 shows the Air Force vision for how emerging and existing technology fit together [58].

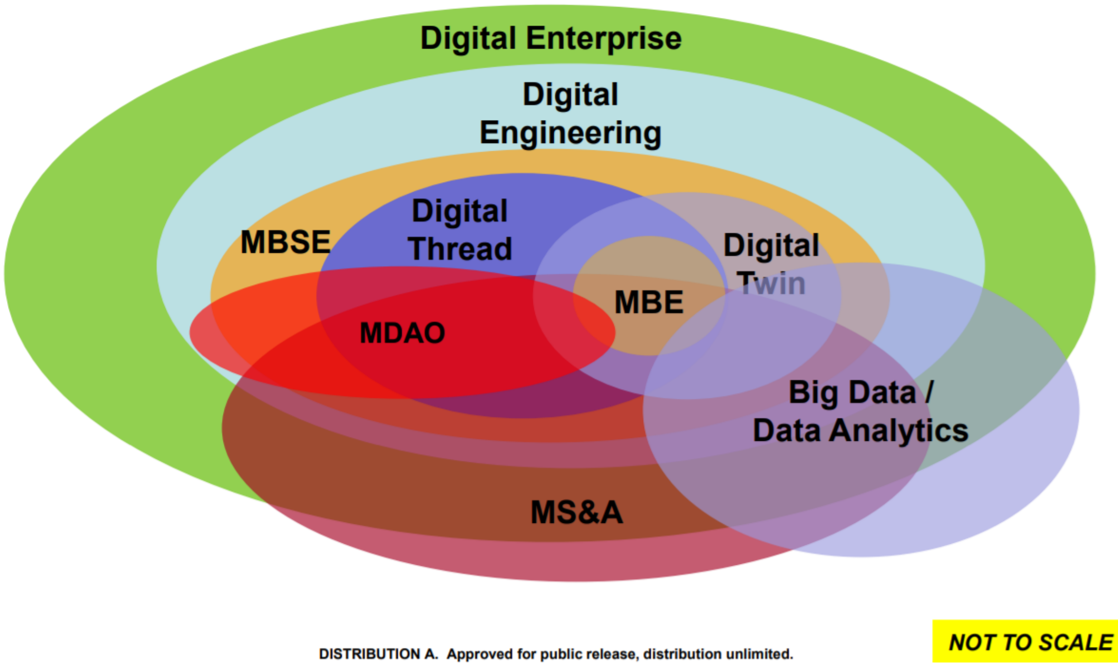


Fig. 6 AFRL (Air Force Research Lab) Digital Enterprise [58].

B. Trends in Artificial Intelligence, machine learning and natural language processing:

QUID® [59] was used to survey the global market using the Boolean, ["artificial intelligence"]("artificial intelligence" OR "machine learning" OR ai OR "neural networks" OR "natural language" OR "image recognition" OR nlp OR "deep learning" OR "Deep Learning"). The primary use of AI at NASA has been in the communications, guidance and navigation fields. This includes the use of neuromorphic computing, smart radios and smart grids.

AI has held promise for several decades as the cure-all, but computational resources have not allowed us to realize the maximal potential until recently. Fig. 7 shows news articles and blogs that have mentioned the promise of AI and ML over the last 8 years. It appears that the hype peaked by 2017 with much of the hype generated by stories around the dangers of AI, ethical use of AI and natural language processing (NLP). The steady stream of news and blog articles from 2014 to 2021 center around advancements in AI and ML, while the hype peak features legal actions, government discussions around ethics and media buzz around AI beating humans at games. It appears that much development in AI/ML/NLP is being publicized in gaming related applications, the automotive industry and in social media. These might be points of collaboration related to computational hardware and AI/ML modeling for physics in the case of gaming, development of natural language processing (NLP) in the case of social media and training data that might have relevance to aerospace in the case of the automotive industry. The cluster labeled 'London-delhi Dreamliner Flight' should be ignored. It shows up due to the repeated use of the term Air India that also uses the acronym AI. Other clusters that were excluded form analysis include the Chinese artist Ai Weiwei, comedian Ai Ai delas Alas, a movie named 'Ai', neurolinguistic programming that is also known as NLP which while related to is not to be confused with natural language processing. Other seemingly irrelevant terms with the acronyms AI, NLP or ML were also excluded.

Fig. 8 shows the distribution of companies involved in artificial intelligence across various industry segments. The non-engineering sector is an early adopter with medical imaging, facial recognition, FinTech, sports, gaming, social media, automotive industry and cybersecurity leading the way. The energy sector is also investing in AI for intelligent power management, smart grids, and health monitoring for early failure detection [60]. Real estate and finance are also seeing a rise in platform development and apps to bring service to consumers. There may be a way to leverage these developments to bring more people into the aviation industry through ideas such as community owned airlines or crowdfunded design and development. Some outliers in the data were instructive such as warnings from companies involved in deep learning and NLP regarding the computational and energy costs of deep learning [61]. For example, the Israeli company AI21 labs estimated that the cost of training models with millions or billions of parameters can run from thousands to millions of dollars [62]. The added costs come from the need to use cloud solutions, data storage and management. Strubell et al. [63] found that training one NLP model with a big transformer that includes neural architecture is responsible for approximately 626125 pounds of CO_2. The average CO_2 emitted by a car including fuel use on the other hand is only 126000 pounds. This clearly warrants attention and we should be judicious in our application of AI/ML.

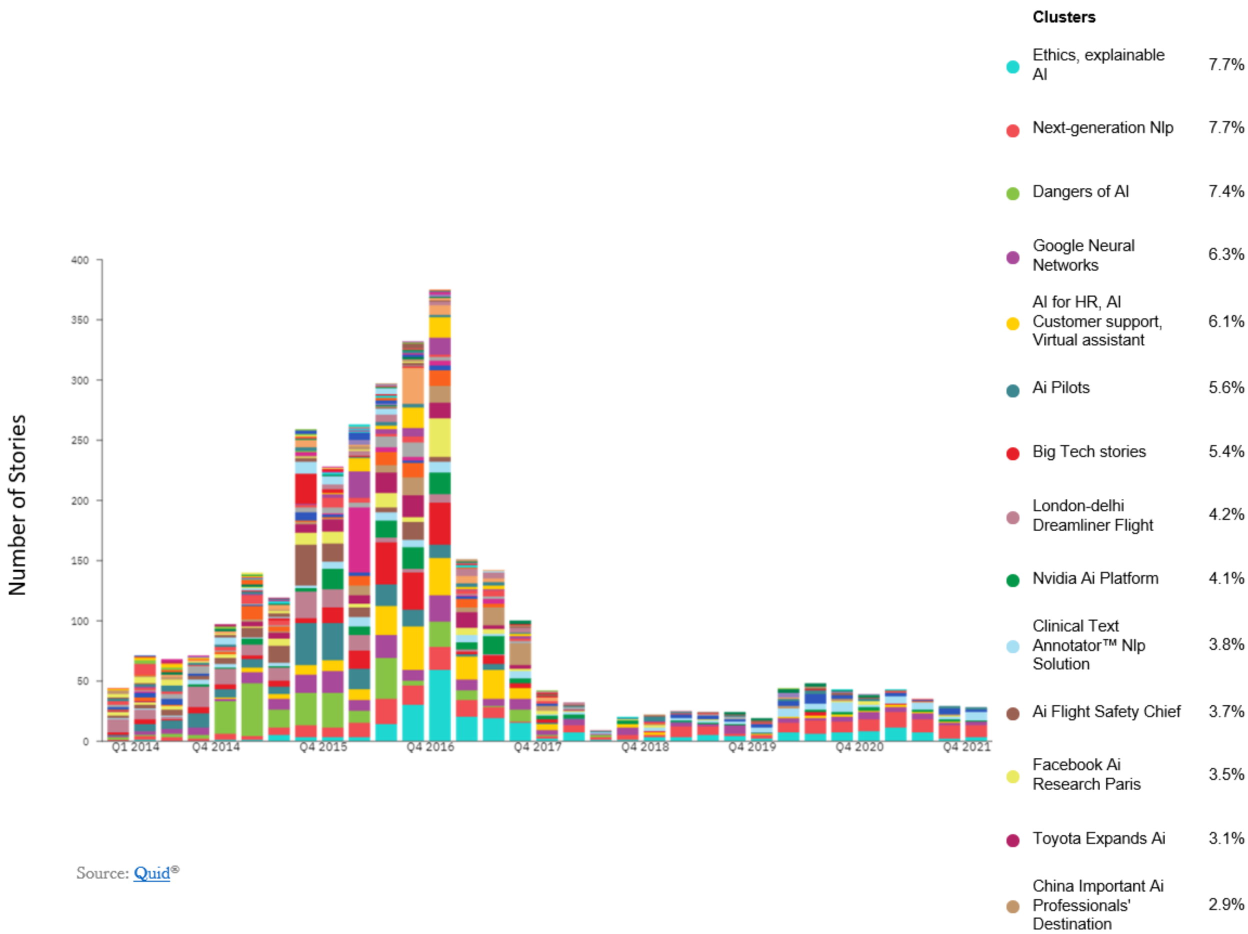


Fig. 7 News and blog articles related to machine learning and artificial intelligence from December 2013 to December 2021. There is a marked peak between 2015 and 2017.

Fig. 9 shows clusters of activity within AI/ML with colors showing subclusters. Most of these companies appear to be investing in machine learning model training, deployment and use of data science. Advertising and productivity tools are next in terms of number of companies investing in this area. Fig. 10 shows that the U.S. has the largest number of companies working on AI/ML with most in the imaging/medical field. China on the other hand appears to be investing in automation, robotics and manufacturing although employment seems to be highest in the electronics and facial recognition areas as seen in Fig. 11.

Fig. 12 shows investments in AI/ML within the United States with the largest investments being in medical imaging, diagnostics and facial recognition. Investments are clearly growing and the number of areas being invested in is also growing. Video analysis investments are being made in the sports industry to generate highlights, recognize activities and for analysis. These developments may have value in the aerospace industry for flow visualization, automated ontology generation, diagnostics, fault monitoring and reverse engineering. As an example, it may be possible to watch the design, development and operation of an aircraft and use activity recognition in combination with NLP to automatically recognize the parts, functions and ways in which the functions are accomplished. These may then be used to populate an ontology that can be used to inform systems models and form the backbone of digital twins. Another application might be to record biological models and extract structure, function behavior for use in biomimetic applications.

