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Daydreaming factories

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ABSTRACT

Optimisation of factories, a cornerstone of production engineering for the past half century, relies on formulating the challenges with limited degrees of freedom. In this paper, technological advances are reviewed to propose a “daydreaming” framework for factories that use their cognitive capacity for looking into the future or “foresighting”. Assessing and learning from the possible eventualities enable breakthroughs with many degrees of freedom and make daydreaming factories antifragile. In these factories with augmented and reciprocal learning and foresighting processes, revolutionary reactions to external and internal stimuli are unnecessary and industrial co-evolution of people, processes and products will replace industrial revolutions.

1. Introduction

This paper aims to present an implementable framework for production systems to achieve breakthroughs. It attempts to formalise the process based on advances in multiple areas of manufacturing systems research to outline a future roadmap for similar advances. Although defining what constitutes a “breakthrough” is challenging, if not impossible, the term is used to denote when the system undergoes a significant change that affects its core processes and, perhaps, even its structure. Improvements that can result from adjustments in parameters are thus largely excluded from the scope of this paper.

Consideration of such improvements is critical under the current context of manufacturing and a system that is not capable of this type of change would be fragile. The fragility may manifest in response to internal inertia or external stimuli from disruptions.

The core principle of this paper is that, in a breakthrough, the production system uses its spare learning capability, notwithstanding the identity of the learning agent, to consider possible future eventualities and act based on the learning that is achieved because of imagining such scenarios. As this process is, ideally, taking place concurrently with core value generating processes of the system as well as gradual improvements resulting from reflection on historical data and prognostics, the term “Daydreaming” is used to capture the semantics [136].

Where, habitually, factories cannot risk to experiment with hypothetical futures, daydreaming aims to explore and learn from scenarios without hampering primary processes. Daydreaming traverses exploration spaces to identify unexposed opportunities for optimisation, advancement and exploitation of the factory’s organisation and technology, leading to coherent sets of envisaged improvements.

The paper starts by presenting the overall framework of a daydreaming factory, identifies the constituent elements and demonstrates that substantial ongoing research fits in parts of this framework and corresponds to the overall aims of capturing the process of industrial breakthroughs.

In the remainder of this section, a historical review gives a narrative of the most significant industrial breakthroughs in the past in the form of Industrial Revolutions. Considering that breakthroughs are results of learning, the concepts associated with learning and their use in the production system context are then introduced and the motivation for developing the daydreaming framework is presented.

Sections 2 to 5 outline the four key elements of the daydreaming framework: scenario generation, learning from simulations, learning from analytics and the implementation of the learning in the production system. The paper concludes with the prospect of future AI-assisted foresighting factories that predict and plan for industrial breakthroughs and the roadmap to realise such factories. The term foresight is used in contrast to insight [46] to emphasise that foresights are based on possible futures [161].

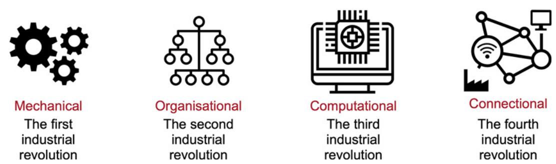

Fig. 1. The key breakthrough dimension in each industrial revolution.

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1.1. Optimisation, breakthroughs and reflection in consecutive industrial revolutions

There are many papers that provide an overview of industrial revolutions and their effect on production systems. The best of these papers extrapolate and offer predictions for future breakthroughs and outline prototypes for future manufacturing systems. With a focus on identifying the process of a breakthrough and how it was achieved, it is worth investigating the past industrial revolutions [34] as shown in Fig. 1.

The hypothesis is that reflection was a key enabler. However, not all of this reflection was on what had happened in the past – although that was certainly an important aspect in identifying the problems – but partly it was on what could be the future. Once this notion of future was crystalised into a foresight, it created the drive for the technology to enable the breakthrough.

Traditional research in manufacturing systems is often focused on "optimisation". This is an attempt to find the best possible set of operating parameters to achieve the best possible output in a system and is fundamentally different to a breakthrough [119].

The first industrial revolution was one based on mechanisation. The core principle was replacing the biological agents of mechanical work with mechanical replacements [130]. The breakthrough, in this case, was enabled, along with other factors, through a better understanding of physics (or to use the term that would have been utilised at the time, the natural philosophy), a desire to increase the scale of operations and imagining what the next generation of factories would be like. The second industrial revolution was enabled by a more thorough understand of issues pertaining to increasing the scale of operations. It became evident that systematic methods of organisation of resources were necessary to make sure that the complex array of mechanical and human resources could be coordinated to achieve the desired production rates. Around this time, the imagination of many elements working together in harmony was a major factor in development in the industry. Optimisation of parameters became an important factor in achieving performance targets and operations research was born.

