Flexibility and Real Options in Engineering Systems Design

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Abstract

Designing engineering systems for flexibility is of utmost importance for future generations of systems designers and operators. As a core system property, flexibility provides systems owners and operators with the ability to respond easily and cost-effectively to future changes. It contributes to improved economic value, sustainability, and resilience by enabling systems to adapt and reconfigure in the face of uncertainty in operations, markets, regulations, and technology. The field of flexibility in design has steadily evolved over the last two decades, emerging from the area of real options analysis, which focuses on quantifying the value of flexibility in large-scale, irreversible investment projects. Flexibility in design goes further by developing and evaluating novel design methods and computational procedures to enable flexibility as a systematic value enhancement mechanism in engineering systems. This chapter provides an overview of how the field has developed over time as well as design frameworks, computational methods, and algorithmic procedures to support such design activities in practice. It discusses important challenges and limitations with supporting case studies in aerospace, automotive, energy, real estate, transportation, and water management. The chapter highlights future directions for research, involving sustainability and resilience, data-driven real options, empirical studies and simulation games, machine learning, digital twin modelling, and 3D virtualization.

Keywords

Engineering systems · Engineering systems design · Flexibility in design · Real options · Risk management · Stochastic optimization · Uncertainty analysis

Introduction

Motivation

"First, we created a marvellous technological achievement. Then, we asked the question of how to make money on it" (MacCormack and Herman 2001). This quote from Iridium's former CEO serves as motivation for this chapter on flexibility and real options in engineering systems design. Iridium is a low earth orbit (LEO) satellite infrastructure deployed by Motorola in the 1990s to enable phone calls all over the planet. Back then, Motorola designed and deployed the system based on anticipation of a large user base of more than a million subscribers by the end of the decade. The system architecture and satellite design were based on a fixed constellation that would maximize coverage for the anticipated user base. In May 1997, the first five satellites were launched, and by September 1998, a 66-satellite constellation was launched and fully operational. The technology was functioning as designed and won several technology awards.

Unfortunately in the 1990s, land-based cell phone technology started to emerge, which reduced the demand for Iridium's services. Because all system capacity had been deployed, with satellites designed to remain in the same orbital configuration, nothing could be done to adapt and reduce the economic impact of this un-anticipated scenario. Iridium revenues did not grow fast enough to cover debt payments. In the early 2000s, the venture declared bankruptcy and was sold for less than 1% of the original US $4 billion investment (Hesseldahl 2001).

Iridium is an important case study for engineering system design because it highlights the need to consider uncertainty very carefully in early architecture and design activities, in order to prepare the system to deal with future changing operational conditions and risks. Uncertainty is difficult to account for in design, since prevalent on so many facets, including operating environment, economics, geo-politics, global health, etc. It requires designers to address important questions, such as the climate outlook in 10, 20, and 30 years and possible future regulatory standards, the timing and likelihood of the next global recession or pandemic, or how could the systems be attacked by cyber or physical terrorists. All such questions are obviously difficult to address and may even be uncomfortable for engineers used to deal with certainty and well-understood technologies.

There are typically two approaches to deal with uncertainty in engineering systems design. One approach relies on design robustness, which aims to provide the best performance despite wide variations in operational conditions (Jugulum and Frey 2007). This approach focuses on designing a system so it does not have to change or reconfigure to perform well under uncertainty. It involves methods such as Taguchi and other statistical design of experiment techniques (Taguchi 1987). Another approach relies on design for flexibility (de Neufville and Scholtes 2011). This approach promotes designing systems that are adaptable, changeable, and reconfigurable, in order to reduce impact from downside conditions and capture upside opportunities. This chapter focuses on the latter, discussing development of design frameworks, computational tools, and algorithmic processes to support the design of engineering systems for flexibility, as a way to improve expected performance under uncertainty.

Definitions

Flexibility in engineering design is an important paradigm to improve the expected economic performance and value of engineering systems (Cardin 2014). Many recent studies have shown that it improves expected performance by 10–30% – often more – as compared to standard engineering design methods, both in terms of economic and social value. For systems and mega-projects requiring large investments, in the order of $100–1000 million (or Euros, Sterling), the improvement potential can be significant. Flexibility "enables system owners and managers to respond easily and cost-effectively to changing circumstances" (de Neufville and Scholtes 2011). It is often referred to as a *real option*, providing the "right, but not the obligation, to change a system in the face of uncertainty". This technical (and almost legalistic) definition of real options is inspired from the financial options literature, from where the field has evolved. Real options analysis focuses on quantifying the value of flexibility in irreversible investment projects (Trigeorgis 1996).

This chapter exploits the notion of a *flexible systems design concept* to describe a design concept that provides an engineering system with the ability to adapt, change, and be reconfigured, if needed, in light of uncertainty realizations. It is different conceptually from a robust design concept, which makes systems functions more consistent and invariant to changes in the environment, manufacturing, deterioration, and customer use patterns – see Jugulum and Frey (2007). A flexible systems design concept is typically comprised of two components: (1) a strategy and (2) an enabler. The former is similar conceptually to the definition of a real option "on" a system by Wang and de Neufville (2005), also referred as a real option "type" by Mikaelian et al. (2011). It represents the aspect of the design concept that captures flexibility or how the system is designed to adapt to changing circumstances. Example strategies inspired from the real options literature include recognizing the ability to abandon a project that is doomed to fail, which helps reduce the impact from unexpected downside conditions, or deferring an investment until more favourable market conditions arise, leading to better upsides. Other examples include expanding production capacity or contracting it to accommodate fluctuating demand or prices, staging capacity deployment in smaller modular phases instead of all at once, switching between different types of inputs and outputs, investing in R&D to access more diverse cash flows in the future, or combining the above (Trigeorgis 1996). An important difference between a strategy and enabler is that an enabler – or *engineering option* (de Neufville et al. 2019) – requires deep engineering and technical knowledge about the system. An enabler is similar to the definition of a real option "in" a system by Wang and de Neufville (2005) or a "mechanism" by Mikaelian et al. (2011). It captures what needs to be done to the physical design and/or in terms of management to provide and use the flexibility in future operations. Enablers take a different form for each system, depending on the flexibility strategies selected and the uncertainty sources considered in the analysis.

