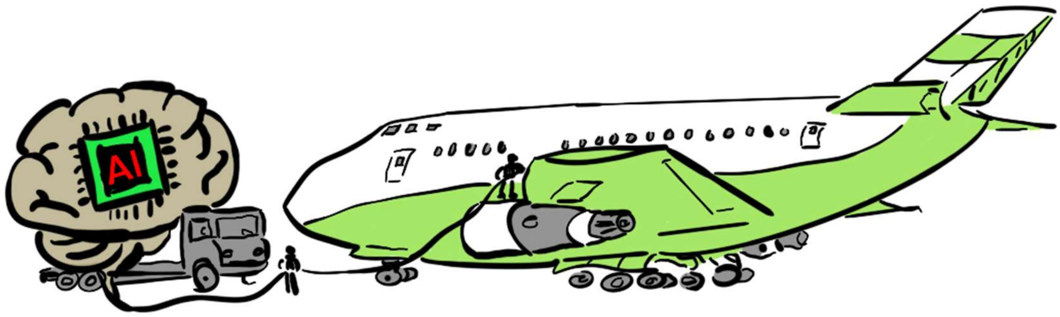


Greener Aircraft with AI

USAIRE Student Awards 2020

The targets are set: 189 nations committed themselves to keep the global temperature rise this century well below two degrees Celsius in comparison to pre-industrial levels [1]. The European Union is even more ambitious, it aims to be climate neutral in 2050 [2]. Global air traffic contributes to climate change with almost one billion tons of CO_2 emissions per year [3]. Currently, this is just two percent of mankind's total carbon footprint, but unlike emissions in almost all other domains, it has not been decreasing anywhere on the world (until recently). Although, it clearly has to to achieve the common targets.

It is not the case that passenger airplanes do not become more fuel efficient; in fact, each new generation every circa 25 years consumes about 20 to 25% less fuel [4]. However, the growth of air travel has been outpacing these improvements and the corresponding CO_2 reductions, compromising climate sustainability. In consequence, either technological progress must accelerate, or global air traffic must drastically and permanently reduce. The latter seems to be almost impossible since 80% of the CO_2 emissions originate from flights over distances larger than 1500 km for which ground transportation is usually not a feasible alternative [3]. Furthermore, it is difficult to reject the desire of citizens of emerging countries for air travel comparable to the extent which the western world is used to for decades. To conclude, we must find technological solutions that will ultimately lead us to carbon neutral flights. For this, engineers – including me – dream of revolutionising commercial aviation with hybrid-electric or even fully electric aircraft. Additionally, chemists are working hard on climate-neutral biofuels. However, revolutions have always been a challenge for the aerospace industry due to the unmatched high safety requirements, the high investment costs, and the deep supply chains. In this case, the immaturity of the technologies adds to these challenges. E.g., only small prototypes of electric aircraft have been realised by now [5, 6] and current biofuels are three to four times as expensive as traditional aviation fuels and need deep supply chains, many resources, and large production sites all of which will require a long time and effort to establish. In conclusion, it will take decades until both technologies will enter the mass market, but we cannot wait that long; we must significantly reduce aviation's carbon footprint already until the mid of the century. With average airplane service times of 25 to 30 years, we must act now, and we must act fast. I.e., we must think about an evolution ra-

> *"Climate change is the greatest challenge of our generation." – Airbus* [39]

ther than a revolution of our current designs, too. This evolution must be achieved with short development cycles and must allow for easy and commercially viable integration into existing aircraft designs. This is especially important due to the financial pressure on the aviation industry in the current times reducing the scope of major investments into innovations. But how can we significantly improve existing designs, although, thousands of experienced engineers have already spent years optimising them? Is that even possible? The answer is most likely yes. Airplanes are some of the most complex pieces of engineering that have ever existed. Certainly, the whole plane but also many components have many more design dimensions than even a team of experts can exhaustively explore in years. So, most likely many possibilities for improvements are hidden in this vast design space. But how to find them? Maybe with the help of *artificial intelligence (AI)*!? This set of technologies has shown quick and disruptive changes in many other domains, especially since deep learning is emerging in recent years. It stands out due to its ability to scale, i.e., to cope with huge amounts of data and to perform millions of iterations within seconds in the cloud. Two points that are impossible for humans. Another special feature is that AI can address many different engineering problems with similar approaches, i.e., it is a general purpose technology [7].