With the advent of computers, for the first time, there was a viable replacement available for not only the mechanical aspects of what a human could do but also the mental aspects. Imagining how calculations and control hitherto carried out by the human brain could be replace by the work done by machines in the industrial context was a major factor in the third industrial revolution where many of the repetitive cerebral tasks that required a high level of human skill were offloaded to computers. The importance of optimisation and operations research increased as the result of the ability to numerically control the parameters much better at the optimum point. In the last ten years, the fourth industrial revolution has been heralded based on connectivity. Visionaries such as Merchant identified the positive effect of connectivity in manufacturing many years ago [126]: "... the manufacturing system, developed as a unified, coordinated and automated whole, will produce a revolution in the field of manufacturing as we know it ...". The latest industrial revolution is framed around gathering information from every corner of a well-controlled, computer-enabled mechanical factory, network of factories and global production networks [90] with well-informed human operators, imagining the additional gains that could be achieved through realisation of cyberphysical systems (using the connectivity to make hybrid software-hardware systems), digital twins (using the connectivity to make software entities that mimic and control their hardware counterparts) and big data analytic (using the connectivity to consider internal and external data to achieve more globally optimally tuned systems).

1.2. Cognition, learning and knowledge models

In these revolutions - as well as in many of the less pronounced developments in production systems - a pattern can be observed: a set of enabling technologies give rise to new engineering potentials that after testing become new production knowledge models. These models are then imagined in a number of new scenarios and the effects are predicted to create foresight about what could happen. Changes are then carried out in the physical systems to implement the most promising scenarios to realise the aims of a strategy that underpins the mission and values of the value generating enterprise.

The consolidation of potential effects of imaginary scenarios and capturing such reflections in a coherent foresight can only take place in the presence of cognition. In production systems, traditionally, this level of cognition has been solely available as a human trait. In more recent times, there has been significant research in characterising the cognitive ability of system and both artificial and blended systems that combine human and machine abilities have been explored [211]. [34] define cognitive adaptability as exhibiting attributes such as self-planning, self-healing and other knowledge-based adaptive responsiveness. [82] recognised this transition between human-based cognition through to what they termed as cognitive robots and proposed a cyber-physical framework based on it. [33] enumerated the related definitions for a "learning organization" to underpin the collective cognition that would take place in this setting of connected people and machines. Cognitive digital twins were identified as one possible solution to achieving such amalgamation of machine and human resources [42]. The role of cognitive machines in emerging manufacturing systems is to extend the human boundaries of computational capacity together with the ability to manage knowledge and uncertainty [146]. Organisations that employ cognitive machines and structures extend their intelligence and autonomy in dealing with uncertainty and can employ reciprocal learning [8].

One approach to achieve such cognitive abilities would be to consider hypothetical scenarios - even unlikely ones - learn from the predicted outcomes and then learn from the aggregate of these learnings. The related concept of "meta-learning" in cyber-physical systems where a deeper level of cognition is achieved as a result of learning from learning is demonstrated in [158–160]. The word 'reverie' has been used in this paper to denote aggregate learning from what is learned from many explorations regardless of how likely they are to occur.

1.3. The framework of a Daydreaming factory

Formalising the process of learning from the past and present in an organisation has been studied in different domains including "The Learning Organisation" [143] but a new framework is necessary to formalise learning from potential futures in factories. Daydreaming is consequently defined as using an innovative understanding of the world in the form of a digitised representation of a system based on engineering models, conducting reveries by generating multiple scenarios and gathering insights from the potential outcomes. This is followed by implementation of changes in line with the strategy of the enterprise. It is proposed that daydreaming forms the basis of the framework that embodies major breakthroughs in value generating organisations. Fig. 2 shows the articulation of such a framework for the specific cases where the system is in an industrial value-generating entity (a factory).

The framework has the digital representation of the factory at its centre with information coming to it from the enterprise strategy (left of the diagram) and engineering models (top of the diagram). The reverie function investigates the exploration space (as depicted on the right side of the diagram) and learning from the exploration closes the loop.

The digital representation of the physical factory is generated by twinning the physical elements of factory in cyberspace and keeping them up to date based on the operational data that is obtained from physical sensors embedded in the system [128,138]. The digital representation may be used as the basis to control and intervene in the operations of the physical factory.

The formation of the digital representation is reliant on the definition of the context based on the strategy of the enterprise, as well as the best abstract understanding of the engineering principles available at the time (henceforth referred to as engineering models).