Fig. 13 and Fig. 14 show sentiment regarding AI/ML in 2018 and 2021 respectively. Coverage of AI/ML in the news and in blogs appears to have become more positive. This market analysis may be useful in identifying potential collaborators and areas of convergence.

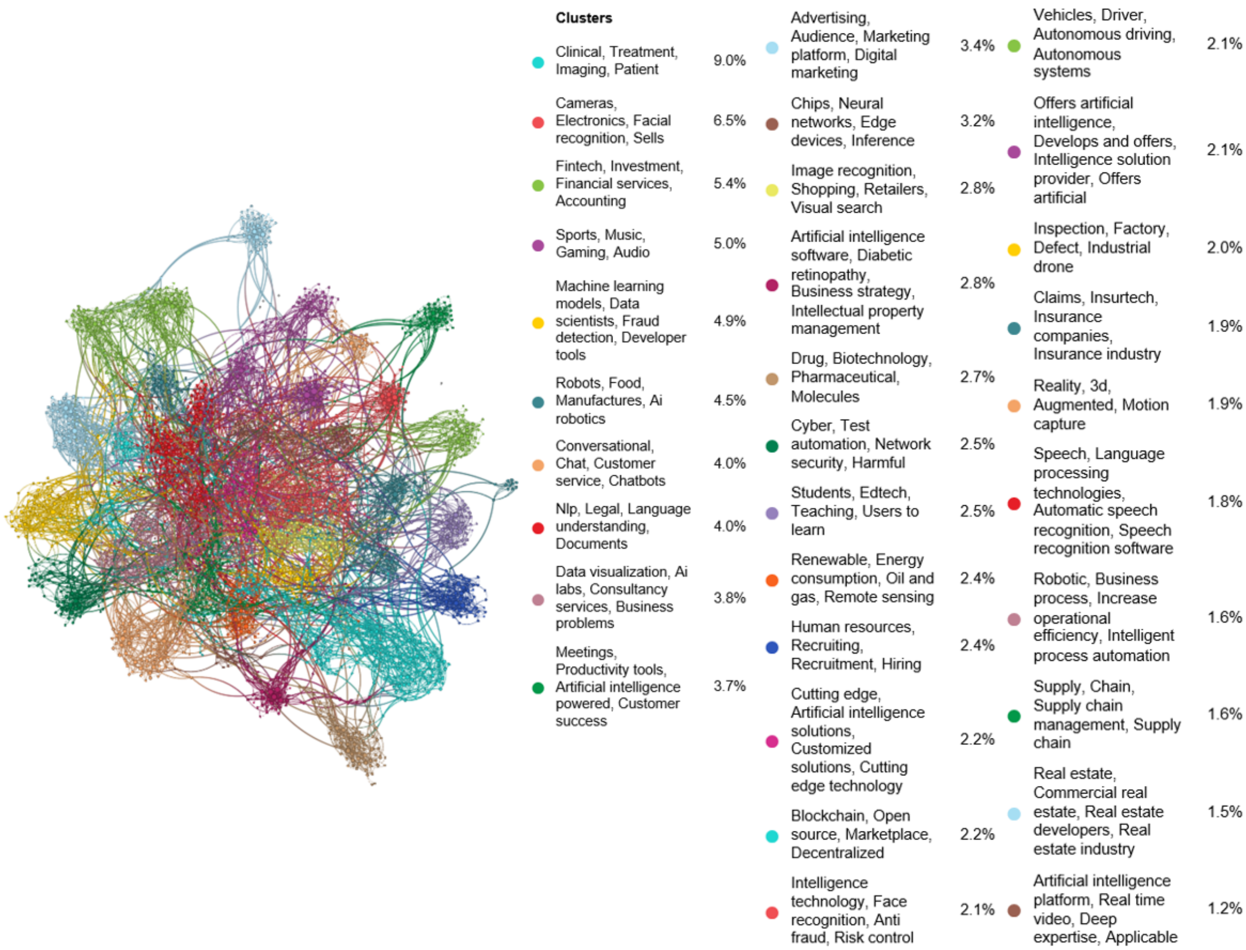


Fig. 8 Unsupervised clustering of 1526 companies involved in AI/machine learning/natural language processing using QUID in 2021. Legend shows percentage of companies per cluster.

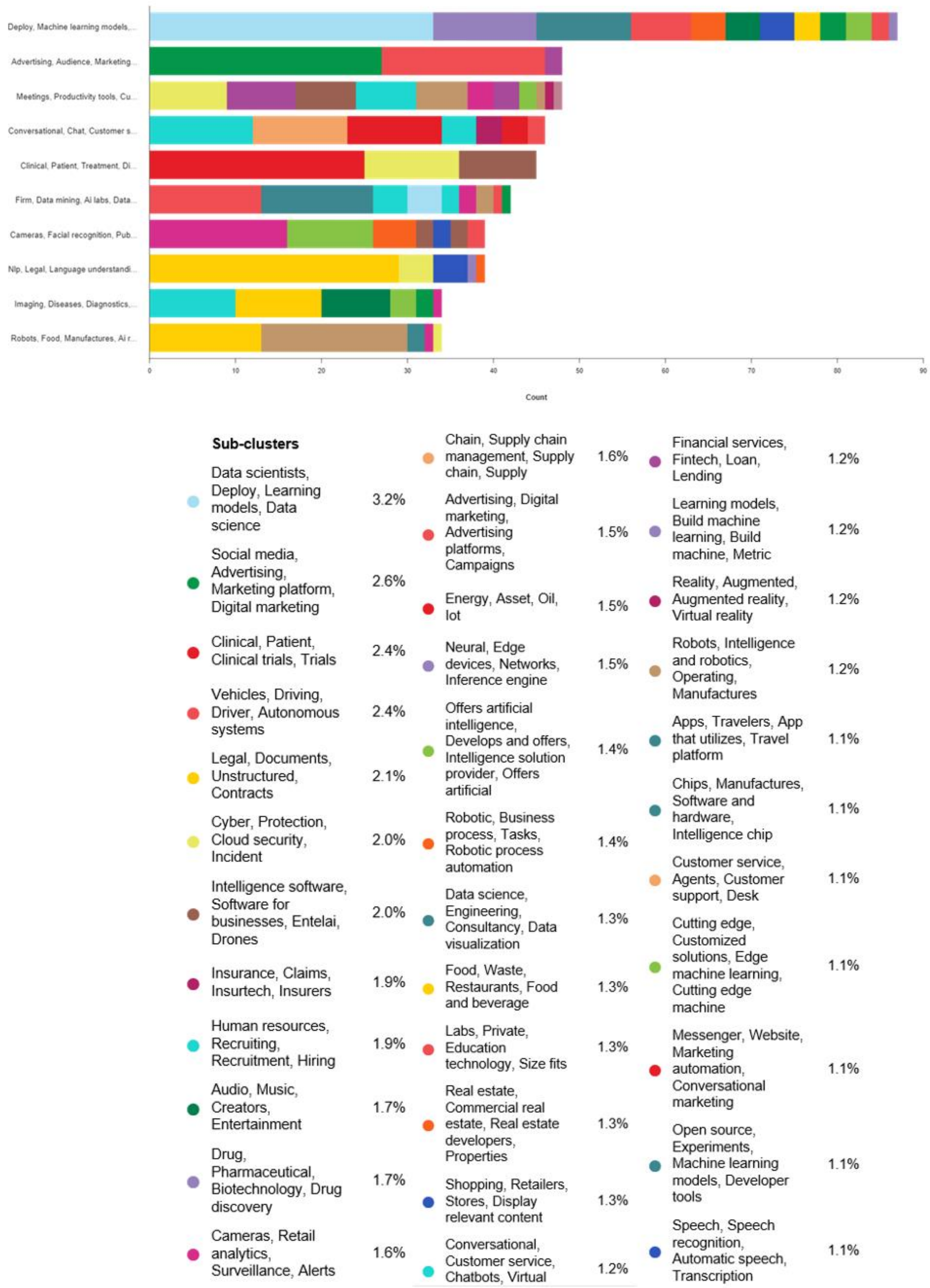
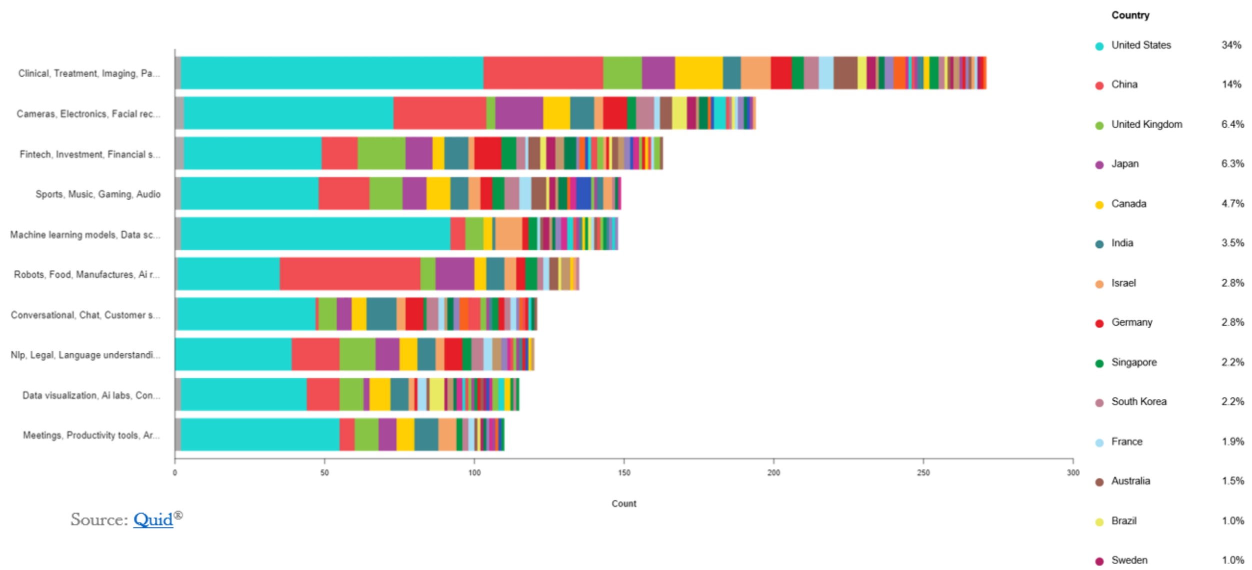
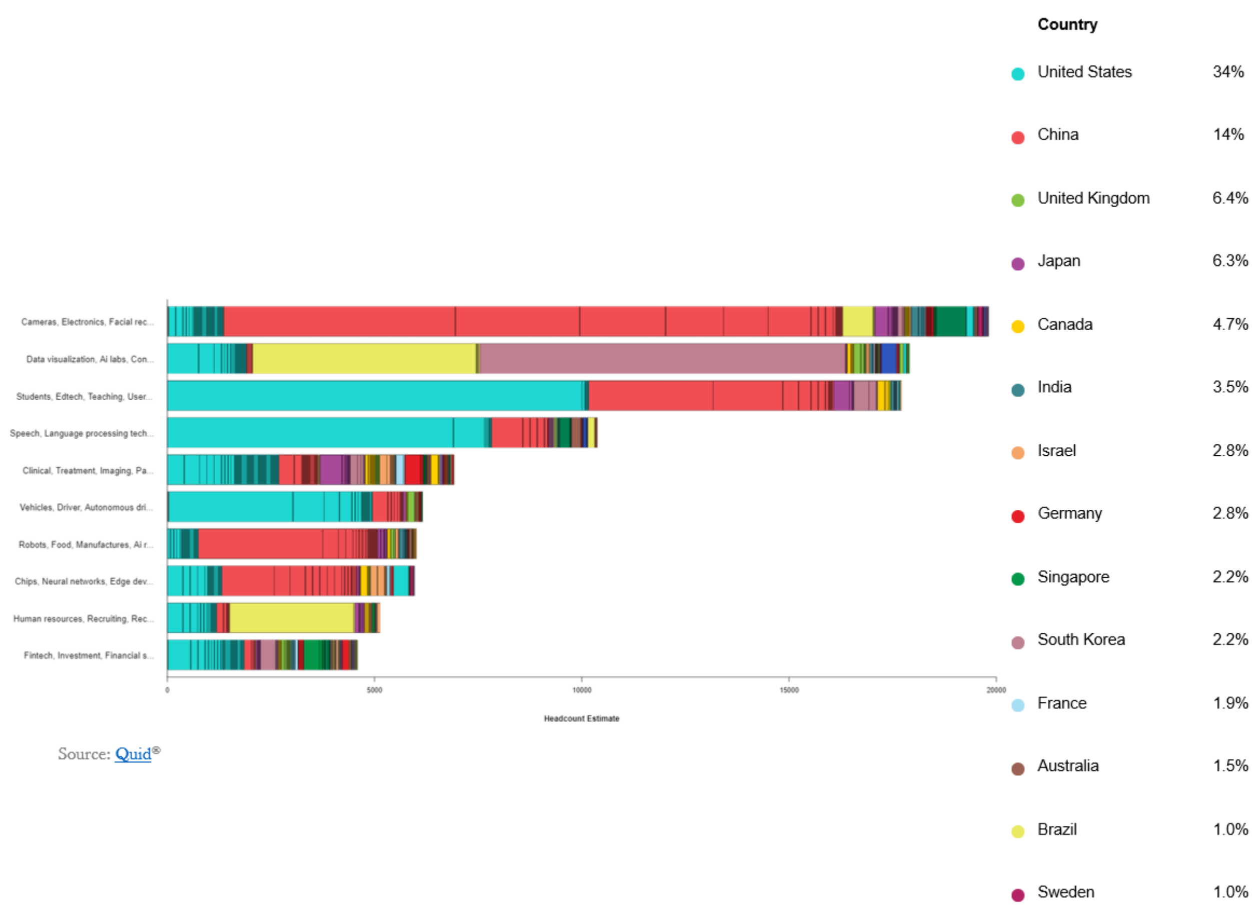