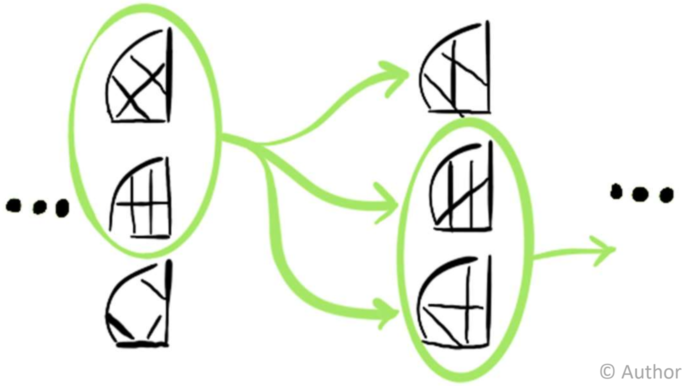
> *"We've made substantial progress, but there's more work to do." – Environment report, The Boeing Company* [38]

In my essay, I am going to approach the question if and how AI can help to design greener aircraft. For this, I am not primarily going to address a specific aspect of aircraft design and how it can be improved with the help of AI. Instead – and this has not been done before to the best of my knowledge – I am going to consider different AI technologies, briefly describe their core working principles, how they can be used for aircraft design, visit existing application examples, and estimate their future potential. Namely, this essay covers ***generative design using genetic algorithms***, *surrogate neural networks* to replace physics-based models, and *reinforcement learning*. The whole analysis will focus on the grand challenge how to make future aircraft greener, i.e., how to accelerate the decarbonisation of air traffic such that the aviation industry is able to meet the set climate targets.

Genetic Algorithms for Generative Design

Generative design has been first used in architecture and styling [8]. Case studies have demonstrated that this type of AI can support or even take over creative design tasks that were typically carried out by humans. However, creative design is not only done by architects and artists. Engineering often requires creativity, too, especially in early stages of product design and development when engineers quickly draft solutions guided by their intuition without evaluating all possibilities in detail [9]. Computer-aided optimisation, such as topology optimisation, is – if at all – usually only employed in later stages to refine the initial designs [8]. Although, this procedure has been proven to be efficient and successful by generations of engineers, it does not guarantee the optimality of the final solution. Especially, if the design space is large, it is impossible to exhaustively explore it manually and we must rely on the engineer's intuition.

Generative design aims to assist engineers in the creative conceptual stage by allowing them to explore a much larger range of possibilities [9]. Unfortunately, the concept suffers from a lack of clear definition; different researchers and companies label different concepts as generative design. This essay focusses on generative design with genetic algorithms, whose main idea is to mimic nature's evolutionary approach to design through genetic variation and selection.



Genetic algorithms select the best designs out of a population and combine them to generate an improved generation.

How it works

In principle, a genetic algorithm is just a specialised solver for a mathematical optimisation problem. Such a problem is defined by constraints, which limit the solution domain, and an objective function, which is sometimes called the fitness function [10]. A genetic algorithm starts with an initial population of candidate solutions, which can be randomly generated within the constraints. Next, two stages alternate, selection and genetic variation [11, 12]. In the selection phase, certain designs in the existing population are chosen to breed a new generation. For this, the fitness function evaluates every candidate. Configurations that score higher are more likely to be selected for breeding. The algorithm generates a novel generation by combining the selected designs using two genetic operators, crossover and mutation. On the one hand, crossover merges two high-scoring configurations. On the other hand, mutation introduces some random changes to guarantee variability. An alternation of these two steps statistically leads to a set of configurations with high – if done correctly nearly optimal – fitness.

The main advantage of genetic algorithms is their ability to cycle through millions of complex configurations within seconds, a fact that has become reality only in recent years with the availability of large amounts of affordable and readily available compute power in the cloud [13, 14]. Additive manufacturing – another emerging technology that has entered the commercial aviation market during the past 15 years, – especially 3D printing, can produce parts of almost any geometry. Furthermore, it allows mixing of materials with different properties in different zones of the same part. For both reasons, it dramatically increases the design space, which cannot be exhaustively explored by human designers and engineers anymore. Therefore, additive manufacturing is an ideal domain to apply the power of genetic algorithms to overcome this limitation [14].