Examples of engineering models at different fidelities are Newton's laws of motion, Navier-Stokes equations for motion of

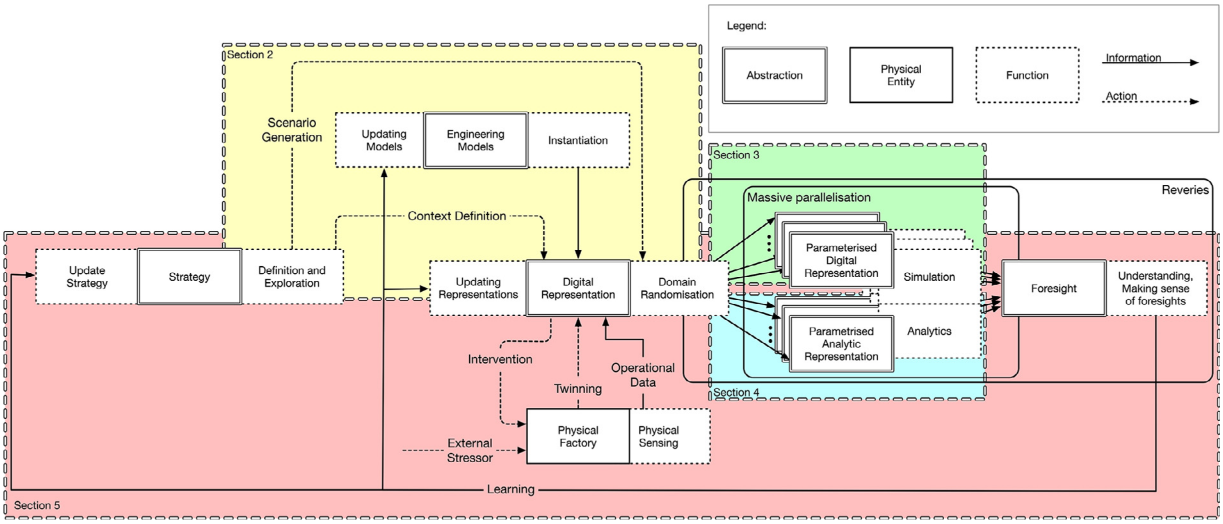

Fig. 2. Overall framework of daydreaming factories.

viscous fluids, Merchant's model of orthogonal cutting, Hooke's law and Little's law.

In a daydreaming factory, the will to explore different strategies or consideration of new engineering models leads to the application of scenario generation based on structured randomisation of variables within the active domain to generate many different potential futures in a form that is suitable for study either using analytic techniques (parameterised analytic representations) or simulation (parametrised digital representations).

The result of applying simulation or analytic techniques to these representations yields outcomes that in presence of human, artificial or blended cognitive ability is transformed into foresights about what could happen in the future of the factory if the new technology is employed, the new understanding of the engineering model is correct, or the new strategy is adopted.

Cogitation on the foresights yields practical measures that are adopted by (1) modifying the strategy of the firm; (2) updating the engineering models with the improved understanding; and/or, (3) updating the digital representations.

The intervention in the physical system that then follows completes the framework. The intervention could be as minimal as changing parameters on physical devices or as fundamental as introducing new technologies or business models.

In this paper, with a focus on the latter, the disparate research efforts being carried out around the world are presented in the daydreaming framework with the relevant sections of the paper for each aspect of the framework highlighted in Fig. 2 to show how they underpin parts of this framework and can be brought together to provide a blueprint for future industrial breakthroughs without unexpected disruptive revolutions.

2. Scenario generation to initiate reveries

Daydreaming is habitually related to potential futures [26,104,105] that envisage advantages over the current situation. In this, daydreaming goes well beyond operational issues and short-term forethoughts. It explores potential futures while the primary processes in the factory remain uninfluenced until underpinned decision-making leads to the implementation of the daydreaming outcomes. With that, daydreaming probes scenarios, where learnings can originate from positive as well as from negative prospects. The feedback loop of modification of parameters, prognostics based on artificial intelligence and big data analytics and optimization of the system as articulated in [48] is not the principle topic of discourse in this paper. The focus is instead on applying a constructivist approach to giving voice to a company's strategy, contextualised by technological and organizational developments. The constructivist perspective aims to explore possibilities, without a-priori giving in to impediments or circumspections related to limitations, feasibility, risks, uncertainty, etc.

In this sense, daydreaming can be seen as divergently establishing a so-called exploration space and ultimately converging it into a solution space [79] – without a problem space necessarily being present. The exploration space does not only represent all potential outcomes, but it also defines a set of orthogonal dimensions that construct it. The set of dimensions is instrumental in analysing, evaluating, and assessing solutions and enables convergence into relevant solution candidates. Hence, in the convergence the viability and optimization of the solutions are addressed in a structured and purposeful manner.