Why Flexibility Matters

Flexibility in engineering systems design matters because it enables better value, both social and economic, by generating designs that improve the *distribution* of possible performance outcomes, as opposed to optimizing a design for a particular projection of the future. Flexibility takes the designer out of the comfort zone of designing for a particular future scenario. It uses uncertainty as a way to stimulate

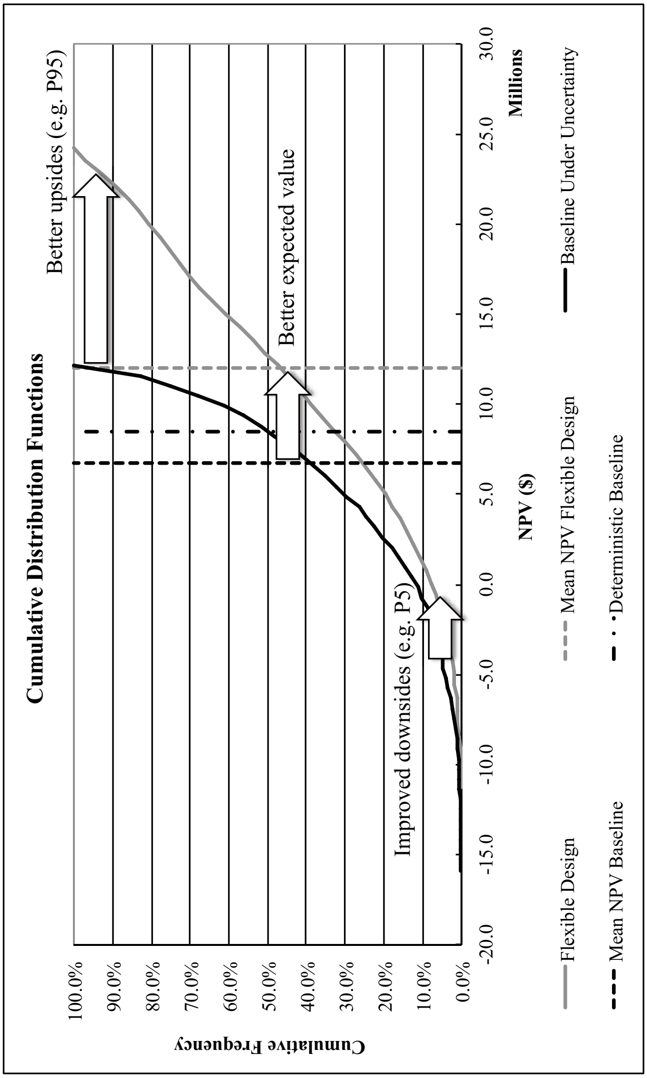

Fig. 1 Flexibility as an enabler of better value in engineering systems. (Republished with permission of the American Society of Mechanical Engineers, from "Enabling Flexibility in Engineering Systems: A Taxonomy of Procedures and a Design Framework, M.-A. Cardin, volume 136, 2014"; permission conveyed through Copyright Clearance Center, Inc.)

creativity and to consider other alternatives that would not normally be considered using standard design approaches. Figure 1 illustrates the typical impacts of flexibility on systems value using hypothetical cumulative distribution functions, where net present value (NPV) is used as performance metric. Such distributions can also measure the system performance along other non-economic metrics, e.g., emissions produced and transportation time. Here NPV measures the total discounted profit that a system generates over its lifecycle; thus higher NPV is generally indicative of higher economic performance and value. On the figure, the dashed vertical line depicts the distribution for a system optimized under deterministic conditions. This latter approach assumes 100% probability of this one scenario occurring – which is unrealistic. In contrast, the two cumulative density functions illustrate the distribution of possible value outcomes for a particular design, subject to a range of probabilistic operating scenarios. The analysis recognizes that performance of a design can only be characterized probabilistically. Flexibility aims to reduce the impact of downside scenarios (captured by the lower end tail on the left), while also providing for better upside potential (higher end tail on the right) than a more rigid design. The net effect is to improve the expected (or mean) performance of the system by shifting its entire distribution toward better value outcomes.

Different flexibility strategies act differently on the probability distribution functions of design alternatives. Some strategies are better at reducing the impact from downside conditions (e.g., abandonment), and are therefore analogous to put options in the financial literature. Other strategies are best at improving upside potential (e.g., capacity expansion). Some strategies are more valuable than others and may have different costs. It is the designers' role to evaluate different strategies and combinations to find the ones that improve value as much as possible, and compare it to the costs of enabling flexibility in the system design (see section "Flexibility Costs" for further discussion).

There are many real-world examples of engineering systems that were designed for flexibility. The 25 de Abril Bridge connecting Lisbon to the municipality of Almada in Portugal is one such system. The bridge was originally designed to carry four car lanes, but engineers designed in the infrastructure the possibility to add more lanes in the future, as well as a railway on its lower platform, should usage and demographic patterns warrant it – an example of capacity expansion flexibility. This flexible design later allowed expansion to the current six car lanes and two-railroad tracks infrastructure that exist today. This design required a smaller initial investment than if full capacity had been deployed upfront, and deferred additional costs to the future, taking advantage of the time value of money by lowering their economic net present value. It also enabled more traffic between the two cities today, contributing to a growing economy several decades later.

Another example is the Health Care Services Corporation tower in Chicago, USA. While facing market uncertainty in the 1990s, the owner company designed the skyscraper carefully to accommodate 27 additional stories on top of an initial vertical development (Guma et al. 2009). The flexibility could be exercised only if there was a need for additional office space. In the 2000s, the company realized faster growth in personnel needs than expected. It decided to exercise the flexibility strategy to expand office capacity, and deployed the second phase, completed in the early 2010s. The strategy was carefully enabled in design by allowing for stronger structure and additional floors, enabling the company to deal proactively with market uncertainty at strategic times. Examples of flexibility exist in many other sectors, for instance, in car manufacturing, where companies design for standard components across different models and enable different elements of the design to be changed to produce different car variants (Suh et al. 2007) – an example of switching flexibility.

There are also a number of examples where systems were designed with too much rigidity or lack of flexibility. The Iridium system is one example. In the aftermath of the bankruptcy, a follow-up study showed that a flexible staged deployment strategy combined with satellites designed to change orbital configuration would have helped the system to cope better with changing market conditions, resulting in about 20% expected lifecycle cost savings (de Weck et al. 2004). The strategy involved deploying the constellation in phases instead of all at once to adapt gradually to rising demand, requiring the orbital configuration to change in space to accommodate growing coverage areas. This strategy would have led to a significantly different design than the one considered and actually launched by Iridium. It would have required designing each satellite to change orbit, thereby enabling the system to change the orbital configuration as demand and coverage evolved.

The IUT Global waste-to-energy system in Singapore is another example, surprisingly similar to the case of Iridium. The system was originally designed to convert large amounts of food waste into electricity, fertilizer, and biogas. The original design planned for a capacity to process up to 800 tons per day and power up to 10,000 homes. Launched in 2008, the system was ultimately shut down in early 2011 at a time where it was treating only120–130 tons per day, providing electricity to only 500 homes, and showing no signs of increasing needs for additional capacity (Lim and Ng 2011). Many examples of rigid systems exist in other sectors, such as Ghost Cities in China, where real estate developers (and government) planned for a particular future that did not materialize in terms of renting needs, wasting much time and valuable resources (Brown 2009; Cardin and Cherian 2017).

The examples above exemplify the need to consider uncertainty and flexibility more systematically in the design of engineering systems. The engineering discipline is becoming increasingly complex and is exposing our critical systems to significant threats from climate change, cyber or physical terrorism, and pandemics. This reality requires a fundamental shift in the way that system design activities are conducted. It requires new approaches that will enable future generations of engineers to create better value for society, and to better protect the environment (Whyte et al. 2020).