Fig. 9 Areas of focus for companies working on AI/ML.



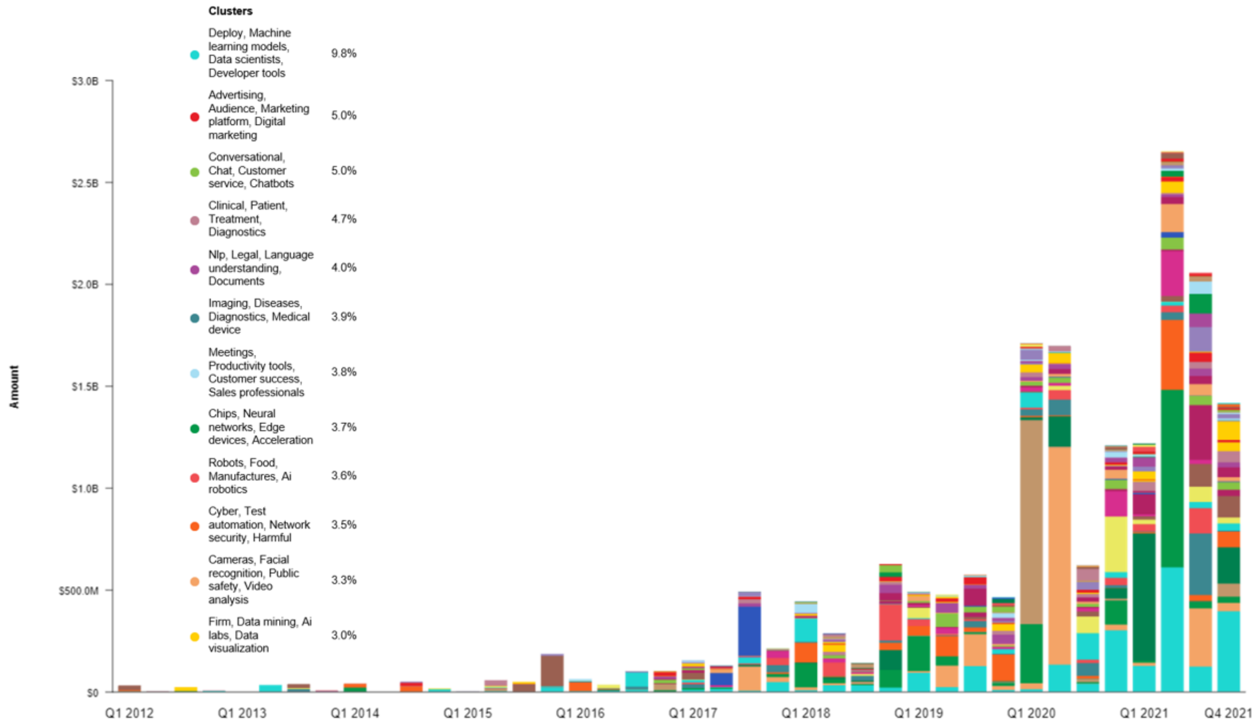
Source: Quid®

Fig. 10 Areas of AI/ML by number of companies (x-axis) and by country (color).



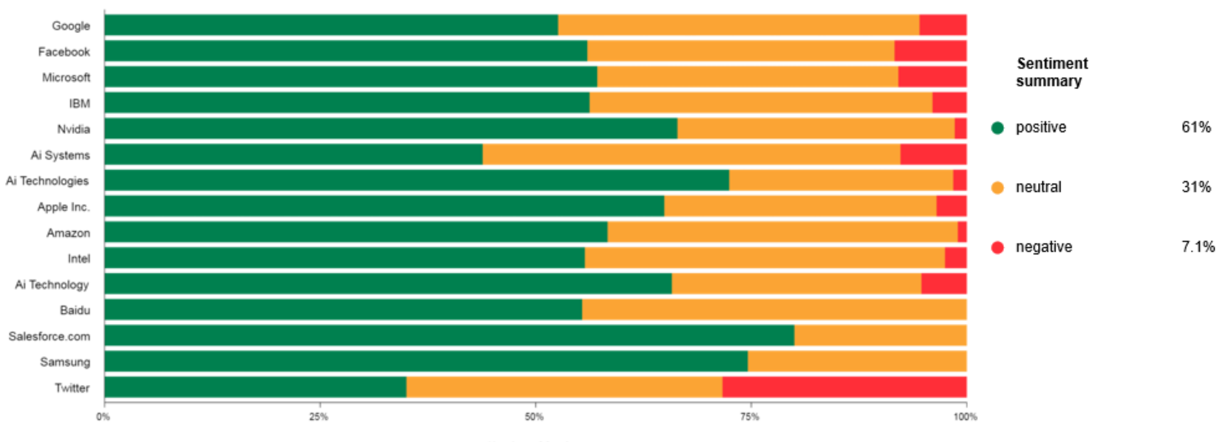
Source: Quid®

Fig. 11 Number of people employed by AI/ML area and by country.



Source: Quid®

Fig. 12 AI/ML investments in the United States.



Source: Quid®

Fig. 13 sentiment summary in 2018.

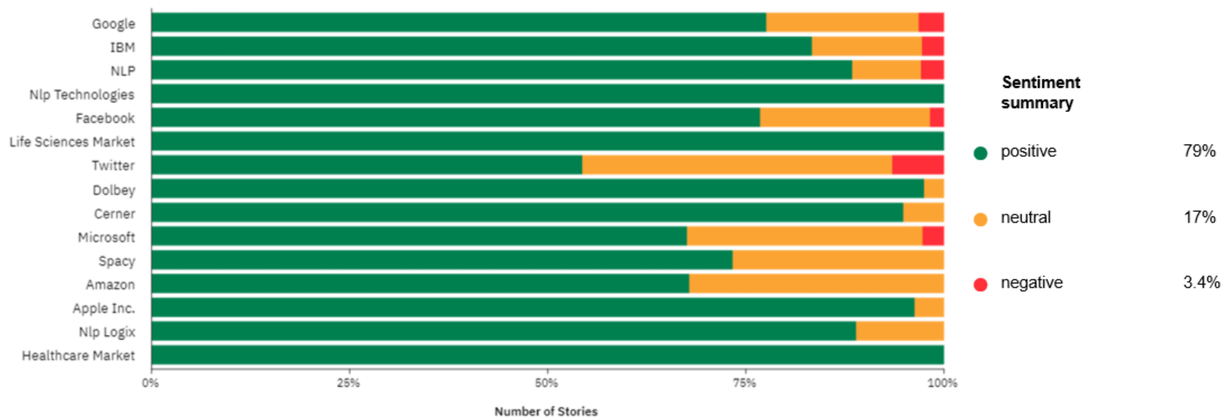


Fig. 14 Sentiment summary in 2021.