In considering the exploration space as being representative of a potential future reality for a factory, two parallel perspectives can be discerned:

1) The structure that underlies the factory and allows it to display any behaviour. This structure acts as the foundation in which all processes and initiatives find their backbone.
2) The 'behaviour' of the factory that is driven by the way in which the product-portfolio, the available assets/resources, the manufacturing strategies and the ability to change any of these is converted into real life demeanour and performance.

In terms of the exploration space, the two perspectives mentioned above, align with the dimensions of the exploration space and the content of that exploration space respectively. In a daydreaming factory, both perspectives amalgamate, which allows for a factory impression in which the planning, control and evolvement can be more than merely mechanistic and deterministic. Here, daydreaming exceeds the potential of individual simulations, by using scenarios in which the value of parameters, but also the parameters themselves are subject of exploration. Moreover, the scenarios are not necessarily completely connected to existing realities, rendering the outcomes of daydreaming suitable as seeds for potential futures.

Consequently, probing potential futures for a factory can be based more on deliberate exploration, postulation, and hypothesizing rather than on stepwise and pre-defined acts and optimizations. The main risk of such a daydreaming approach is that the attempts become open-ended and divergent; consequently, an effective and efficient framework for governing the evolvements is required, hence the need for the daydreaming framework in Fig. 2.

2.1. Conducting realistic reveries – context definition

The framework that underlies purposeful reveries combines two essential functions: adequately capturing the current situation as well as representing envisaged or future factories in realistic states. Realistic states are those that are potentially possible in the physical world as determined after the scenario is generated. It is especially the relation between the current and potential situation that is instrumental in daydreaming as it drives both the exploration and all converging processes.

Moreover, in any reverie, it is important to distinguish the as-is from the to-be situations as well as establishing a feasible route between the two. For open environments like factories that typically have myriad and extensive interfaces [190], no depiction of the as-is situation can ever be complete, conclusive, or certain. Moreover, merely the dynamics of the context, e.g. related to technological developments, would enforce an volatility and agility on the as-is model that is impossible to achieve or to maintain. This renders a digital representation (see Fig. 3) where the daydreaming factory exists alongside its digital system reference. The daydreaming factory is the physical reality, and the digital system reference captures the as-is and to-be models of that reality with the required/possible accuracy, at the appropriate level of detail and apt time horizon and predictability.

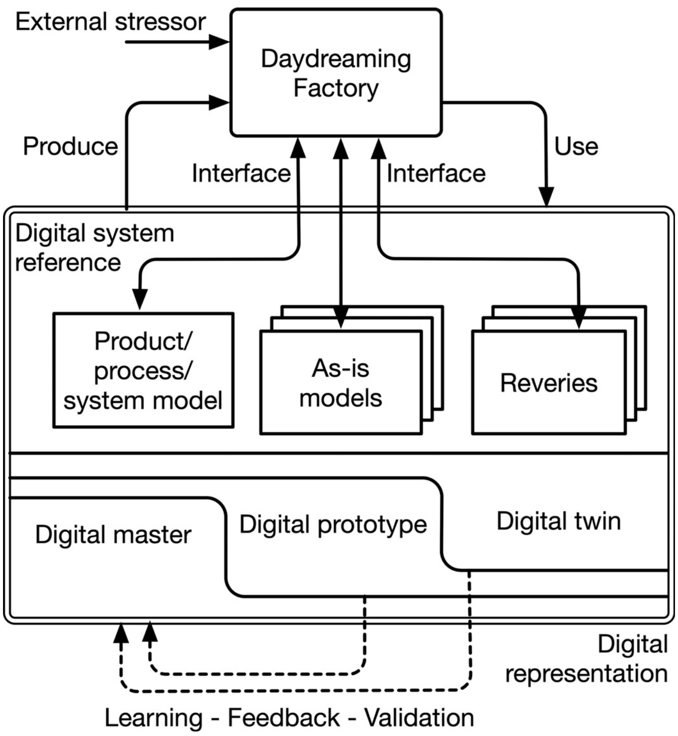

Fig. 3. The internal structure of the digital representation and links with the daydreaming factory (adapted from [104,196]).

The interfaces of the factory environment that are not modelled in the digital system reference are referred to as external stressors. Such stressors can have favourable and unfavourable impacts at varying scales/magnitudes, with varying frequencies, and more importantly, with various levels of predictability. The more predictable a stressor, the more feasible it is to model it and its probable consequences. However, especially in complex, emergent systems like factory environments, unforeseeable stressors will often have the biggest impact. Such 'black swan' events [186] can not only undermine the established understanding of the as-is situation, but they [26,104] can also eliminate the added value of any to-be prospect.

Hence, the digital system reference should exhibit a system response that is tolerant to unanticipated stressors. This does not only imply that it can aid in envisaging an adequate response of the physical reality, but also that the conditions for daydreaming may be enabled: every stressor (either internal or external) may extend the exploration space in terms of content or number of dimensions. With that, the digital system reference (and consequently, the daydreaming factory itself) would no longer be fragile and would go beyond being merely robust [184].