Background

From Options Theory to Real Options

Real options analysis emerged from the development of financial option theory. Financial options (e.g., calls, puts) provide the "right, but not the obligation, to buy (or sell) a stock at a pre-determined price". Note that this definition is very close to the one used above in the context of engineering systems design. In essence, financial options are instruments that provide flexibility to purchase (or sell) financial assets like stocks, crypto-currency, futures, etc. Their price quantifies the value given by the market to this flexibility. In the 1970s, the Black-Scholes formula was developed to quantify this value as a function of the spot price of the underlying asset S_t, time to maturity t (for a call, when the asset is purchased at the strike price), volatility of the underlying asset σ, strike price K (the price agreed upon to buy the underlying), and risk-free rate r_F (Black and Scholes 1973). The formula for the price of a call option C is shown in Eq. 1 (a slightly different structure exists for put options, and other exotic options). The structure of the Black-Scholes equation dictates that the cash flows of a call option can be replicated by buying a stock with borrowed money – assuming the right proportions, captured by the terms (d_1) and (d_2). The equation gives a good approximation of the price of the option, so long as a number of assumptions can be fulfilled. Example assumptions are that the portfolio (consisting of fractions of stocks and bonds) can be purchased in a frictionless market (e.g., no transaction cost or commissions) and at equilibrium between supply and demand (i.e., arbitrage enforced pricing). The idea is to find the corresponding parameters in the real options problem (e.g., volatility of the

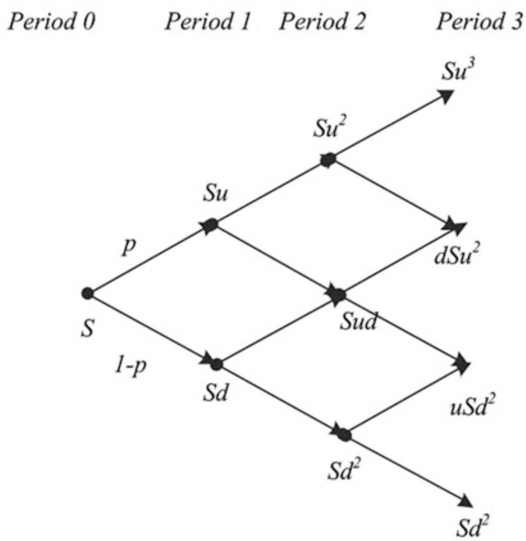

Fig. 2 Example binomial lattice as proposed by Cox et al. (1979) to value financial options. (Reprinted from Transportation Research Part E: Logistics and Transportation Review, Vol. 107, S. Zhang and M.-A. Cardin, Flexibility and Real Options Analysis in Emergency Medical Services Systems Using Decision Rules and Multi-Stage Stochastic Programming, pp. 120–140, 2017, with permission from Elsevier)

underlying, strike price), and assume that the value of the financial option corresponds to the value of the real option, provided the strategy is akin to the corresponding formulation of the Black-Scholes, i.e., the real option is similar to a call option, so one can justify using the form in Eq. 1:

$$C = N(d_1)S_t - N(d_2)Ke^{-r_F t} \tag{1}$$

where $d_1 = \frac{\ln\frac{S_t}{K} + \left(r_F + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}$ and $d_2 = d_1 - \sigma\sqrt{t}$.

Cox et al. (1979) later proposed a simplified model to price financial options that converges to the Black-Scholes formula when $t \rightarrow 0$ (or equivalently the number of periods $n \rightarrow \infty$), exploiting binomial lattice and dynamic programming principles (Fig. 2). The idea is that a stochastic process (e.g., price) can be conceptualized as either moving up or down every time period, which helps simplify the computational problem. A backward induction process is then applied starting from the last period (or stage) using Bellman's recursive formula, enabling to value the option at time $t = 0$.

Toward the end of the 1970s, Myers (1977) suggested that options exist on real investment projects, thus coining the term *real options*. An example of real option is land, akin to a call option. Buying a piece of land gives the owner the "right, but not the obligation, to build a house or building", which will in turn generate income as rents and capital gains, in analogy to a stock paying out dividends and gaining capital value. Because of this analogy between real and financial options, the Black-Scholes and binomial lattice approaches, combined with simulations, became predominant to quantify the value of flexibility in real investment projects (Copeland and Antikarov 2003). Engel and Reich (2015), for example, used such technique to evaluate architecture options in many relevant industries.

From Real Options to Flexibility in Design

With the development of real options came the need to develop methods and procedures to better support the design process to enable flexibility in engineering systems design. The field of *flexibility in design* emerged in most parts from a real options approach to flexibility analysis. Flexibility as a design concept, however, is not new and has been studied for a long time, for example, in manufacturing and product development (Sethi and Sethi 1990; Linsey et al. 2005). In contrast, the study of flexibility in the broader context of engineering systems design emerged in the early 2000s. An important distinction between the fields of real options and flexibility in design is that the former focuses on quantifying the value of flexibility – effectively aiming to price the real options – while the latter focuses on methods and procedures to embed flexibility in engineering systems design, as a systematic value-enhancing mechanism. Flexibility relies on value quantification in a similar fashion as done in real options theory, but more as a mechanism to rank order the possible design alternatives to support the design decision-making process (perhaps to a lesser extent to find the right "price" for the real options). In other words, most of the research in this field aims to extract important lessons from real options and engineering design theories, and then adapt or develop new methods to make those ideas more suitable for engineering design practice.

State of the Art

Design Frameworks

The point of a design framework is to provide engineers with a systematic approach to a given design problem. Many academics have proposed systematic frameworks to design flexible engineering systems (Nilchiani and Hastings 2007; Mikaelian et al. 2011), along with literature reviews to organize the research in the field (Ferguson et al. 2007; Saleh et al. 2008). The frameworks vary in form and substance (e.g., stepwise or flow process, different number of steps and activity types), but they generally involve the following phases synthesized by Cardin (2014) (see Fig. 3): (1) baseline design, (2) uncertainty recognition, (3) concept generation, (4) design space exploration, and (5) process management. Designing for flexibility rarely starts from scratch and usually evolves from an existing design referred as baseline. The arrows capture the fact that the process is not linear, but rather may circle around

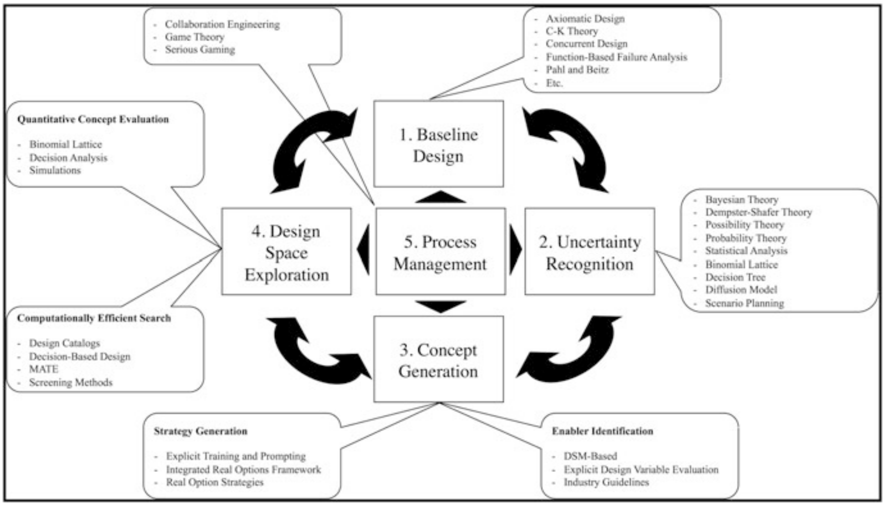

Fig. 3 Design framework for flexibility in engineering systems design, along with proposed procedures to support design activities in each phase. (Republished with permission of the American Society of Mechanical Engineers, from "Enabling Flexibility in Engineering Systems: A Taxonomy of Procedures and a Design Framework, M.-A. Cardin, volume 136, 2014"; permission conveyed through Copyright Clearance Center, Inc.)

the different phases, going back and forth as needed, until valuable designs are identified and selected in early conceptual activities.