IV. Approach

To help identify challenges, opportunities and to infuse digital transformation into practice the following steps were taken:

1. Listening to input from industry, academia and other government agencies through workshops (public) and targeted discussions (proprietary)
2. Assessing the state of the art in design and engineering of propulsion systems
3. Conducting a literature survey of applications of AI and ML in propulsion and related areas
4. Conducting a literature survey on the state of the art of AI and ML in general
5. Identification of potential applications to mission through discussion with NASA and external stakeholders
6. Drawing from ongoing activities in systems engineering, digital transformation within NASA
7. Creating a vision, strategy and roadmap to address the questions posed in the problem statement

To this end, input was sought from industry, academia and other government agencies on ongoing data science work, challenges and potential areas of collaboration to focus on for pilot efforts.

A. Workshop 1: Gathering for Artificial Intelligence and Natural Systems (GAINS) 2018

In October of 2018, a workshop [64] was held at the AAAI (Association for the Advancement of Artificial Intelligence) Fall Symposium Series in Arlington, VA, jointly organized by IBM and NASA, to determine the challenges in training models for the discovery phase of design using current data sets. This is a subset of the problem faced by the entire design and engineering lifecycle of propulsion systems (next step) but incorporates key features required for this next step such as identification and consideration of interfaces, degrees of freedom, selection of workflow based on data, expertise and user. The workshop focused on the intersection of AI and natural systems. Topics included

1. Artificial intelligence and machine learning algorithms and methods
2. Application of natural systems in the development of tools
3. Application of tools for bio-inspired design

Fig. 15 shows an example working document from the workshop. The participants identified the following challenges in order of priority.

1. Lack of data standards and repositories.
2. Low data volume and relevance at the design phase. There is much scatter in the data and data is highly siloed. For example, it is difficult to find stress, life, aero and thermal data for the same test article unless at the system level. This is a major hurdle for training algorithms in physics.
3. Data is biased to use for performance. This means data on reliability, durability, cost, choice of design philosophy or tools or manufacturing methods is not considered.
4. Low quality and unreliable literature, especially for emerging technology or fields. Using scraping or Natural Language Processing (NLP) can result in noise in the data.
5. Lack of awareness of data sets. This is a theme echoed across multiple domains and is a result of specialization.

6. Handling of copyrights and IP. Two sides – final product recognizing value-added chain and lack of access to final product to inform models.
7. Lack of standards to interpret papers (tagging) can pose difficulties to NLP.

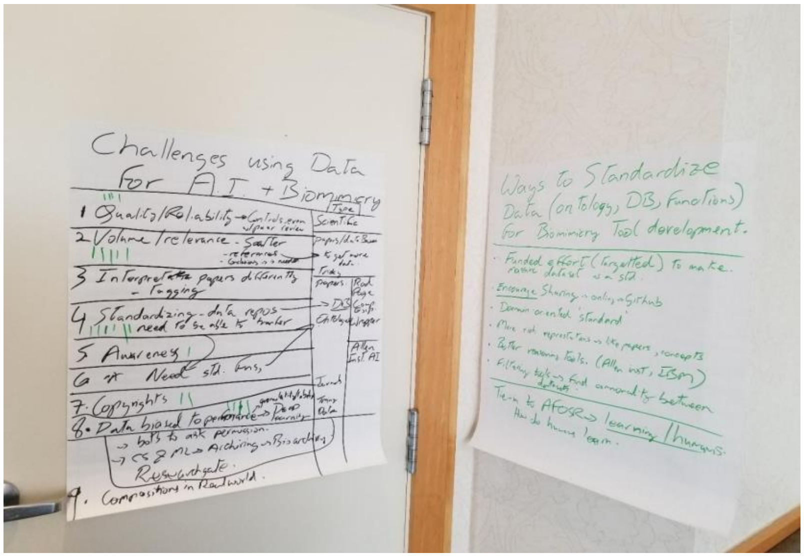


Fig. 15 Participant input on challenges of using or sharing data (poster on the left) and approaches to standardizing data (poster on the right).

The workshop also generated ideas on ways to standardize data (top challenge):

1. Fund an effort targeting an area of mutual benefit (to industry, academia, government) to generate a massive data set as a standard through NLP (natural language processing), workshops, web portals. This is addressed in workshop 2 (IDEAS 2019), leading to a benchmark problem.
2. Encourage storage of rich information (papers, concepts, videos and images). This means moving away from SQL databases and using a combination of ontologies, graph databases and unstructured databases.
3. Develop better reasoning tools.

B. Workshop 2: Intelligent Design and Engineering of Aerospace systems (IDEAS) 2019

Following the GAINS workshop in October 2018, a workshop on Intelligent Design and Engineering of Aerospace systems (IDEAS) was held at the Ohio Aerospace Institute in Cleveland, Ohio, on August 15 and 16, 2019, to obtain industry and academia perspectives on integrating AI into propulsion system design. The workshop was attended by industry, academia and other government agencies. The complete attendee list is available by contacting the first author. The workshop covered the topics of data, applications and identifying NASA's role. Salient features were identified as follows:

A. Data.
   a. Identify data, determine the quantity of data, and classify the quality of data available
      i. The majority of data is related to maintenance, vehicle operations, sensors and diagnostics
      ii. There is little public domain data to train multiphysics models

   b. Identify data management methods/practices
      i. Most industry participants use internal cloud storage
      ii. There is no standard of practice yet
      iii. There is an interest in generating ontologies for propulsion and related fields to simplify data retrieval, analysis and management.

   c. Identify top challenges/barriers related to data

a. Storage – Databases, knowledge graphs, cloud vs. local
b. Sharing – the ability to share across industry, government and academia while preserving privacy or classification of data
c. Collection and curation
d. Use

B. Applications
  a. Generate a list of available tools, platforms and applications: Most participants use a mix of existing tools, frameworks and platforms such as Python, TensorFlow, neo4j and commercial services such as Microsoft Azure, Google Cloud and Amazon Web Services coupled with developed wrappers and automation in-house through teams of subject matter experts and data scientists.

  b. Identify a model problem/challenge as benchmark
    i. Most participants indicated that thermal management is an appropriate common problem due to its wide-ranging applicability and the ease of generating datasets through rapid prototyping and modeling.

    ii. Some applications include multifunctional, lightweight gas turbines engine components such as structural heat exchangers, additively manufactured blades and vanes incorporating complex cooling, low grade waste heat management from motors, generators and electronics for Urban Air Mobility and Boeing 737-class vehicles.

C. Identify roles for industry, academia and government. The following were areas that participants identified as roles for NASA.
  a. Define a challenging problem
  b. Organize more workshops on AI
  c. Be the interlocutor (between academia, industry, other government agencies)
  d. Provide incentives for data sharing
  e. Develop large databases
  f. Identify mechanisms for protecting different types of data

Fig. 16 shows the results of ideation sessions around barriers to adopting state-of-the-art data science practices. Fig. 17 shows the challenges associated with data management and Fig. 18 shows some factors that participants thought might enable collaboration on data science including NASA's role.

Fig. 19 and Fig. 20 resulted from an ideation session in which participants were asked for ways in which we might overcome barriers to data science adoption. In addition, input from NASA subject matter experts indicates that a significant portion of tasks are repetitive and tedious, software solutions do not communicate with each other, security concerns pose a barrier to engaging academia and industry. A survey of 350 Granta contacts (35% N America, 45% Europe, 20% elsewhere; 25% current customers, 75% not customers) in July 2012 revealed that 40% of all material data is used once and then discarded with 33% of organizations duplicating at least 25% of existing material tests.