With sufficient exploration, it should at least be resilient [132], if not antifragile [1],[228]. A comparison between the expected responses of a fragile, a resilient, a robust and an antifragile system are shown in Fig. 4. It is notable that this is a simplified visualisation with a single performance measure in pursuit of diagrammatic clarity, whereas in most systems multi-criteria decision support is a key attribute of the divergent exploration space that characterises daydreaming.

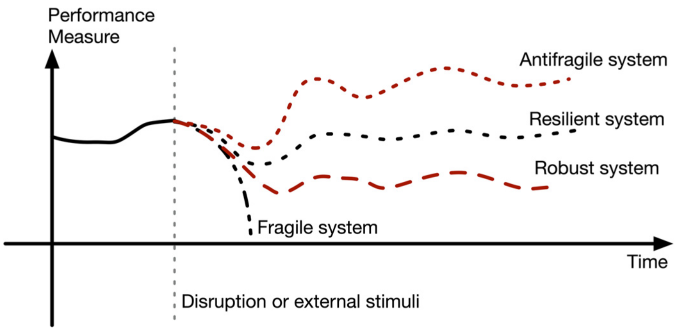

Fig. 4. Fragility of systems (adapted from [187]).

Where a fragile system may break as a result of external stressors (i.e. technology disruptions, global events, etc.), a robust system can continue functioning at a reduced rate, perhaps recovering eventually and a resilient system can recover relatively quickly.

An antifragile system, on the other hand, takes advantage of the possible opportunities brought on by the external stressor to attain a higher rate of success than the previous state. The breakthrough required to achieve this higher rate of success is one that can be enabled by daydreaming factories. So while precisely defining a breakthrough is challenging as mentioned in Section 1, the attribute of a system that enables breakthroughs, which is the ultimate goal of daydreaming factories can be defined as seen in Section 6.2.

It should be noted that antifragility here implies that the digital system reference assimilates stressors and responses and consequentially increases the predictability and predictive capability, by processing feedback and learning. In other words, if the physical reality (by means of the as-is model) gives rise to improved interpretations, the as-is model will evolve with the physical reality, also leading to more delineated to-be models.

2.2. Digital twinning as the basis of reveries – digital representation

The digital system reference employs a digital twin as the designated approach for capturing the as-is model. Whereas many definitions of the notion digital twin exist (see e.g. [181]), for daydreaming factories the precise definition is less significant, as long as the digital twin is seen as a 'digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviours by means of models, information, and data within a single or even across multiple life cycle phases [180].

Yet, for daydreaming factories, a representation of the as-is is sheerly the basis for exploration [124]. After all, potential futures have to be captured as well, and they might be formulated in terms that the as-is digital twin cannot digest. Moreover, as the distinction between the as-is and to-be models is the main driving force in foreseeing as well as evaluating and assessing reveries, next to the digital twin, a digital master is used [196]. This digital master captures the blueprint of the to-be model, thus representing a possibly desired future state for the physical factory.

As daydreaming inherently focuses on prospecting potential futures and their consequences, there is a clear need to additionally model the different states that might exist between as-is and to-be.

In other words, an intermediate could-be model, or digital prototype, is required that connects reality to envisaged futures.

This connection can be established at different levels of aggregation between the digital twin and the digital master model. Intermediately, the digital prototype allows for what-if analyses that allow for variations in both the 'as-is' (e.g. what if the portfolio was different?, the sensor data were different, and there were three of these machines?) and the 'to-be' (what if the strategic goal was different?, what if products were modularised, or what if the scheduling was done differently?).

A compartmentalised digital representation as shown in Fig. 3 signifies that multiple instances of each sub-element can exist and distinguished based on unique identifiers. As many digital prototypes can exist simultaneously, and the differences/variance between them can be parameterised, these prototypes allow for concurrent simulations or evaluations and are thus instrumental in effectively and efficiently driving the analyses and evaluations that guide the daydreaming. The main issue is then to carefully establish which parameters could play a role in the anticipation of any future (state of the) factory, as sometimes the perspective is a rather narrow elucidation of parameter values (e.g. in closed optimisation [116,165]), and sometimes it is a wide exploration of multitudinous dimensions and influences (e.g. in reveries [60,91]).

With that, this leads to a scoping to embed all initiatives to establish potential future situations. Moreover, the could-be model is not dependent on a specific perspective on the daydreaming factory and can therefore be employed to balance the interests of different stakeholders.