In Phase 1, designers generate one (or several) design that will serve as baseline, in order to compare the value generated by the flexible design alternatives in subsequent phases. This phase recognizes that, to design a flexible engineering system, one does not need to reinvent the wheel, so the process may start from existing expertise and past design experience with the system. This phase is important to quantify the benefits from flexibility later on, as compared to the cost of enabling it in the design. In Phase 2, designers consider the various uncertainty sources that may affect the system performance. This step is crucial, as it will help define and narrow down the types of flexibility strategies and enablers considered in subsequent steps. In Phase 3, flexible system design concepts are generated to deal with the main uncertainty drivers in Phase 2, considering the baseline designs generated in Phase 1, relying on creativity and other techniques (e.g., Design Structure Matrix). In Phase 4, the design space is explored systematically, essentially looking for the best configurations of the flexible systems design concepts generated in Phase 3, while explicitly modelling the uncertainty sources from Phase 2. Phase 5 captures the interconnections between all four phases and multi-stakeholder interactions needed to support the conceptual design activities. This is because flexibility rarely relies on the knowledge of one group of stakeholders (e.g., engineers). It requires inputs from other parts of an organization (e.g., executive management, marketing, sales) to provide information on the socio-technical context in which the system is called to evolve.

Iridium Example

The purpose of the design framework above is to support the design process for flexibility. This section illustrates how the framework could be used to revisit and improve (in hindsight) the conceptual design process for Iridium, building upon the analysis and solution proposed by de Weck et al. (2004) and design tools available in each phase (see circles in Fig. 3 and further descriptions below). In Phase 1, a standard design is considered for low earth orbit satellites. A baseline concept proposed by de Weck et al. (2004) is considered, consisting of 50 satellites operating along 5 circular polar orbits, at an altitude of 800 km and elevation angle of 5°, with communication capacity for 80,713 duplex channels. Assuming a 10-year lifecycle, 10% discount rate, three million users, and average monthly activity of 125 minute/month, the authors estimated the expected lifecycle cost of such design at $2.01 billion, close to the actual development cost for Iridium (MacCormack and Herman 2001). In Phase 2, user demand is identified as the main uncertainty driver and modelled as a geometric Brownian motion diffusion process. In Phase 3, a phased deployment strategy is recognized as best to adapt to uncertain – but assumed growing – user demand. The system must be designed with smaller initial capacity, and enable flexible deployment of more satellites over time. To do this, the constellation must be designed to reconfigure in space to accommodate new user demand patterns and geographical coverage, as uncertain demand is realized, and more satellites are added. The design of individual satellites must cater for this strategy, and this is where the solutions starts departing from the actual Iridum system. In Phase 4, a lifecycle cost model is developed to quantify the performance of different design and deployment alternatives. To evaluate a large number of possible design configurations and expansion strategies, de Weck et al. (2004) conducted a tradespace analysis, similar to the one proposed by Ross et al. (2004). They found that the optimal initial design would require 28 satellites distributed over 4 orbital planes, at an altitude of 1,600 km, and 5° elevation, converging over time toward a 364-satellite constellation over 14 orbital planes, 800 km altitude, and 35° elevation. The analysis produces a radically different design solution than the baseline, which the authors show to reduce expected lifecycle cost from \$2.01 billion to \$1.46 billion, a 27% improvement. The savings arise from the ability to reduce exposure to downside risks, by requiring a lower initial capital investment, in case demand does not grow as anticipated. It also positions the system to capture more upside potential, should demand grow faster than expected. The strategy helps deferring satellite deployment until sufficient demand is realized to require more capacity, thus making a more sustainable use of limited material and financial resources (i.e., reducing the likelihood of unused capacity). This, in turn, contributes to reducing further the expected net present value of costs. For Phase 5, a setting that is most conducive of a productive design process in phases 1–4 should be considered. Ideally, such setting should bring together the key stakeholders and experts to cover various facets of the problem, e.g., engineering, financials, markets, and senior decision-making. ESA's Concurrent Design Facility or NASA's Integrated Design Center are example facilities promoting productive conceptual design activities. The facilities should enable teams of experts from different disciplines to work closely together on highly complex problems and improve overall efficiency of system design activities (European Space Agency 2021; National Aeronautics and Space Administration 2021).

Design Procedures

In Fig. 3, example design procedures are listed in the circles to support the design activities involved in each phase. The procedures in Phases 1–2 are well known and researched, e.g., Pahl et al. (2007), scenario planning, etc. The latest developments in the field have occurred in Phases 3–5, leading to a significant number of novel design methods and computational procedures, most of them thoroughly evaluated through empirical and case studies in various sectors. For example in Phase 3, as part of the integrated real options framework, Mikaelian et al. (2011) proposed a systematic approach to stimulate creativity and generate flexible strategies in UAV systems, by nudging designers to think explicitly about possible combinations of real option types (i.e., strategies) and mechanisms (i.e., enablers) ahead of the detailed design phases. Bartolomei et al. (2012) proposed the engineering system matrix, a holistic variant of a design structure matrix that represents the system-level dependencies within socio-technical systems. Their approach can be complemented by change propagation analysis (Suh et al. 2007) to identify flexibility enablers systematically, by looking at the ripple effects of changing design elements on to other design elements throughout the system, and identifying change multipliers as design components that are good candidates for flexibility – since those generate more change if unchanged, so worthwhile making more adaptable. Broniatowski (2017) compared system decomposition and layered designs as approaches to embed flexibility in design. Allaverdi and Browning (2020) proposed a new approach exploiting related principles to identify opportunities for flexibility in large-scale systems. Many researchers also considered methods to design systems and products that exploit "ilities" related to flexibility, such as evolvability, pliability, and survivability (Luo 2015; Mekdeci et al. 2015; Richards et al. 2008; Patou and Maier 2017; Patou et al. 2016).