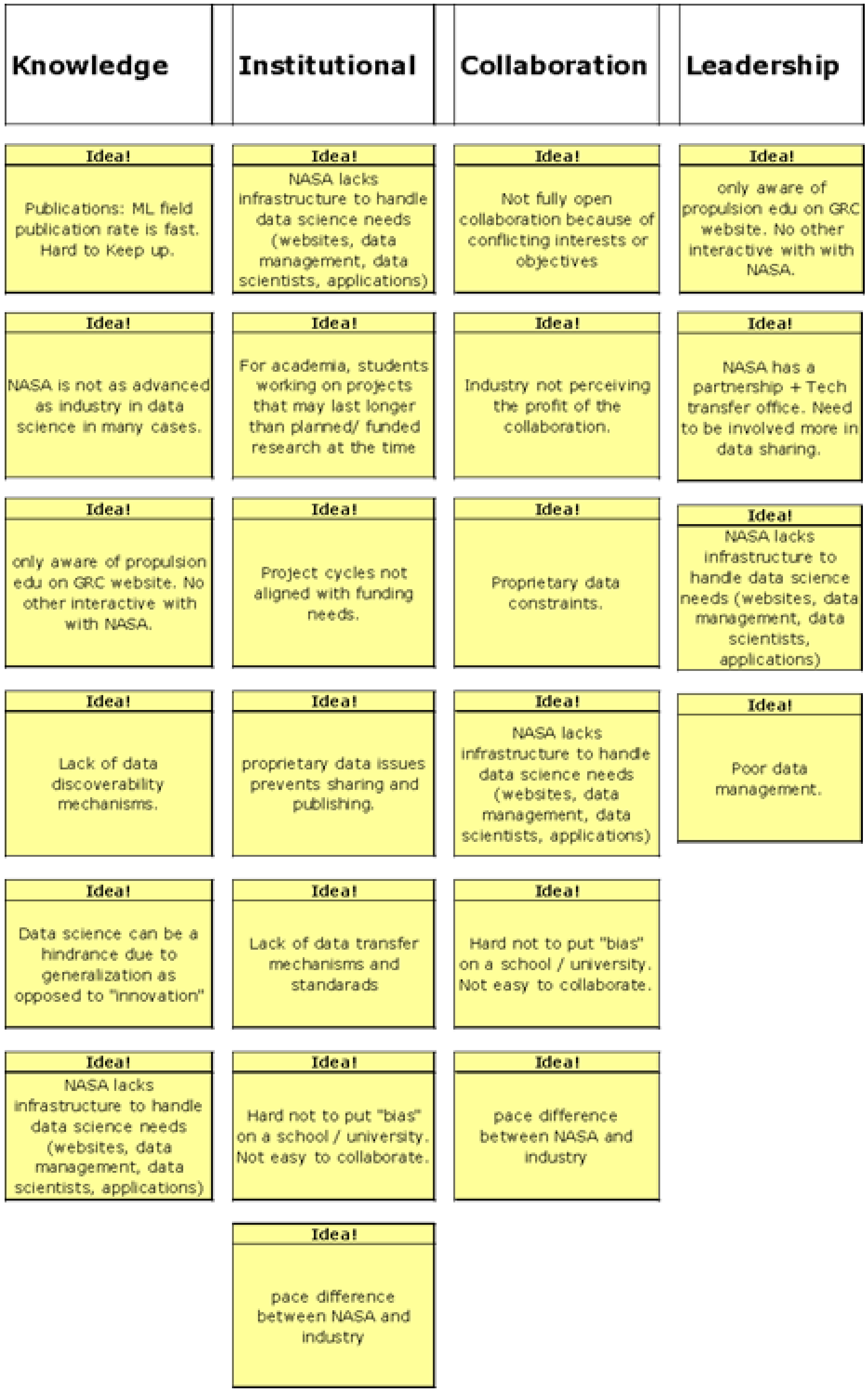


Fig. 16 Barriers to data science for NASA, industry, academia collaboration around propulsion – knowledge, institutional, collaboration and leadership.

Fig. 17 Barriers to managing data for data science in propulsion.

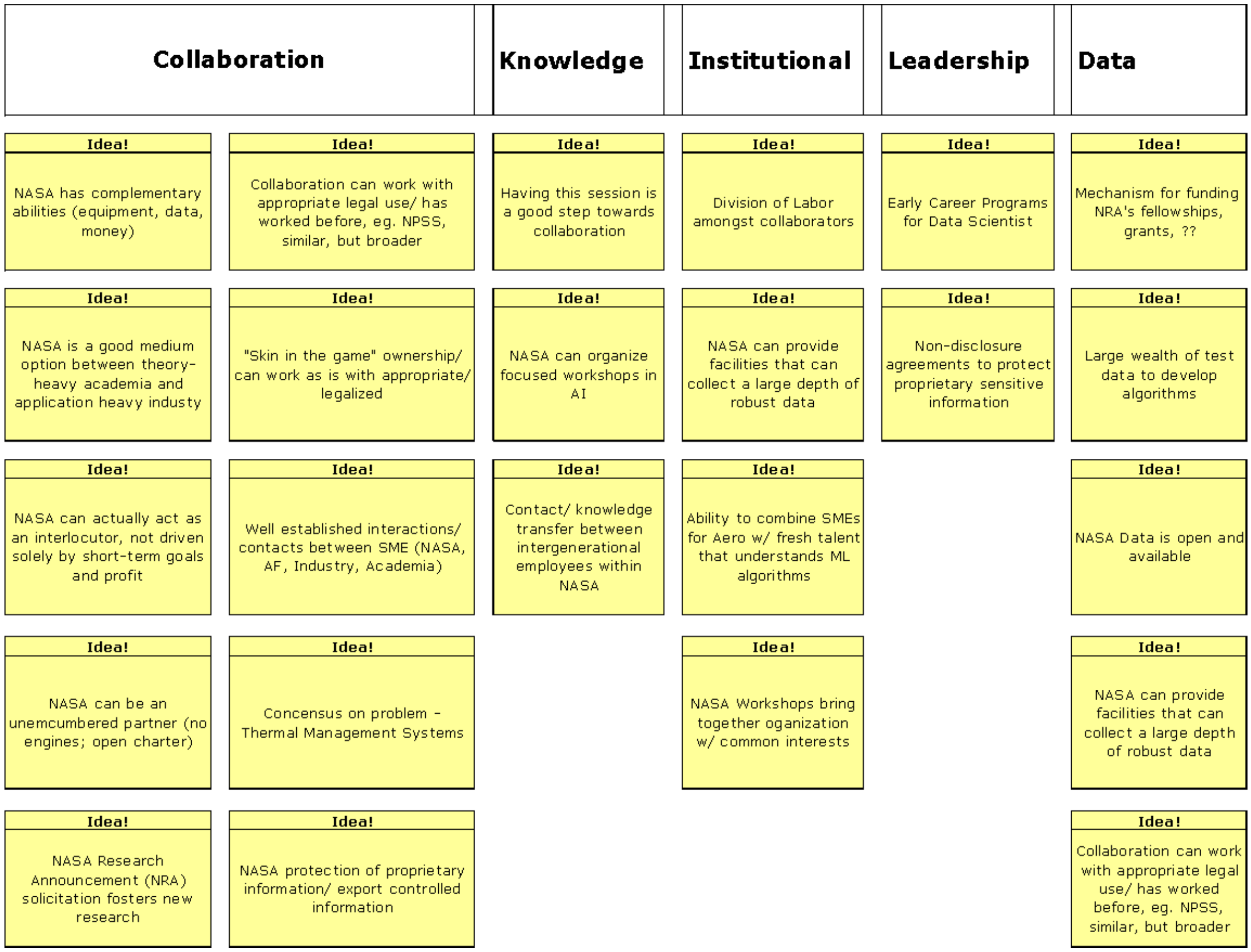


Fig. 18 Factors that enable collaboration around data science for propulsion.

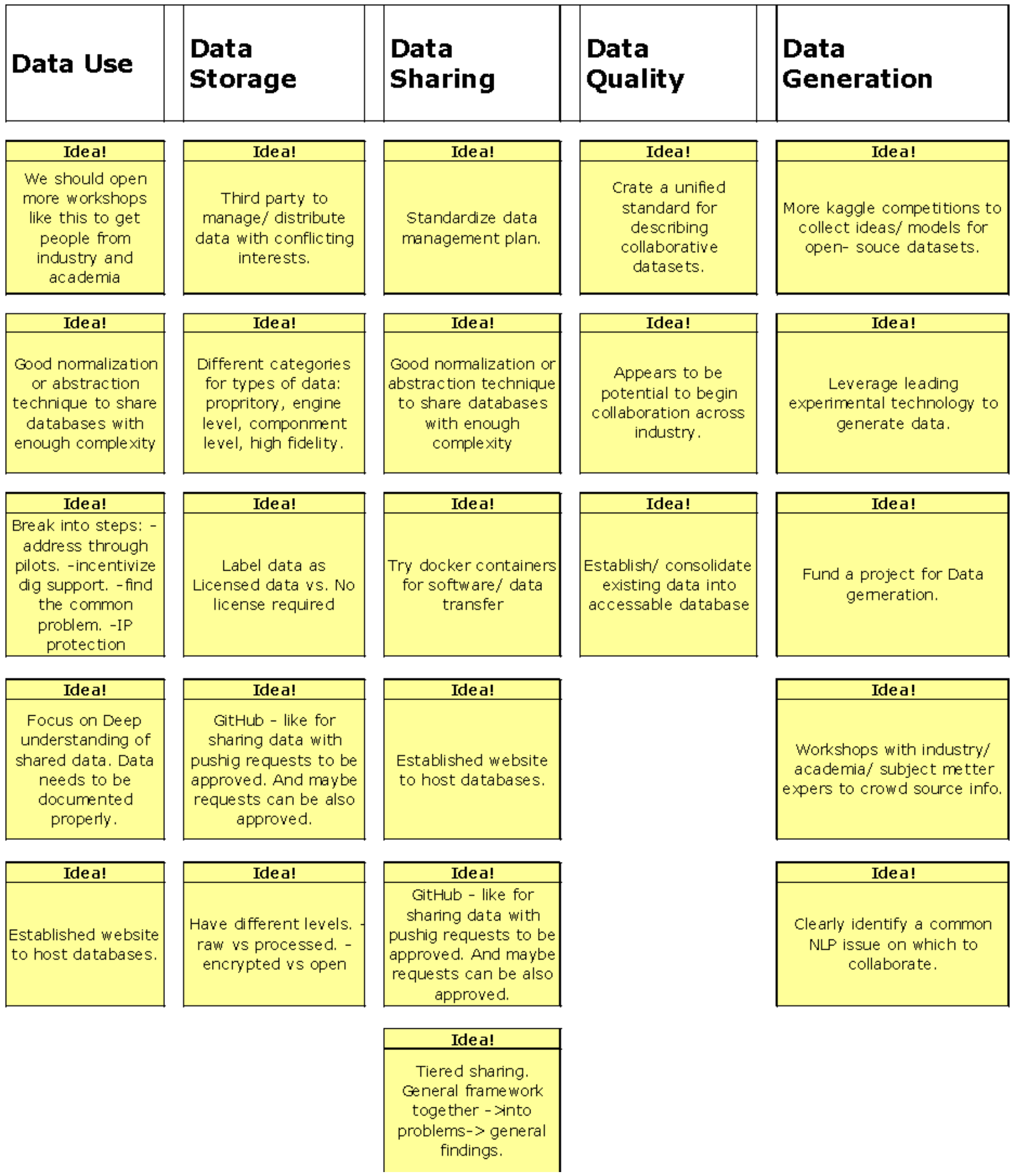


Fig. 19 Ideas on ways to overcome data-related barriers for data science in propulsion - input from IDEAS 2019 workshop attendees.

Based on the input from participants a challenge statement was formulated for a benchmark problem to capture the spirit of the workshop:

To design and build a system that is not possible with current technology and design methods that engages new workforce, tackles climate change, global threats and infuses new technology into the existing program structure.

A sketch of global issues and potential solution vectors relevant to this challenge are shown in Fig. 21.