The first step – defining the optimisation problem – is still carried out by humans [15]. The constraints of the problem can capture mechanical and geometrical requirements as well as properties of the material and the manufacturing process and their costs and the objective function can target minimum weight [8, 9]. An airplane's CO_2 emissions are approximately proportional to its weight. The population of initial configurations is, e.g., a set of randomly generated CAD models of part designs that lie inside the constraints [9]. The fitness function selects the designs with minimum weight, and they are merged with each other using the genetic operators to obtain an improved generation. The two steps alternate until, ultimately, they output a set of similar light-weight designs that are ready for production.

Example

Airbus is already using genetic algorithms for interior design since 2016 [14]. Together with Autodesk, a team of engineers rethought the design of a partition that separates the passenger compartment from the galley in the A320 cabin. At first, they defined requirements, i.e., constraints for the optimisation, including mechanical properties such as resistance to stress and geometrical properties such as anchor points, thickness, and cut-outs. This allows for a relatively simple replacement of the existing part without the need for modifications of other aircraft components and simplifies part certification, too. Furthermore, they defined the material, a metal alloy developed by Airbus, and the manufacturing method, 3D printing, which impose additional constraints. Subsequently, they applied generative design to automatically find the solution in this design space that minimises the weight. The resulting part is as strong but 45% lighter than its predecessor. If rolled out in all A320s, just this one part could save 500,000 tons of CO_2 per year. In addition, the process uses only 5% of the raw material that the traditional process of milling parts down from a metal block uses, which helps to reduce the company's environmental impact, too.

Airbus' AI-designed cabin partition in the 3D printer (left) and assembled (right) [14]. Generative design explored the full design space offered by 3D printing to find this configuration with minimum weight but equal strength.

The peculiarity of Airbus' re-designed part is its extremely complex and organic looking structure, which optimally addresses the given problem. Furthermore, it is the largest aircraft component that has ever been 3D printed – a single piece without fasteners. This design would have almost certainly never been found by a human engineer in a reasonable amount of time; just drawing this single configuration using CAD would have consumed days. This underlines the advantages of generative design, which can generate and evaluate millions of designs within seconds and with little resources [15, 13].

> *"The reason why we were able to reduce the weight of a component like the bionic partition by 45% is simply because we combined generative design and 3D printing." – Bastian Schaefer, Innovation Manager, Airbus* [14]

Outlook

A weight reduction of almost half sounds game changing; just imagine the fuel savings resulting from an airplane that is overall 50% lighter. However, most likely, Airbus picked a part for their first generative design project that was expected to allow large material savings. So, 50% must be expected to be an upper bound for the reductions that are achievable with the current state-of-the-art technology. Nevertheless, advancements of the 3D printing hardware and the algorithms, e.g., deep generative models, as well as experience gains by the engineers and an increase of available training data for the algorithms are expected to enable further improvements in the future. In addition, generative design is becoming more accessible, even for employees with little programming knowledge, since it is becoming part of commercially available CAD/CAE platforms [16, 17].

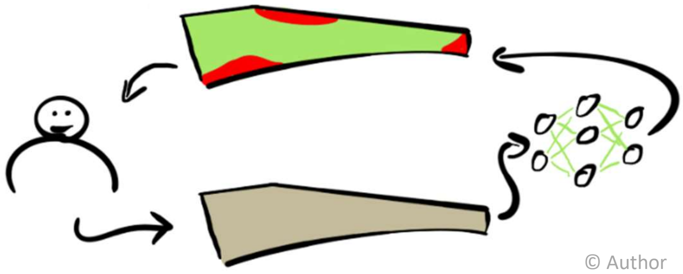
Airbus plans to apply its methods to larger structures inside their planes, e.g., the cockpit wall, which is twice the size of the partition and needs to be bulletproof, or the structure that houses the galley for food and beverage service [14]. The company has the vision of a bionic airliner in 2050 [14]. Further steps towards this vision would be to re-design and manufacture small and medium size parts such as hinges, brackets, and further interior components [18]. Similar weight reductions can be expected for these parts. In addition, some of them allow to incorporate the cooling and ventilation functions of then-obsolete adjacent components. This is because of the non-solid structures with internal cavities or lattices that are achievable with AI-designed 3D printed parts and allow for improved airflow.