Phase 4 is the most demanding from a computational standpoint and warrants further details. Here, designers' focus is twofold: (1) developing models to quantify the benefits of flexibility and value added, using economic (e.g., net present value) and/or non-financial metrics (e.g., emissions levels, average route duration in subway systems), and (2) finding the recommended design configurations using advanced optimization and statistical methods. In terms of value quantification, standard valuation methods typically include decision analysis, binomial lattice analysis, and Monte Carlo simulations. The expected value of flexibility is quantified as the difference between the expected payoffs from the best (or stochastically optimal) baseline design(s) and flexible design(s). Decision analysis relies on decision trees and a backward induction process as used in dynamic programming (Bellman 1952). Starting at the final stage, the decision maximizing expected lifecycle performance is made at each decision point going backward in time. The folding back process goes backward until the initial stage is reached, where the overall expected lifecycle performance of the system is calculated. The decisions available at each stage represent how the system can adapt. For example, in Babajide et al. (2009), a flexible oil platform was carefully designed with additional subsea tieback connection slots to expand oil production capacity, while a rigid system could not. When oil reserves were found higher than expected, the sequence of decisions would reflect the ability to expand production (and revenues) as compared to a rigid design, affecting terminal payoffs. Binomial lattice analysis is similar to decision analysis, with the exception that in each stage the uncertainty can either go up or down relative to the previous state (see Fig. 2). To reduce the number of possible outcomes, path independence is assumed, and lattice nodes are allowed to recombine. A process similar to dynamic programming is applied to quantify the value of flexibility. de Neufville (2008) used this approach to value the flexibility to abandon a mine pit project subject to copper price uncertainty.

Under a simulation approach, a large number of uncertainty scenarios (e.g., price, demand) are generated using stochastic techniques such as geometric Brownian motion, mean reversion, or jump models. The idea is to emulate the system's behaviour under each individual scenario, measure the performance or value, and then collect meaningful statistics on the distribution of performance outcomes. This is best done using *decision rules*, which are akin to sign posts, or triggering conditions that must be met for the system to adapt to changing conditions. Decision rules emulate the decision-making process in operations in an intuitive manner, similar to an IF-THEN-ELSE statement, e.g., IF *demand reaches a certain level*, THEN *expand capacity*, ELSE *do nothing*. They combine both physical design elements (e.g., amount of capacity to expand) and managerial aspects (e.g., which threshold level to consider for expansion) in succinct statements, and can be optimized using simple spreadsheets, or more advanced methods like multi-objective simulation optimization, stochastic programming, or robust optimization (Cardin et al. 2015b, 2017b; Caunhye and Cardin 2017). While the example above is simple, an important benefit of a decision rules approach is to enable analysis of more complex multi-variable design problems and uncertainty sources. Such approach is also well suited for a deep reinforcement learning formulation – see section "Future Directions". Figure 1 provides an example generic output from a simulation using decision rules, comparing the performance of different system design alternatives. Measuring statistics like mean performance, value at risk (e.g., fifth percentile), value at gain (e.g., 95th percentile), and standard deviation gives decision-makers a good idea of the performance, for different risk profiles. For example, a risk-neutral decision-maker may be interested in design solutions maximizing mean performance, since it balances downside risk mitigation and upside potential. Similarly, a risk-averse (seeking) decision-maker might prefer maximizing worst (best) case scenarios, thus focusing on value at risk (gain). The approach provides decision-makers with a range of solutions to select from, based on their risk tolerance profile.

Simulation models often lead to significant computational and mathematical challenges due mostly to the large number of possible uncertainty scenarios, metrics, design, and decision rule variables. Computationally efficient methods are needed to identify the best flexible systems design concepts, while dealing with the possible computational overhead. For instance, the Multi-Attribute Tradespace Exploration (MATE) framework proposed by Ross et al. (2004) explores the design space based on the configurations providing highest perceived value, based on decision-makers' utility attributes and costs. A Pareto set characterizes the designs of highest utility for each possible cost value. This tradespace captures transitions from one design state to another, exploring design alternatives via the concept of filtered out degrees, i.e., a design changing from a previous state, acceptable to a decision-maker based on development time and/or cost. Screening methods are also effective statistical approaches to reduce the number of samples needed to replicate the objective performance function. Such methods construct rapidly a simplified function or model and then identify best configurations using optimization methods – at the cost of sacrificing global optimality. Three general approaches exist and have been applied to analyse flexibility: bottom-up approaches use simplified versions of a complex, detailed design model (Lin et al. 2013), simulators use statistical techniques (e.g., response surface methodology) and/or fundamental principles to mimic the system's response (Yang 2009), and top-down methods use representations of major relationships between the parts of the system to understand system responses, as in systems dynamics (Sterman 2000).

Phase 5 addresses the social and collaborative setting under which flexibility can be generated in early design activities. It includes considerations of institutional and inter-organizational aspects in important projects involving multiple stakeholders. Phase 5 proposes and explores tools and procedures to either (1) provide a setting under which practical design activities in Phases 1–4 can be conducted, and for managing flexibility in real-world projects, or (2) provide an environment to better understand the conditions under which design activities are conducted through research. It includes methodologies to reduce barriers to implementation, to stimulate creativity, and to study agency problems and information asymmetries affecting the value of flexibility. For example, Phase 5 may be embedded in the design process through approaches like concurrent engineering (Kusiak 1992), to exploit task parallelization and new developments and technology to improve efficiency of collaborative design activities. Different governance structures can be set and explored to address the collective action problem arising from inter-organizational developments in projects exploiting flexibility (Gil et al. 2015). In terms of supporting research, game theory can be used to shed light on how different asymmetries affect the value of flexibility in major infrastructure system projects involving different stakeholders (Smit and Trigeorgis 2009; Smit 2001; Ferreira et al. 2009). The research can be complemented with empirical approaches like serious gaming – or simulation games – defined as "experience-focused, experimental, rule-based, interactive environments where participants learn by taking actions and by experiencing their effects through feedback mechanisms that are deliberately built into and around the game" (Ligtvoet and Herder 2012). Several researchers have relied on gamification to investigate the best methods to support the design and management of flexibility in engineering systems and projects (Cardin et al. 2015a; Gil et al. 2015).

Example Studies

The work on flexibility and real options spans a wide range of industry sectors and applications. Over recent years, a growing number of academics have studied flexibility in design in sectors such as aerospace, automotive, energy, real estate, transportation, and water systems (Silver and de Weck 2007; Chen et al. 2020; Koh et al. 2013; Sapol and Szajnfarber 2020; Kang et al. 2018; Strbac et al. 2020; Nie et al. 2017; Ma et al. 2017; Cardin et al. 2017a, c; Melese et al. 2015, 2017; Buurman and Babovic 2016; Esders et al. 2016; Geltner and de Neufville 2018; Gil and Tether 2011; Lethanh and Adey 2015; Hino and Hall 2017; Zhang and Babovic 2012). Many studies look into development and evaluation of new procedures to support the design process, with real-world demonstration applications. These witness the growing health and rising opportunities in this emerging and exciting field. This sub-section provides an overview of the work done, or in progress.