Knowledge	Institutional	Collaboration		NASA Role	Models
Idea! Have industry partners with good established data sharing, management practices share their knowledge to this area	**Idea!** Collaborative research campaigns.	**Idea!** Reduce amit of legal barriers to post data	**Idea!** Data terminology and asssumptions. Very helpful to have all parties look at data together. Otherwise - confusion.	**Idea!** NASA lead Problem identification / benchmark problem	**Idea!** Follow a model analogoy to NASA ARC dashlink or prognostic/ Diag. Data Repository
Idea! More frequent NASA communication with research groups so that NASA is updated with current research efforts.	**Idea!** Start NASA Early Career Programs for Data Scientist	**Idea!** Memoramdoms of agreement clearly defining roles/ responsibilities	**Idea!** Pick a few problems and find who is putting up what $ to select the general problem.	**Idea!** Legalized data/ cafeful data security	**Idea!** Analogy to NASA's ASME rotor 37 blind test case.
Idea! NASA can organize focused workshops in AI	**Idea!** Break into steps: - address through pilots. - incentivize dig support. - find the common problem. -IP protection	**Idea!** Use a "Black Box" approach. Input -> Intellectual Property -> output	**Idea!** Break into steps: - address through pilots. -incentivize digital support. -find the common problem. -IP protection	**Idea!** NRA's can be focused in AI/ data science topic areas.	**Idea!** Research. Metals Affodability Initiative (MAI) which is a seccessful collaborative platform for OEMs and Air Force research
	Idea! Grant secured access to data	**Idea!** Develop common models.	**Idea!** Get common funding (DOE)	**Idea!** Established website to host databases.	**Idea!** Look at european ERCOFTAC consortium model.
	Idea! "Website" where all people can have access and contribute.	**Idea!** Establish MOU between collaborators rather than individual agreements	**Idea!** Agree on investment commercial usage. How would they know? Admission Fee equal investment, equal access to tool.	**Idea!** NASA can organize focused workshops in AI	**Idea!** Break into steps: - address through pilots. -incentivize dig support. -find the common problem. -IP protection
	Idea! Put forth benchmark or challenge problems.	**Idea!** Data science needs broad, diverse databases to learn effectively. NASA can work w/ industry to develop large diverse datasets for learning/ benchmarking	**Idea!** Develop separate tools, share without trained algorithm. describe but not share data.	**Idea!** Possible middleman to connect Industry and academia and maintain project for both sides. Data housing?	

Fig. 20 Ideas on ways to overcome barriers on data science in propulsion, potential NASA roles and models to follow.

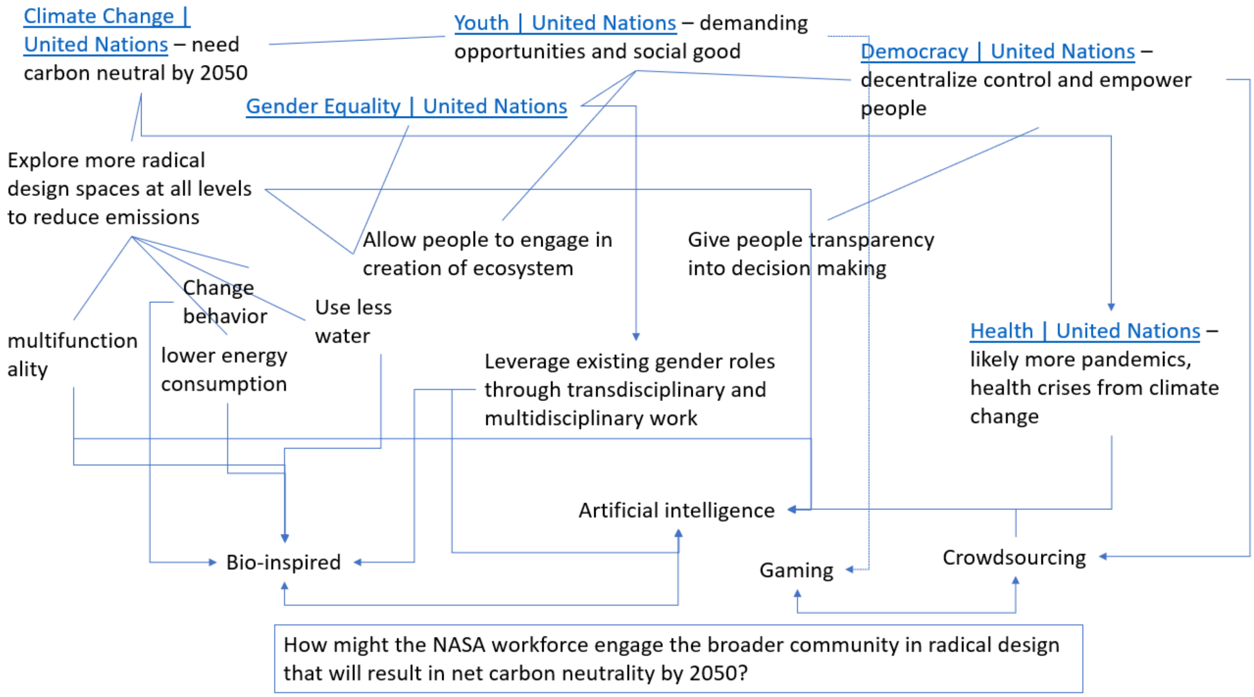


Fig. 21 Mind map of global issues and potential solution vectors.

V. A Path Forward

Design and build a system that is not possible with current technology and design methods that engages new workforce, tackles climate change, global threats and infuses new technology into the existing program structure.

The workshops served to identify a benchmark problem to focus a joint effort between industry, government and academia. Thermal management was identified as the common area of interest with additional topics to be determined through future workshops. The rationale for choosing thermal management is that it has wide applicability across not just aerospace applications but almost all industries. The growing use of cryptocurrencies, AI/ML and large volumes of data being stored on servers not only contributes to global warming through CO2 emissions but also through direct heating as a result of inefficiencies in power conversion. Electric cars and aircraft need thermal management solutions to manage heat generated by batteries, cables and motors. A unique challenge with aircraft is the need to make these thermal management solutions light weight. The application of ground based thermal management to aviation can lead to thousands of pounds of extra weight being added to aircraft thus compromising range. Concepts such as conformal batteries, multifunctional and conformal heat exchangers, vascular thermal systems that move heat from one area to another are increasingly being explored. Participants expressed value in NASA coordinating this effort as shown in the feedback received (Fig. 18 - Fig. 20). The objectives of the focused problem are as follows:

1. Develop a design database around a benchmark problem to train machine learning models that lend themselves to designing multifunctional thermal management systems (TMS).

2. Develop technology to enable adaptable multifunctional TMS for aerospace. This includes structures, coatings and liners, fluid transport, energy transport, heat sinks and heat sources. Also included are passive control mechanisms such as fluidic diverters, shape memory alloys, solid state switches. The system should mimic natural systems that are able to thermoregulate, transport fluids and maintain structure with minimal use of energy, resources and while employing non-toxic chemistries.

3. Develop tools to prescribe a TMS given requirements and constraints. This is to be interpreted in 3 parts. First, tools that speed up the use of existing computational software. Second, tools that replace computational software. Third, generative design tools that directly prescribe geometry given system requirements.

In addition to the short-term benchmark problem, a vision of the digital system architecture and a long-term vision for a system that may be enabled by the digital system architecture were put forward. Fig. 23 shows the IDEAS vision that combines learning from digital and physical tools and data to enable AI/ML and automation to design, develop and deploy built for purpose solutions. The benchmark problem tackles key elements of this vision system. The datasets generated, research articles mined, websites scraped are to serve as the initial populations for the data lake. The digital tools are to be connected to each other to enable an automated and seamless workflow. This includes a discovery and ideation phase that allows for abstraction and transfer learning across domains. This leverages work on PeTaL [65]. Two optimization frameworks are considered, OpenMDAO for gradient-base optimizations and GlennOPT [66], a multi-objective optimization tool developed for IDEAS to complement gradient based optimization and to work with computational fluid dynamics codes. In many cases, it is faster to test prototypes than to run simulations especially in the case of multiphase flows. Lab automation to enable this rapid testing is key to training physics informed models. In addition, AI/ML and uncertainty quantification reduce the time to calibrate instrumentation and inform designs of experiment. Three phases of technical development are envisioned as detailed below in reverse chronological order.