The digital system reference is applied as the basis for establishing and exploring the exploration space, where the convergence towards appropriate solution candidates is arranged by means of comparing and altering the various digital prototypes that are the bases for simulations and evaluations. In a daydreaming factory there is no ambition to select likely scenarios; only to learn from as many potential feasible futures as possible. To avoid combinatorial explosions, some specific strategies may be employed to stop the consideration of scenarios that are infeasible or those that are specifically designated as not being interesting through human input.

In particular, the digital system reference may apply four different strategies: i) by hypothesising potential futures, not all potential solution routes need to be fully evaluated, ii) validation is imminent, ceasing infeasible routes, iii) based on likeliness and envisaged impact, parameter variations in the prototypes can be prioritised, and iv) during simulations/evaluations the results are immediately fed back in the digital prototypes, so the models/routes can converge more purposefully. It is notable that despite such strategies to reduce unnecessary computation, the exploration space in a daydreaming factory would still be relatively large and that it is important to characterise this space in contrast to the solution space of traditional optimisation approaches.

2.3. Exploration space and solution space – scenario generation

The open-ended and hypothesis-based framework of reveries in a daydreaming factory result in an unconfinable exploration space, rather than a well-defined solution space or even a possible solution with a (small) bandwidth of variations allowed as is the case with optimisation problems. Professor Kanji Ueda pioneered the thinking in manufacturing systems about classes of problems based on the availability of information about the space that is considered [206]: class I comprising problems with complete descriptions, class II problems with incomplete description of the environment but the presence of full specifications, and, class III comprising problems with incomplete description of the specification and the environment.

The exploration space in a daydreaming factory falls in class III and is the result of diverging activities (or reveries), whereas the solution space in optimisation is the rendition of the convergence process, defining the more delineated sub-space that captures the realm of viable, feasible and unequivocal potential outcomes. Where solution spaces are often constructed in a bottom-up manner (quite applicable in e.g [168].), the exploration space instigates the search space in a more top-down manner.

Navigation in a structured and continuous solution space is the basis of many mature approaches [182] in a wide variety of topics in production, ranging from design [107] via toolpath optimisation [140] and fabrication [39], to assembly [4] and life-cycle aspects [102]. Furthermore, this approach has been used to achieve joint optimisation across some of these stages as well [200]. A variety of moethods can be instrumental in navigating the solution space, whether they address the entire solution space or a specific subset of all aspects [202]. Moreover, different mechanisms are used to increase the efficiency of the optimisation process, ranging from (smart but) brute force, via linear optimisation [185], genetic algorithms [135], simulated annealing [89] and AI [35] based techniques. So, as soon as such a solution space can be defined, such approaches can be used to single out promising solution candidates. These approaches are infeasible for the more divergent exploration. The main reason for this is that the solution space is suitable for navigation based on interpolation, whereas the exploration space requires extrapolation. Additionally, many reveries result in an exploration space that is

- subjective; different stakeholders have different interpretations of the same subject or aspect. This potentially renders a point in the exploration space simultaneously valid and invalid – dependent on the perspective involved.
- incomplete; as the exploration space is the result of diverging activities, it will not form a continuum. Rather it may contain individual markers that replicate insights. Moreover, any insight may be defined in only a subset of the available dimensions.
- uncertain; the exploration space captures insights that are not necessarily underpinned or validated (yet). Hence, these insights are capricious and potentially deceptive steppingstones in deterministic optimisation.
- dynamic; the diverging activities that shape the exploration space engender continuous adaptations of that space as well as path-dependency. Moreover, as feedback and learning are inherent to the daydreaming factory (see Fig. 2 and section 5), this path dependency is an inherent way to shape the exploration space – rendering parts of the exploration space sparse and other parts dense.

In a different representation, the exploration space captures the impressions of scenarios prefiguring potential futures, where the solution space renders the consolidated and consistent version thereof. In terms of the digital system reference (Fig. 3), both the exploration and the solution space relate to the digital master and prototype, albeit with different tools and techniques to process them.

Whereas myriad approaches exist for closed and continuous solution spaces, navigating the open-ended and fragmentary exploration space takes certainly a different attitude and more inductive, demiurgic, and creative approaches. At the same time, simultaneously navigating in the exploration and solution space does add value for daydreaming, as both spaces can reinforce the navigation processes while guiding both the diverging and converging activities concurrently. Consequently, daydreaming factories sidesteps the traditional hierarchical way of organising production environments and decision mechanisms.

2.4. Sources of creativity in reveries – definition and exploration

As the digital system reference for daydreaming is rooted in the depiction of current, envisaged, and prototypical situations, the basis for daydreaming rather lies in the information content that in overarching and prescriptive process models. With that, daydreaming relies on combining, aligning, evaluating, assessing and selection information entities.