Furthermore, nothing stops engineers from applying genetic algorithms to fuselage or airframe designs. However, the demanding stress requirements for these structural parts most likely drastically reduce the achievable material savings. Also, 3D printers that are large enough to manufacture them do not exist yet and additive manufacturing techniques that are currently feasible for those parts – composite manufacturing with automated tape lying (ATL) / automated fibre placement (AFP) – are different and require further adjustments. Additionally, only few large airplanes – namely the Boeing 787 Dreamliner and the Airbus A350 XWB – are dominantly built using additive manufacturing. A 787 is made of 50% composites, including fuselage, wings, tails, doors, and interior [19], and a A350 53% including wing box, fuselage, and empennage [20]. In consequence, these planes offer more possibilities for weight reduction with designs optimised by generative design. However, changes to structural parts require expensive and time-consuming certification processes. Furthermore, establishing production facilities with capacities for much more composite parts will take time and money, too, e.g., Boeing invested more than one billion dollars in to its new Composite Wing Center just to replace the aluminium wings of the 777 with parts made of composites [21]. Nevertheless, most companies are already planning to substitute more and more components with composite or 3D printed parts [22, 20, 23, 21, 24] and AI-driven designs might render this transition commercially viable even earlier.

Artificial Neural Networks as Surrogate Models

Generative design requires a given objective function and a given set of constraints. This is true for any design optimisation technique, even if it is performed manually. Mathematical functions map design candidates to properties that characterise, e.g., aerodynamics, loads, flight dynamics, weight, structural strength, or producibility [25], which appear as constraints or objectives in the optimisation problem. While some of these properties can be easily and directly derived from designs, others require complex physical models and simulations and some mappings are even unknown or rely on heuristics. Because precise physical modelling is time-consuming [26, 25, 27], this slows down or even prevents the commercially viable introduction of novel materials, part designs, and manufacturing techniques. Furthermore, it can happen that newly introduced parts and processes that are expected to be optimal in some sense do not fulfil the expectations because the chosen model, on which the optimisation was based, was wrong or at least imprecise due to attempts to limit the modelling effort.

A solution is to derive complex physical models from existing data with machine learning instead of attempting to explicitly model them based on expert knowledge [26, 25, 27]. The idea of using neural networks as surrogate models is not new and has already been applied to aircraft design more than 20 years ago [27]. However, the advancements of efficient algorithms that can handle large amounts of data, address complex engineering problems with many dimensions, and quickly run on tailored computing hardware such as GPUs, especially deep learning, enable new possibilities.



Artificial neural networks provide valuable feedback for engineers about the producibility of their part, e.g., a wing skin, allowing for iterative design optimisation.

How it works

Like any other model class that is used in engineering, artificial neural networks are functions that map a set of input variables to a set of output variables. Their design is inspired by biological neural networks such as brains. Specifically, they consist of layers of nodes called neurons, which can be several millions in deep neural networks. All neurons are connected to neurons in adjacent layers. At first, the inputs, i.e., real numbers, are fed into the first layer. Each neuron weights them differently and applies a non-linear activation function to the weighted sum. If the sum is high, then the neuron's output is high, if the sum is low, then the neuron's output is low, too. The second layer uses the outputs of the neurons in the first layer as inputs, weights them with different weights and calculates activations again. In this way, the inputs are propagated through the whole network until the last layer provides the desired outputs.

This structure is very flexible and allows to approximate almost any mathematical function. The first step when using artificial neural networks as surrogate models is to collect training and test data, i.e., exemplary inputs and outputs of the physical process that we attempt to model. In the training phase, we feed this data into the neural network and the weights of the connections are optimised such that the test outputs are best approximated. Subsequently, we can take novel component design proposals and use the model to predict the outcomes, e.g., lift and drag values [27, 25], noise, emissions, and weights [26], or moments of inertia [27].

Example

My own project when I was working as a tool engineering intern with The Boeing Company in 2018 serves as an example for this section. The company currently replaces the wide-body jet airliner family 777 with the next generation – the 777X, – which saves weight and, therefore, fuel with wings made of composite material rather than aluminium leading to increased efficiency by 7% alone [28]. Boeing produces the composite wing skins with automated tape lying (ATL) [29]. A heated robot head sequentially places layers of carbon fibre following pre-defined courses. This a very complex physical process. Therefore, it is challenging for engineers to come up with part designs that can be easily, quickly, and reliably manufactured [30]. In the initial phase of the use of such an alternative production technology, it may happen that the machines run with reduced speed and manual inspection and rework may be necessary to ensure the quality of the final product. This is because no physical model exists that can accurately predict the producibility of part designs with ATL. To support the timely introduction of novel components like wings, which are crucial for the efficiency gains of a redesigned airplane, a solution is to develop a neural network as surrogate model that uses the part geometry as well as several machine parameters as inputs and calculates producibility scores for different areas of the part [31]. These scores can be used by engineers to optimise the design in a closed feedback loop [30] and to adjust machine parameters leading to faster production cycles with lower machine down-times while maintaining the high part quality and reducing the amount of rejected parts.