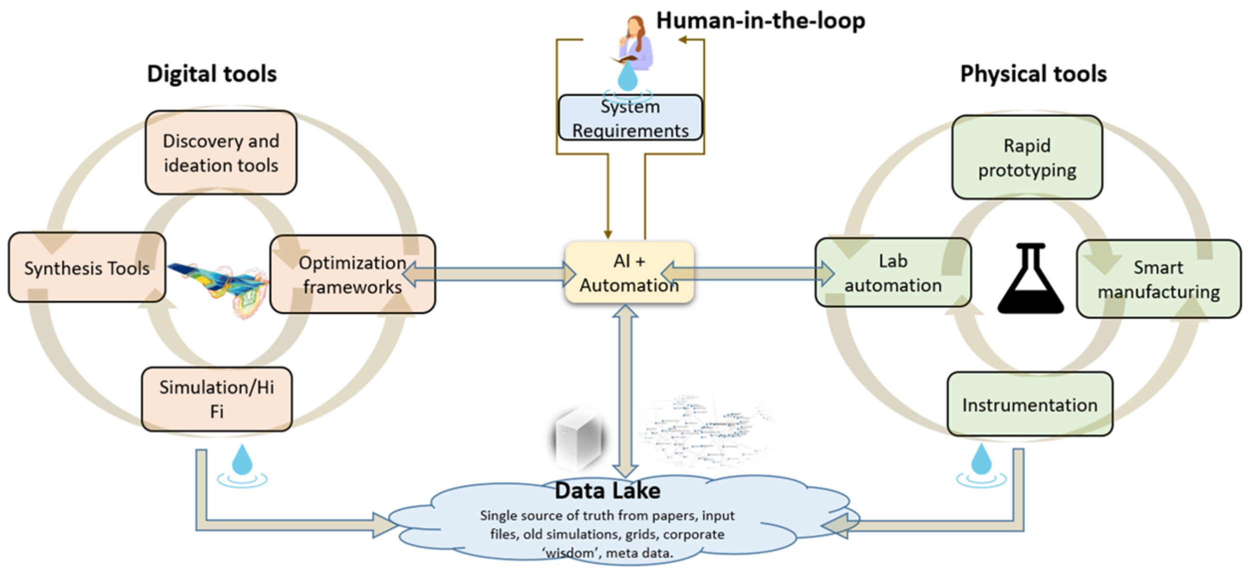


Fig. 22 IDEAS (Intelligent Design and Engineering of Aerospace Systems) vision

A. Long term vision (optimistically 10-20 years given funding and workforce availability): A biomimetic fluidcraft

In a hypothetical but realizable future, the airframe, propulsion, avionics, health monitoring, healing, guidance, navigation and communication may be completely integrated, and functions distributed throughout the aircraft. Aircraft will be resilient and adaptable, able to change mission and structure depending on the environment. For example, if a threat is detected, the aircraft may be able to shift functionality from thermoregulation to structure by rerouting fluid or electrical signals. Fig. 23 shows a concept vehicle that involves self-assembling structures. This concept is called SOFTEE (Self-Organizing Fluidcraft for Terrestrial and Extraterrestrial Exploration) [65]. It should be possible to design tiles or a family of tiles capable of propulsion, structure and power storage. Depending on the way they are assembled, there is a variation in the way attributes of structure, energy and other functions are allocated to the tiles. Such a vehicle would be able to reconfigure based on its environment, recycle its components and regenerate as needed. Key features of the system would be decentralization, modularity, multifunctionality, resilience.

Work toward such technology would be applicable to other areas of society like ground transport (or mixed modes of transportation), construction and housing, furniture and other technology infrastructure. This system would need a ‘brain’ and this brain would need information on the relationships between the environment, its structure and its function. This brain could either be on board or distributed among many vehicles and other structures. It could be a pretrained model or a continuously learning model that adds to its database. Fig. 22 serves as a steppingstone toward this system where the human in the loop would eventually be replaced with environmental input and feedbacks.

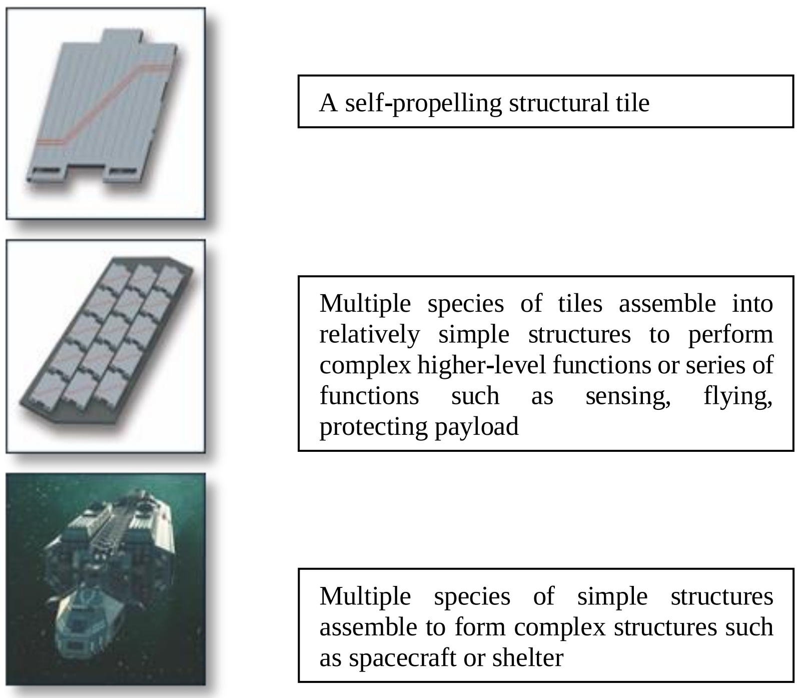


Fig. 23 SOFTEE – Self Organizing Fluidcraft for Terrestrial and Extraterrestrial Exploration.

B. Mid-term technical challenge (realistically 3-10 years): A biomimetic thermal management system for a Boeing 737-class aircraft

The goal is to enable power and energy transfer between all the airframe parts using known components and state-of-the-art design tools through a heat exchanger that acts as a bus connecting the airframe and the engine. The engine and airframe are to be cooled or thermally regulated through a series of arteries, veins or branches that mimic the circulatory system in mammals and transport system in trees and plants. This involves coatings that can radiate heat to the heat exchanger while absorbing noise, the aerodynamic and structural design of the heat exchanger [67] following natural system topologies [68][69] and the design of a vascular network of heat pipes and fluidic devices to connect the turbine and the heat exchanger. This effort is shown in Fig. 24 and involves collaboration with University of California Irvine, Arizona State University, North Carolina A&T, Pennsylvania State University, NASA Jet Propulsion Lab (JPL) and NASA Glenn Research Center. The algorithms being developed are opensource and intended to encourage collaboration with students and other external citizen scientists. Through this process various elements of Fig. 22 are being architected.

The objective is to reduce the time to design a heat exchanger by a factor of 10 as shown in Fig. 25, by replacing the traditional design process with machine learning and generative design. In Fig. 25, the top flow diagram shows a traditional design process for a heat exchanger. The bottom flow diagram shows one that is replaced by automation and machine learning. The intent in the digitized flow diagram, is to integrate manufacturing and testing into the early stages of design. For example, for a 3D printed part, the ML/AI models would generate designs that are manufacturable and that meet durability standards. There may in the short term need to be a post digital twin certification test but as we build trust with the digital system, these tests may not be necessary. To achieve this, databases of multifunctional data are required that combine performance measures with durability, manufacturing constraints, cost and energy use to design. For this phase, NASA’s N+3 engine cycle (CFM-56 class) is considered as the reference engine and a

Boeing 737-class aircraft the reference airframe [70]. A heat exchanger for waste heat recovery is being developed in collaboration with JPL to allow for greater than 150kW of heat to be extracted from the gas turbine engine core's exhaust nozzle. This heat exchanger will serve as the reference to compare the AI/ML designed heat exchanger against. The objective is to use this waste heat productively rather than rejecting it to the atmosphere. As of this writing, the most promising ways of doing this are to reheat fuel, cool relatively hotter components or, aggregate heat from different 'low grade heat' sources into a central location to effectively use a central high-grade heat source (fuel preheat is one). For large engines, dumping waste heat into the bypass stream is not considered the most efficient use of heat exchangers due to the considerable drag added to the bypass and weight penalty of the heat exchangers relative to the thrust enhancement provided by heating the bypass stream. A preliminary study looking at an isothermal turbine is provided by McNichols et al. [71].

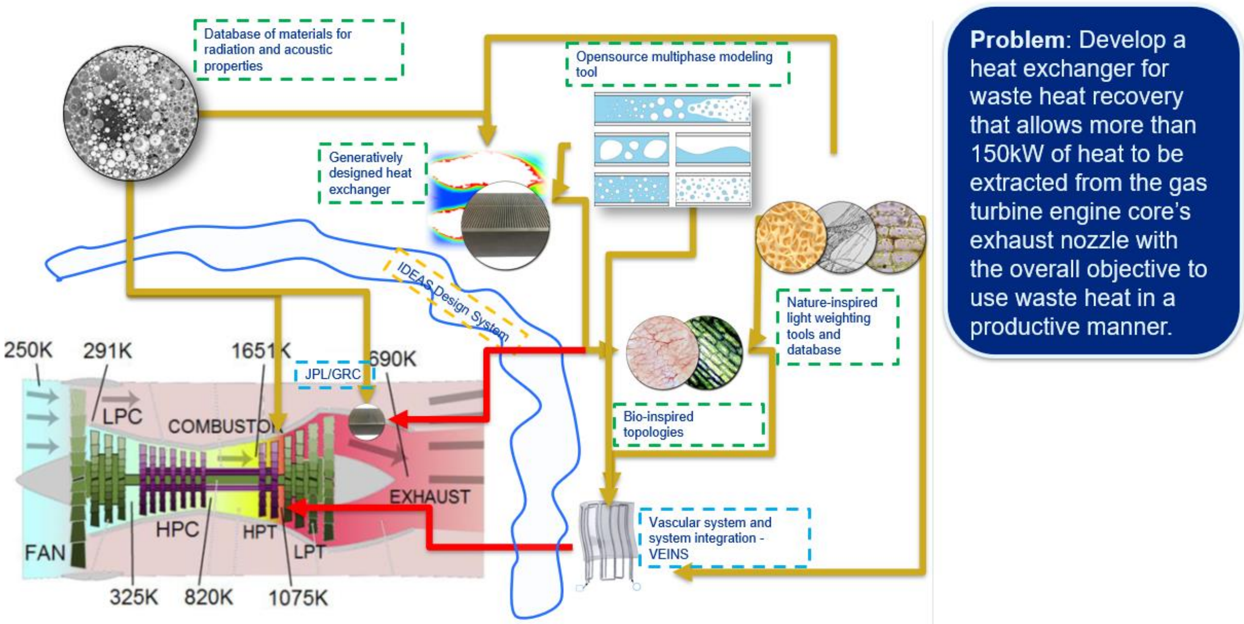


Fig. 24 Ongoing work toward development of a compact lightweight heat exchanger.