Hence, any set of tools, techniques, and methods that can process these information entities can contribute to the effectivity and efficiency of daydreaming. With that, deterministic optimisation techniques, AI approaches, simulations, engineering models, and human engineering skills can conjointly and equivalently partake in creating scenarios [32], assessing potential futures, and in supporting decision making. In this, the crucial creativity can be based on engineering models, but foremost stems from smart engineers, smart algorithms or intelligence evinced by experience, observations, learnings or any other form of acumen. This creativity contributes to finding inward-oriented variations involving originative combinations of existing parts of the exploration/solution space, but certainly also to adding out-of-the box ventures based on intuition, experience, educated guesses or even serendipities.

Whereas these ventures may lead to radical solutions or paradigm shifts, their underpinning is often difficult to establish in a deterministic, structured, or transformative manner, thus relying more on human creativity and ingenuity. Consequentially, the predictability of scenarios and their building blocks may suffer from extensive creativity and out-of-the-box thinking. However, scenarios are embedded in mutually related engineering models, analyses, simulations, and what-if analyses, while being contextualised by both the as-is and the to-be models and are being guided by the strategy definition. Therefore, a scenario will have an inherent coherence (or path-dependency) that is instrumental in establishing its validity and added value. Consequently, scenarios are a kind of preferent vectors in the exploration space, as such spanning and driving the efforts in establishing solution candidates. These efforts involve extensive analyses, simulations and evaluations (see sections 3, 4), so the quality and realism of any scenario (as the storyline that captures a reverie) will have significant impact on the performance of the validation of the scenario. In this, e.g., massive parallelisation (see Fig. 2), does allow daydreaming to explore seemingly disconnected potential futures. Moreover, massive parallelisation is also instrumental in probing the stability of identified potential futures, strengthening the antifragility of reveries.

As, however, reveries are inherently aiming at capturing non-existing solutions or combinations, it is not always possible to assess the realism of reveries beforehand. In essence, reveries in themselves should not be hampered by any a priori sanity check or set of constraints. At the same time, it is essential to keep the scenario generation and evaluation process manageable. Here, the triad consisting of i) digital system reference, ii) captured experience and iii) learning from navigating the exploration space is conducive for budgeting, tailoring, and managing all calculation/simulation efforts involved.

2.5. Learning from explorations of scenarios – updating models

In this, closing the feedback loop is paramount (see the lower arrows in Figs. 2 and 3). It only makes sense to make scenarios, forecasts and unrestrained what-if analyses, if their potential consequences are made explicit and lead to learnings for the factory itself, but foremost to learnings that allow the daydreaming factory to reconnoitre even more appropriate paths for scenarios and what-if analyses. In other words, the feedback and learnings determine how well the daydreaming factory is able and enabled to delineate the most suitable and fruitful part of the solution space mentioned – while inherently considering any (evolving) set of optimization criteria that may be imposed or encountered.

Hence, the daydreaming factory becomes a bi-directional learning factory: the factory is trained based on the input of e.g. scenarios and what-if analyses, but these scenarios and analyses can simultaneously evolve and be steered by what is learned in the factory and in the myriad simulations and measurements at all levels of aggregation: from process conditions (robust optimization) to business models and company strategy. Daydreaming will not single out an 'optimal' scenario or configuration of a scenario, it rather allows a factory to learn from assessing the consequences and outcomes of scenarios. This gives companies a way to harmonise company strategy and envisaged directions for future developments in a purposeful way.

With that, the conglomerate of all aspects yields a sandbox that figuratively allows for daydreaming: asking "what-if" questions and testing consequences thereof, without breaking anything and learning at the same time. Provided that this learning leads to a more profound grip on the behaviour of the factory (1) and a continuous evolvement/improvement of the structure that underlies the solution space (2), a new way of achieving breakthroughs in factory environments comes within reach. This is in contrast to traditional methods of achieving the best possible parameters through optimisation.

2.6. Experiencing potential futures – updating representations

A precondition for this is that anyone that interacts with the daydreaming factory can engage in such a way that he or she will not only be able to 'see' or 'analyse' possible futures, but rather can experience possible futures. In so-called synthetic environments, the daydream factory can actually come to life – combining the real world, the cyberspace bur foremost also the dynamics/behaviour of the factory. This allows for real-time interaction and real-time learning and even interactive evolvement (optimalisation). Technologies such as virtual factories [191] seen in Fig. 5, mixed reality [76], Virtual Reality/ Augmented Reality (VR/AR) [133,201] as shown in Fig. 6, dashboarding [26], and rapid hybrid prototypes [122] all provide promising potential for such evolvement.

Fig. 5. Virtual Factory test setup at the University of Twente.

Fig. 6. Demonstration of AR for interactive evolvement in factory layout planning.