Clearly, this concept is not limited to ATL and can be transferred to other manufacturing domains.

Heated ATL head laying down a wing skin in Boeing's Composite Wing Center [29]. Predicting the part quality and the likelihood of defects that result from a certain pair of part design and machine parameters is a challenge, which is successfully addressed with artificial neural networks.

A major challenge for the design of an AI like this one is how to represent the complex design of a large aircraft component, e.g., a wing skin, which is more than 20 m long, in a lower-dimensional space that can be fed into a neural network. This can be partly achieved by parametrisation of the CAD model and partly by treating the surface of the design like a camera image that consists of discrete pixels [30, 32, 33]. This allows to apply efficient neural network structures that were pioneered for image processing and analysis [32, 33], a domain where AI has been very successful.

Outlook

The given example shows that artificial neural networks allow to mathematically describe physical processes that cannot be modelled with traditional approaches. This can be an important factor to ensure that the introduction of novel manufacturing techniques, novel materials, and novel designs happens on time and on budget. Both is crucial if we aim to quickly introduce greener parts in the next years.

However, AI plays a secondary role in this regard. The primary goal is to design parts with minimum weight. While weight is clearly a physical property of a part, the mapping from the part design to its weight is usually a simple function with well-known parameters, e.g., material densities, and does not benefit from complex surrogate models.

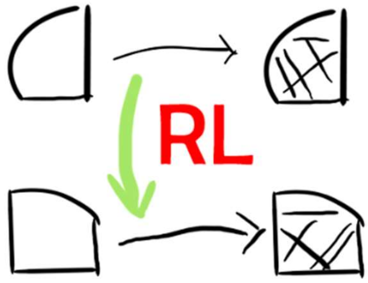
Furthermore, neural networks cannot be considered to be a novel technology in aircraft design, many different application scenarios have already been identified [26, 25, 27]. Its novel benefits originate again from the combination with newly introduced manufacturing techniques as well as the advent of deep learning. Treating part designs like images and feeding them into tailored deep neural networks allows to handle complex high-dimensional problems that cannot be addressed with traditional neural networks.

Reinforcement Learning

Reinforcement learning is an optimisation technique whose structure is close to that of traditional human-driven design processes [15]. In addition, deep reinforcement learning, i.e., reinforcement learning combined with deep neural networks, is currently one of the hottest topics in AI research and let to famous breakthroughs such as the development of Google's AlphaGo in the past decade [34, 35]. However, industry has not adopted the technology on a broad scale yet.

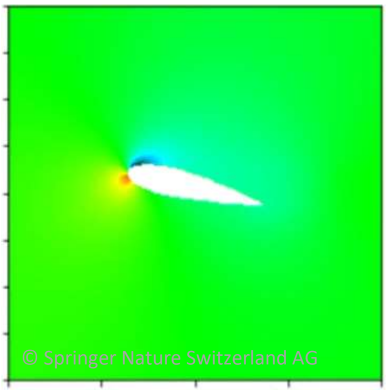
How it works

Again, optimisation with reinforcement learning requires a constraint search space and an objective or reward function that shall be maximised. Unlike genetic algorithms, reinforcement learning starts with a single feasible instance (a state) and probes the space around by evaluating the reward function for close instances. Over time, the algorithm can deviate further from the initial solution to explore unseen parts of the search space. However, the goal of reinforcement learning is not to find an optimal solution for a single given set of constraints. Instead, it learns a policy how to change the initial state towards a better solution, which generalises to different search spaces.



Reinforcement Learning (RL) comes up with policies that transfer designs to different requirements.

In product design, reinforcement learning is employed to adapt design configurations to different but similar requirements [36]. E.g., reinforcement learning can transfer a successful design for one part to other parts with similar requirements. Just as in a board game where a good strategy can counter playing behaviours of opponents that you have not met before.



Simulation of an aerofoil angle of attack optimised with reinforcement learning [36]. Reinforcement learning stands out due to its ability to generalise, i.e., to adapt configurations to different requirements.