In the aerospace sector, Silver and de Weck (2007) proposed a time-expanded decision network to quantify the value of flexibility in design of heavy lift launch vehicles for space exploration. More recently, Chen et al. (2020) proposed a flexibility management framework for space logistic missions, using decision rules and multi-stage stochastic programming. In the automotive industry, Koh et al. (2013) proposed a process to assess levels of changeability (akin to flexibility), using dependency structure matrix, and a probabilistic approach to monitor change propagation, with demonstration in heavy diesel engine design. Sapol and Szajnfarber (2020) looked into the impact of implementation delays in exercising real options in military vehicle design and operations. Kang et al. (2018) proposed an optimization framework to redesign and invest in future vehicles, considering uncertainty in gas price, and emission regulatory standards. For energy systems, Strbac et al. (2020) looked into the role of flexibility and options for better decarbonization of the electricity system. Nie et al. (2017) used a real options approach to analyse flexibility in design and operations of transportation and storage network infrastructures for carbon capture and storage. Along these lines, Ma et al. (2017) studied flexibility in installation and operations of carbon capture and storage facilities using catalytic membrane reactors for hydrogen production. Cardin et al. (2017c) considered flexibility and real options in deployment of new nuclear power plants using a decision rules approach and multi-stage stochastic programming, considering social acceptance as an important uncertainty driver, along with growing demand in emerging countries. Melese et al. (2015, 2017) looked into the concept of flexibility in design and operations of infrastructure networks, such as pipeline-based carbon capture and storage systems. Buurman and Babovic (2016) integrated adaptation pathways, adaptive policy-making, and real options thinking to evaluate new climate change mitigation strategies. In the sector of building and real estate, Esders et al. (2016) looked at the benefits and drawbacks of real options thinking in work programs for building systems. Geltner and de Neufville (2018) proposed a practical "engineering" approach to value real options and flexibility in real estate development, based on a decision rule and simulation approach. In transportation, Gil and Tether (2011) looked into the interplays between flexibility in design and risk management in the context of London Heathrow's Terminal 5 infrastructure project. Lethanh and Adey (2015) considered the impact of real options thinking on design and operations of railway infrastructure systems. Cardin et al. (2017a) considered the value of flexibility in deployment and operations of car sharing systems under user demand uncertainty. For water systems, Hino and Hall (2017) considered real options as adaptation strategies to deal with flood risks. Zhang and Babovic (2012) considered a real options approach to architecture and design innovative water systems under uncertainty.

Challenges and Limitations

Enabling Flexibility

Enabling flexibility in engineering systems is a difficult process. Every system is different, faces different uncertainty sources and risks, and must fulfill different missions and purposes. Despite much ongoing research to develop frameworks and procedures, there is currently no "cookie-cutter" solution applying to all engineering systems. The frameworks and design tools above must be carefully applied to suit the needs of each intervention. The emphasis above is heavily geared toward engineering; however other important socio-technical aspects must be considered. Enabling flexibility is not always just about planning for stronger or shared infrastructures or being able to switch between different technologies. It may also involve setting up the right financial incentives in a contractual agreement or making sure that all stakeholders are agreeable to the flexibility being exercised at some point in the future. This relates to institutional and organizational considerations for embedding flexibility. Different organizations may have conflicting objectives regarding large-scale investments, especially in mega-projects like new airport terminals or railways, which may make it difficult to embed flexibility. Some investors might feel uneasy with the concept of flexibility, raise concerns about not deploying all the capacity upfront, for example, or may require a different capital structure to fund the venture. In real estate, neighbouring buildings may need to be notified of the possibility of a vertical expansion sometime in the future, which may alter their views of the horizon, and the building value. As a whole, flexibility must be considered not just from an engineering standpoint but also from other institutional, organizational, legal, and financial perspectives. Gil et al. (2015) investigated these issues and proposed various methods to deal with such inter-organizational challenges.

Flexibility Costs

Flexibility sometimes requires an additional cost upfront in terms of design, so that it can be used when the system is launched in operations. Without this, the system will not be able to adapt or change in light of operational uncertainties. To use once more Iridium as example, even if the company had wanted to deploy the system more flexibly in stages, it would have required designing the satellites to change orbital configuration, which is different from the way the actual system was designed. In other words, flexibility may have a cost, which is analogous to the premium paid to buy financial options. In the context of engineering systems, the cost may vary significantly depending on the system, strategy, environment, regulations, technology, etc. It is the designer's role to determine the most valuable flexible system design concepts, in view of the possible upfront cost. This upfront cost introduces a risk, of course, just like paying a premium for an option, and never exercising it. It is possible that flexibility will be embedded in the system and never used in operations. Perhaps the system did not encounter any conditions requiring adaptation or change, or perhaps the system capacity was good enough to enable good performance despite varying operational conditions – as in robust design. Recalling a definition of flexibility as providing the "right, but not the obligation, to change a system in the face of uncertainty", it is possible that the option will not be exercised at any point in time. The price paid is arguably lower than the expected value brought by the flexibility, and this value would not be quantifiable unless the procedures and methods described above were used. The premium involved is analogous to an insurance policy. The system operator or owner pays a price upfront to obtain a right, with the possibility that it will never be used. An individual paying a premium for a life insurance would not blame the insurance company for not dying! The idea is similar in the context of flexibility: it is a paradigm to manage risks and uncertainty in the context of engineering systems design, with the goal of improving expected value and performance in the long term.

Keeping Your (Real) Options Alive

Another issue is that a flexibility strategy that focuses on long-term performance improvement suffers the risk of being forgotten. Engineering systems are typically long lived, which means there is a high chance that the original designers, operators, and owners will not be the same individuals or group as those taking on operations in the future. This may create challenges and obstacles to “keep the (real) options alive”. For instance, there is a case where ownership of an infrastructure changed after several years, and the new system owner did not know about the flexibility embedded in the design by the previous owner. So, the flexibility was never used. This is why it is important to document and maintain the system’s capabilities carefully within an organization; otherwise it may very well be lost.

Too Much Flexibility

The goal of analysing engineering systems for flexibility is to identify the most valuable flexible system design concepts. It is not to make an engineering system flexible no matter what or to assume that any type of flexibility should be embedded in the system. Designers should keep in mind in their interventions that the purpose of flexibility is to improve expected future performance and value. Some strategies may be more valuable than others, or cost less, and should be prioritized. The framework and design procedures highlighted in this chapter are useful to rank order different design alternatives, in terms of benefits and costs, along economic and other metrics. Different methods in Phase 3 help generate a large number of possible flexible systems design concepts based on creativity techniques like brainstorming (Cardin et al. 2013), while others based on design structure matrix and change propagation may help narrow down the design space before going into computational analysis (Hu and Cardin 2015). The benefit of creativity-based techniques is that designers may come up with truly innovative solutions, but (too) many alternatives may need to be analysed computationally to identify the most valuable ones. In contrast, design structure matrix techniques go into more details early on, and may help reduce the realm of system design concepts generated and analysed, at the risk of ignoring easily accessible design opportunities that may be very valuable (i.e., losing the “forest” for the “trees”).

Future Directions

The field of flexibility in engineering systems design is highly multi-disciplinary. It is still relatively new (by academic standards!) and therefore still has much to offer in terms of future research directions and opportunities. An interesting aspect is that, given its nature, it often benefits from new research and developments in different disciplines. For instance, recent developments in artificial intelligence, machine learning, and data science are widely applicable in this field, with considerably untapped potential. The same goes for developments in digital twin modelling and 3D virtualization as more tools to support the design and decision-making process emerge. Although not exhaustive, this section provides an overview of potential future directions for research and applications.

Flexibility as Enabler of Sustainability and Resilience

With much uncertainty about the future, and ongoing threats from climate change, cyber and physical terrorism, and pandemics, engineering systems are exposed to massive risks in the coming decades. Such risks may disrupt global financial, urban, economic and political landscapes, as seen recently through the COVID crisis. To minimize risks and deliver a better future, engineers can play an important role by designing and deploying engineering systems that are more sustainable, with a view of making better use of limited resources, and resilient, to adapt and recover quickly from disruptions (Royal Academy of Engineering).