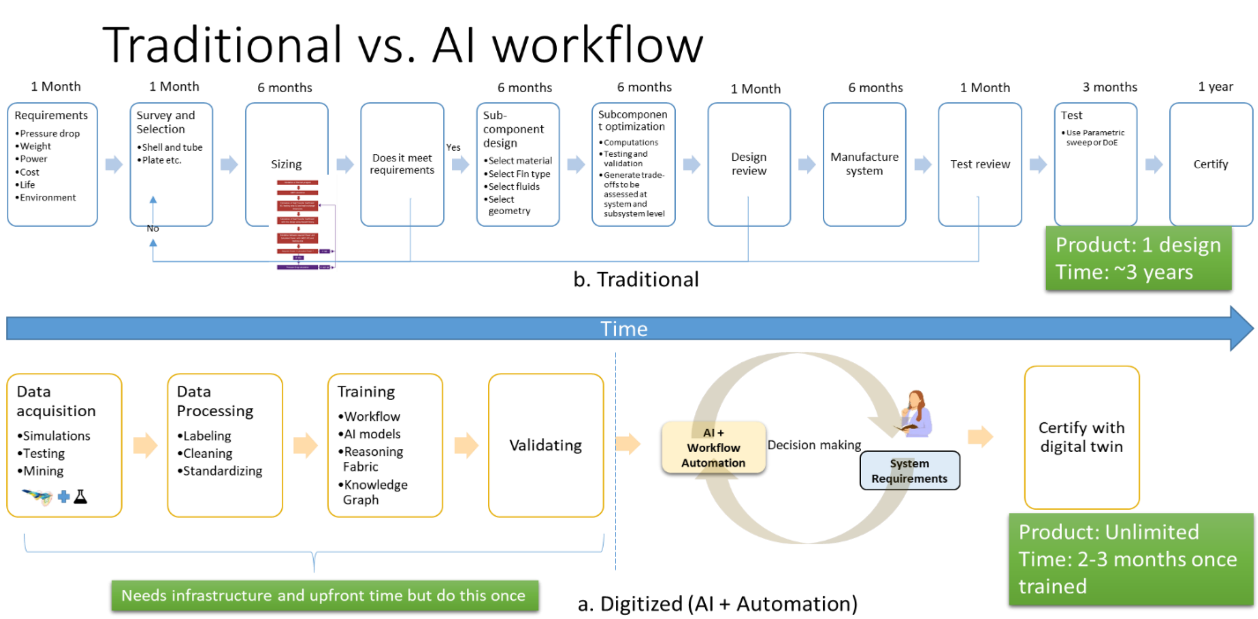


Fig. 25 The difference between a traditional design process (for a heat exchanger) and an AI infused design process.

C. **Short term infrastructure development (conservatively 1-3 years): a fundamental problem to aid in data generation and AI/ML model development**

In this phase, lasting approximately 3 years, the objective is to leverage readily available tools, data and insights to rapidly generate multifunctional data that is amenable to machine learning. Methods to store data such as cloud services, knowledge graphs and other databases are being investigated. A fundamental problem, shown in Fig. 26, is chosen as a focal point to generate the data. This rather simple looking geometry allows for the training of models to generate heat exchanger geometry, fins, turbine blades and many other parts depending on the boundary conditions chosen. The intent is to collect data relevant to heat exchanger designs (materials, geometry, performance metrics, durability, manufacturing constraints) to train an algorithm to suggest a heat exchanger configuration based on requirements. Similarly, data on heat pipes and fluidic transport are being collected and curated that relate performance parameters to geometric parameters and materials (working fluids, wicks, and pipe). This data is to be stored in a repository connected to a knowledge graph. Work on ontologies should commence by discipline with the intent of merging or unifying ontologies in the future to create a master ontology.

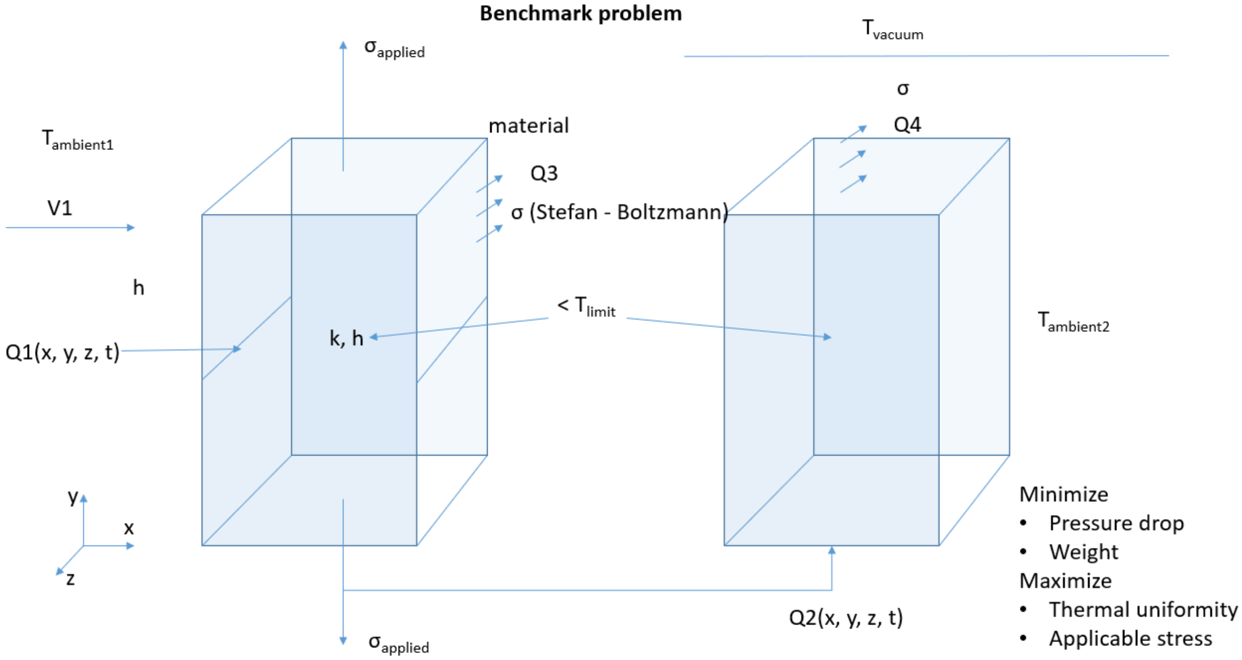


Fig. 26 Benchmark problem for thermal management. Given high level goals (pressure drop, weight, stress, thermal requirements) populate the volumes with an appropriate physical structure).

Overall, the process for thermal management can be repeated for other disciplines as shown in Fig. 27. Some key challenges to answer at each step are shown in the figure. The steps would include stakeholders agreeing on taxonomy, data formats, challenge problems, followed by generation of training quality data, model development and applications to relevant problems. As the diversity of data increases, a master ontology may be achieved along with models that are able to design a system such as that in Fig. 23.

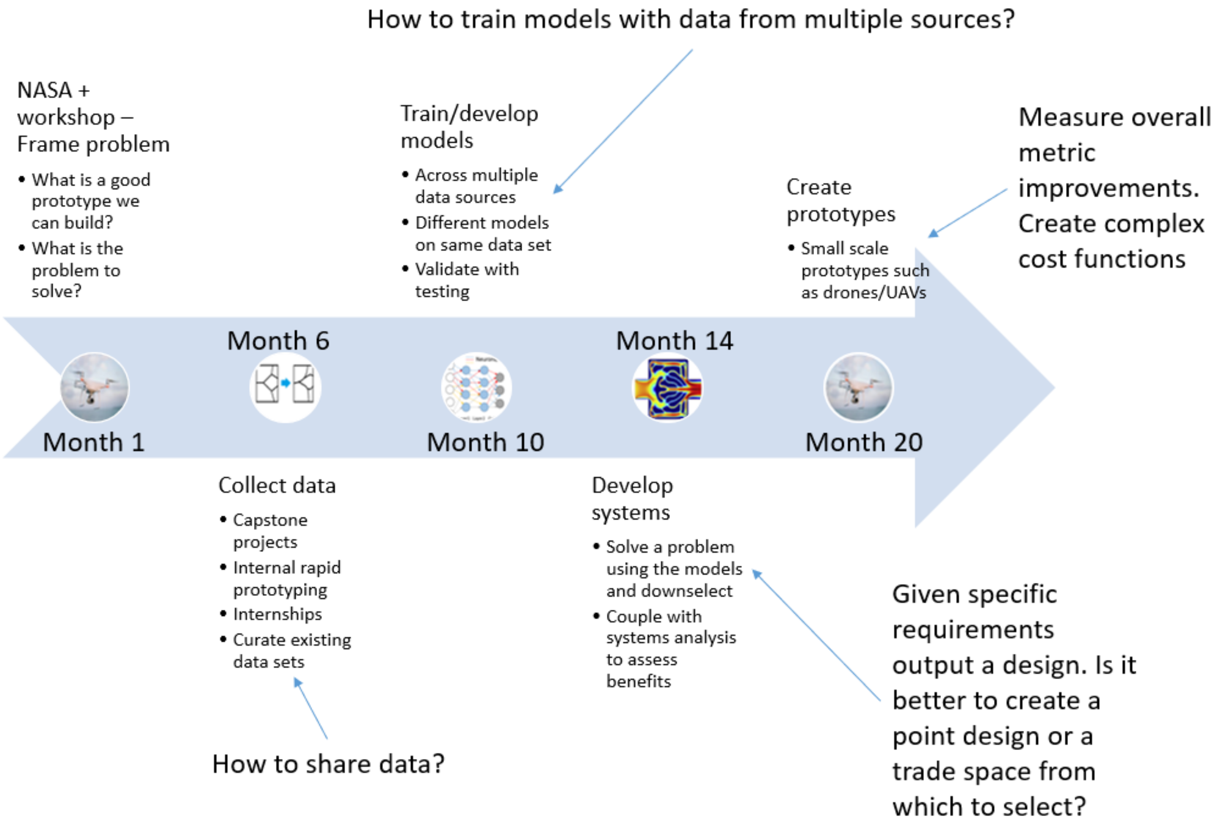


Fig. 27 AI/ML data gathering and model generation sprints

VI. Conclusion

There is an opportunity to address societal challenges stemming from climate change, shortage of resources and the lack of skilled labor by embracing the fourth industrial revolution. Future work around automation, crowdsourcing, gamification and opensource development can increase the workforce engaged in the aerospace lifecycle while training artificial intelligence and machine learning models that help us explore new design spaces in a fraction of the time it takes us to create a state of the art system.

The key to achieving this will be the ability to collaborate on problems previously seen as forbidden due to restrictions around intellectual property, the increased practice of opensource models and the development of robust and reliable privacy preserving networks. While we embark on this journey we must keep in mind ethical concerns in the way we develop algorithms, the way we deploy them and the way we use them to inform our decision making.

From a practical standpoint, much work is needed up front to enable tools to communicate with each other and to establish data generation, handling, architecting and storage practices that ensure the quality and integrity of the data. Security issues with regard to public and private collaboration need to be addressed to enable common model development.

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