Examples

To the best of my knowledge, the aerospace industry has not adopted reinforcement learning for product design yet. However, researchers have shown that reinforcement learning can be successfully employed to optimise an aerofoil angle of attack [36]. Especially, they have used deep reinforcement learning to handle the high-dimensional input data. The algorithm learns design policies that generalise well for different aerofoil shapes.

Furthermore, reinforcement learning has been used to automate the tuning of a sub-component of a rocket engine [37]. The prototyped algorithm is assumed to save “thousands of dollars” and up to three months of testing.

Outlook

The ability of reinforcement learning to adjust existing solutions to different requirements can help to accelerate the design of greener aircraft components. As soon as weight-saving solutions for some parts are found, they can be transferred to similar ones with only little additional effort. Due to the huge number of parts of a modern jetliner, this procedure has the potential to save considerable development time. However, the high-dimensional input space of designs such as Airbus’ cabin partition are still a challenge for state-of-the-art reinforcement – and even deep reinforcement – learning algorithms. Further research in this direction is required and also on more sample-efficient methods, i.e., algorithms that need less training data.

> *“Our solution could save thousands of dollars and cut up to three months of manual testing on expensive testing equipment.” – Edward Mehr, Data Product Management Fellow, Insight* [37]

Conclusions

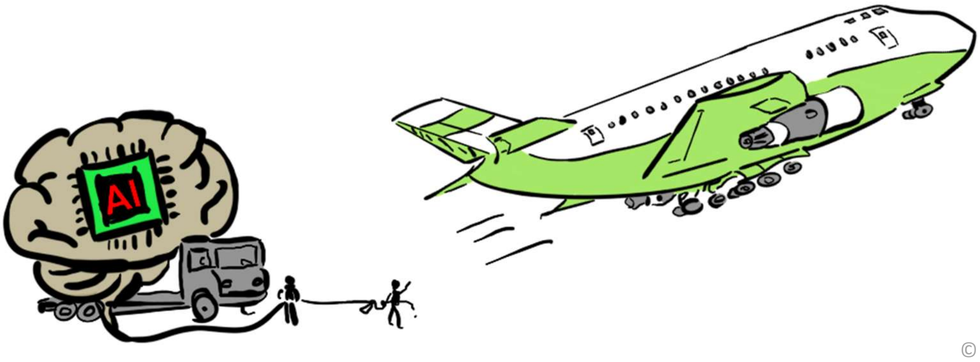
The impact of AI on greener aircraft designs will significantly depend on the chosen application area. It has been demonstrated that state-of-the-art generative design can lead to weight reductions of up to 45% for certain parts, but the gains for others with tighter design requirements might be much smaller. A key component to unleash the power of AI-driven design processes is an increase of additive manufacturing capacities. However, all major companies are already investing into this field and AI-driven process optimisation will help to make these investments commercially viable earlier.

An additional bottleneck is the high complexity of aircraft designs. If research makes progress with developing algorithms that can quickly work with many dimensions, then generative design and reinforcement learning cannot only be employed to make individual components of current aircraft greener, but also for major contributions to the design of the next generation, which will most likely contain significantly more and larger bionic parts than ever before. This will help to decrease the carbon footprint of global air traffic while ensuring that boarding a plane does not become a luxury.

> *"AI automates learning, which is the core of innovation." – Roberto Verganti et al.* [15]

Furthermore, AI-driven design is not limited to commercial aircraft. Replacing parts of fighter aircraft with alternatives that are lighter but equally strong might even be achievable in a shorter time horizon due to their usually smaller size requiring smaller investments into production process changes.

Finally, the use of AI is not only reasonable from an environmental standpoint, but also from an economic perspective. With fuel expenses contributing to airlines' operating costs with 23.7% [3], lighter aircraft will help them to save money and invest into renewals of their fleets – each kilogram of weight reduced on an aircraft can roughly save 3000 $ worth of fuel [18]. Furthermore, other industries have demonstrated that AI has a short time to market and (deep) neural networks, generative design, and reinforcement learning are already part of common engineering software. This lowers the amount of needed skill training as well as the time spend in development cycles. In general, AI is a digital technology, which requires very low investments in comparison to production equipment that is used to build aircraft. In consequence, it is a perfect companion for novel manufacturing techniques and knowledge-based aircraft re-design, which will altogether make the future of air travel greener.



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