Research shows that flexibility can play a crucial role as a core, enabling paradigm to sustain and improve value in engineering systems design and make systems more resilient. Flexibility can help provide actionable strategies to mitigate risks and secure a better future. Flexibility enables sustainability – defined by the United Nations as “developments that meet the needs of the present without compromising the ability of future generations to meet their own needs” – by generating better value for systems that are already sustainable (e.g., renewable technologies), and by enabling system operators to deploy capacity and resources *if and when needed*. This reduces costs in present value terms, makes better use of limited financial and material resources by avoiding unnecessary capacity deployments (a valuable idea for future generations to satisfy their needs!), and thus adds value to society. Flexibility enables resilience, because it promotes “the ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions” (United Nations). It provides important properties like adaptability and reconfigurability after an unexpected shock, so as to regain quickly pre-disruption performance.

An important future opportunity is to develop a systematic, agile design framework that helps address ostensible confusion and indecisiveness in design practice that may exist due to wide ranging and diverse views on sustainability and resilience.

One benefit from flexibility is to provide a unifying framework to enable *both* concepts in engineering systems design, thereby enabling designers to be more focused in their efforts. Even though there are many facets to this important problem (Chester and Allenby 2019; Wied et al. 2020), flexibility is often discussed in both communities as an important enabling system property. This property can help further develop new design frameworks to help generations of future engineers better quantify the added value from sustainability and resilience, whether in terms of economic (e.g., profits, costs) or social (e.g., environmental, social, and governance or ESG) metrics (Schroders 2020).

Data-Driven Flexibility and Real Options

Up until recently, there has been very little work aiming at leveraging the power of data science and machine learning in the context of flexibility and real options analysis. For example, flexibility strategies still rely, by and large, on generic real option strategies (e.g., abandonment, capacity expansion, investment deferral) with exercise rules that are defined through human creativity (e.g., decision rules), and/or through Bellman's expected reward maximization principles (e.g., maximize expected discounted cash flow). Large datasets that are produced or used by engineering systems may provide new combinations or rules, timing, and strategies that may not be intuitive to human designers, but that could very well complement existing approaches, by providing unexplored value-enhancing solutions and reconfiguration policies. For example, one could specify the moves that are allowed for a system to adapt and reconfigure (e.g., deploy new phase, expand or contract capacity, abandon the project) based on a certain set of criteria (e.g., decision rules or policies, timings) and let the system combine these in different ways through a heuristic process to learn valuable strategies *from the data*. In this context, techniques such as deep reinforcement learning show great potential (see Caputo and Cardin 2022) and also generate other exciting new computational and mathematical problems (e.g., how to design optimal rules in a live, data-driven setting). The availability of large datasets also enables generation of better predictive models that can be used to improve scenario modelling in simulations. As a whole, there is a largely untapped potential for the development of a new data-driven formulation (or theory?) for flexibility and real options in engineering systems design.

Simulation Games and Empirical Studies

Another important direction for future research is to understand through empirical studies designers' and decision-makers' thinking and process during design activities and operations. Much research has been done where methods are demonstrated through applications in one or a few case studies. This may not be enough to fully validate a proposed new method.

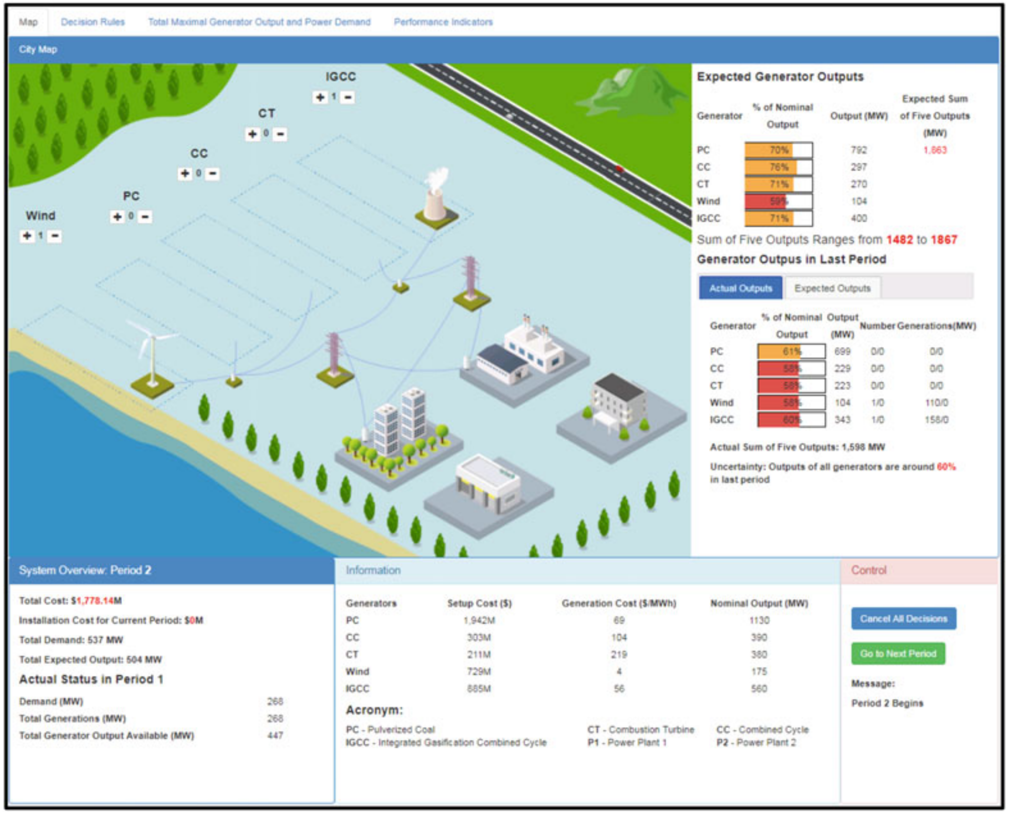

Fig. 4 Example of simulation game to study a decision rule formulation to real options analysis in design and operations of resilient and sustainable power systems. (Reproduced by permission for academic use only, "Development of a Simulation Game Platform for Flexible Generation Expansion Planning and Design of Power Grid Systems" in Proceedings of the 2018 Annual Conference, Institute of Industrial and Systems Engineers)

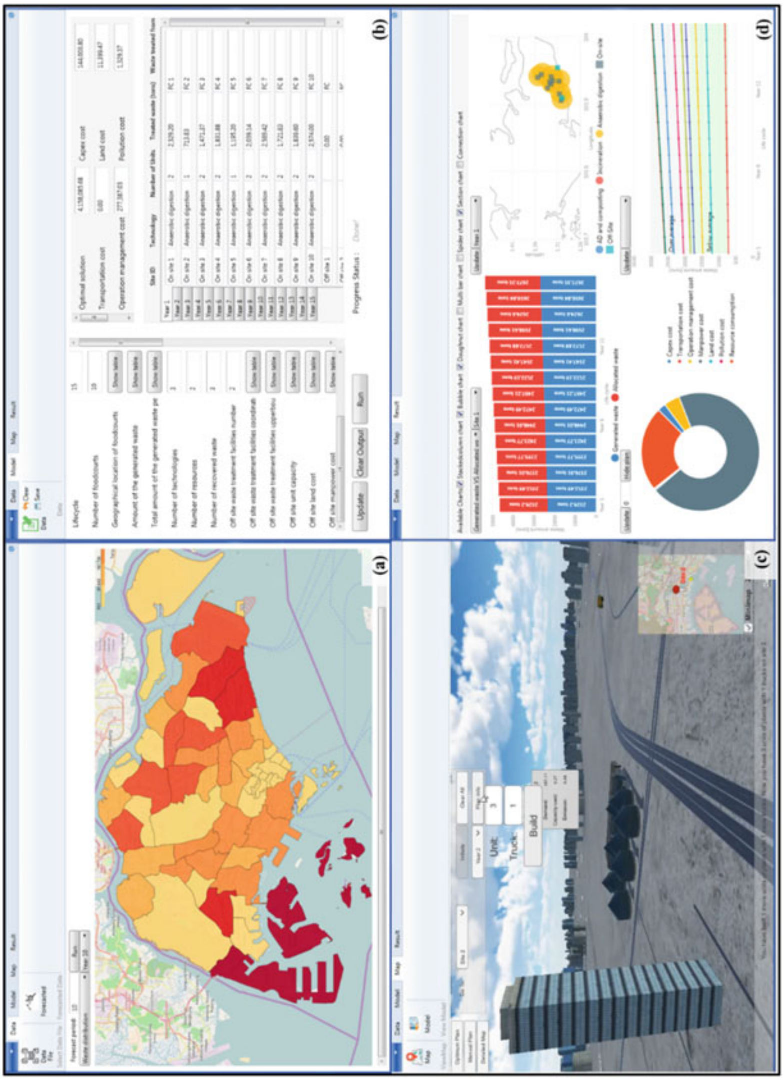

Fig. 5 Example of integrated data-driven decision support system for waste-to-energy systems. (**a**) Data analytics and visualization. (**b**) Optimization variable and parameter input definition. (**c**) 3D virtual environment. (**d**) Optimization output visualization

Empirical studies enable collecting data on design and decision-making behaviour, describe, and make inference based on statistical analysis. For example, one may devise "treatments", i.e., different methods to train designers on how to make best use of a decision rules approach to flexibility analysis. The effect of the different treatments can be assessed as compared to a baseline, or control treatment, along different performance indicators, i.e., dependent variables, such as the number of times the decision rules are used, quantitative performance assessment, etc. While such studies are usually conducted in a controlled environment that may not exactly correspond to the real world, this approach is nonetheless complementary to case study research since it relies on statistical main and interaction effects, as opposed to case study evidence that takes longer to generate, and in smaller sample sets.

Combined with simulation games (or serious games, as used in Phase 5 of section "Design Frameworks"), empirical studies provide a valuable environment to test different design methods and procedures statistically. Inspired from military simulation games – *Kriegsspiel* being considered one of the oldest – they emulate an environment where behaviour and decision-making can be studied more thoroughly (Fig. 4). A few studies have taken an empirical approach to study flexibility in engineering systems (Cardin et al. 2013, 2015a; Jiang et al. 2018; Gil et al. 2015), but many more are needed to thoroughly validate new computational methods, algorithms, and digital processes emerging from research.

Decision Support Systems, Digital Twins, and 3D Virtualization

There is a need to develop and evaluate new computational aided engineering tools to support the design and decision-making process in industry. Many of the methods developed through research take the form of an algorithm or equations that are difficult to visualize for future users. There is a need to embed the research output into relevant software tools that can be used in a practical setting to support decision and policymaking.

This work is taking place at different scales. As mentioned before, recent developments in data science and machine learning provide wide ranging opportunities to make better use of increasingly accessible datasets on engineering systems. For example, at a national level, the UK's Data Analytics Facility for National Infrastructures provides datasets, models, and algorithms on infrastructures for research development (STFC et al. 2020). At a project and portfolio scale, work is ongoing to develop a control room for construction (Farghaly et al. 2021). Figure 5 shows another example through an integrated data-driven decision support system for designing large-scale engineering systems. The system integrates data visualization and analytics capability, optimization input and output visualization, as well as visualization of the optimization outputs in a 3D virtual environment. It overlays an optimization model developed for design and planning of waste-to-energy systems in Singapore (Kuznetsova et al. 2019). This kind of system provides designers and decision-makers with a tangible environment for training and decision-making, in an intuitive setting – as opposed to a set of complex equations.

The ideas above are in line with recent developments in digital twin modelling, where complex high-fidelity models are developed and improved over time from large datasets, and 3D augmented reality (AR) and/or virtual reality (VR) for digital project delivery (Nikoli et al. 2019; Whyte et al. 2019; Whyte and Nikolić 2018; Sacks et al. 2020). Such technologies are useful to support visualization, optimization, planning, and design decision-making under uncertainty in a highly immersive environment. They have been, however, largely unexplored in the context of flexibility in design. They have the potential to enhance significantly design activities, as well as training, and decision-making. By emulating closely a real-world environment and changing environmental and operational conditions, such system can be used to quickly prototype system design alternatives, test their performance in a simulated environment, and find optimal configurations. It can be used to train operators to operate the systems and determine when it is appropriate for the system to adapt, reconfigure, or evolve, which is especially useful for systems operating in a harsh environment, e.g., mining, drilling, and space. New knowledge on explainable AI (XAI) is particularly well suited to enhance the quality of design and operational decision-making. As a whole, digital twin modelling, complemented by AR/VR technology, XAI and decision-support systems yield very high potential for future research developments.

Conclusion

At a time where engineering systems face significant threats from climate change, pandemics, and terrorism, there is a need to change our approach to engineering systems design and management. There is a need to consider uncertainty explicitly early on in the design process, as a way to extract better value for society, through improved economic performance, sustainability, and resilience. Designing engineering systems for flexibility is of utmost importance for future generations of systems designers and operators, policymakers, and business leaders. It prepares systems for change, adaptation, reconfiguration, and evolution in ways that ensure not only better survivability, but also better value in the long term. While the field of flexibility in design emerged in part from real options analysis, it is now evolving on its own, and at a steady accelerating pace. Researchers continually develop and evaluate novel design methods and computational procedures to enable flexibility, as a systematic value enhancement mechanism. The community is growing, as seen by the expanding volume of literature on the topic. This chapter provides an overview of such evolution over recent decades, motivated by an important need in industry and policymaking. It gives an overview of existing design frameworks, methods, and procedures to support design activities in practice and highlights important challenges and limitations. The overview exposes the multi-disciplinarity of the field, which involves finance, engineering design, optimization, statistics, and uncertainty modeling, with applications in many relevant sectors such as aerospace, automotive, energy, real estate, transportation, and water systems. The overview paves the way to exciting and applied research opportunities, much needed in industry and academia, involving sustainability and resilience, data-driven real options, empirical studies and simulation games, as well as AI and machine learning for design decision support, digital twin modelling, and 3D virtualization.

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