2.7. Fidelity of Digital Models - instantiation

Using digital models for exploring potential futures with sufficient confidence in results requires the use of models with the appropriate fidelity. An important consideration would be the fidelity of models required for daydreaming. Consider a cutting tool force model [75] that is used to calculate the cutter mechanics at the interface of a milling operation.

While this model may be useful for estimating the forces at the cutting interface, it is not directly useful for thinking about the dynamic model of the machine tool or trajectory planning. For such purposes a model with a different fidelity such as those presented in [40,219] would be required. When it comes to the high-level toolpath planning a higher-level model, perhaps with simple kinematics such as the one explored in [208] would be necessary. The logistics of moving resources between the different machine tools would require a shop-floor level model such as the model used in [80]. Exploration of the same shop-floor as a constituent of a global production network requires yet another model with a different fidelity [121,207]. Effective daydreaming would take place across multiple levels of fidelity combining foresight that would result from a combination of models with various levels of fidelity as shown in Fig. 7. Multi-fidelity

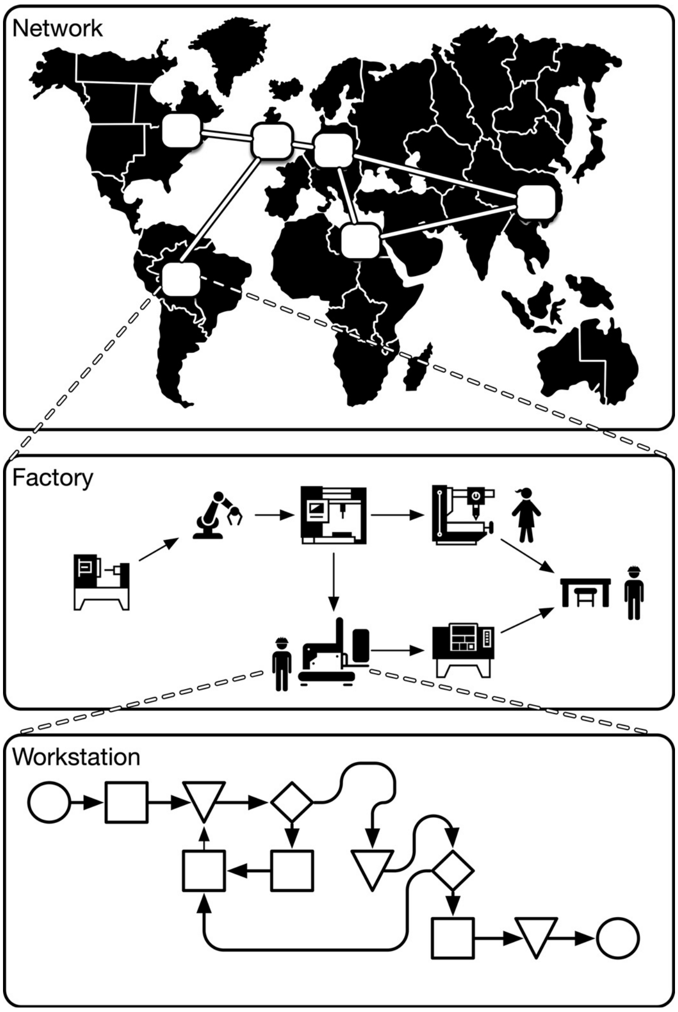

Fig. 7. Examples of models with different fidelities used in daydreaming (adapted from [192]).

modelling is used as an approach in many fields [22,175,224] including manufacturing systems [178,216,220]. It is clear that models with a higher fidelity tend to require more computational power but will result in better precision and less uncertainty in predictions [151]. In an ideal implementation, daydreaming could take place at any fidelity, with the understanding that with lower fidelities the uncertainty associated with the generated foresights will be higher. However, this does not necessarily mean that the foresight will be less valuable as daydreaming is primarily taking place in the exploration space and a vaguely defined area in the exploration space may be translatable to a concrete solution with human intervention. Furthermore, as daydreaming continues as an ongoing process, in the absence of shocks, the accuracy of foresights will increase [106].

With the assumption that daydreaming factories are attempting to converge to an antifragile system against external stimuli and internal inertia resulting from disruptions, exploring the fidelity of models that have shown the greatest promise would be prudent. The types of models in the literature that have focussed on disruptions include: (1) inventory models, (2) configuration models, and (3) distributed manufacturing models

(1) Inventory models: Constrained aggregate inventory models of the total cost (or profit) form an important part of the research literature for disruption management. These are models where the problem is formulated as a mathematical optimisation model with the objective function in the form of maximisation of a function of the order release schedule of products. Such models range from multi-product [117] to those that focus on the role of inspection as early determiners of quality issues [157] to those that consider sustainability as well as disruption [73]. Research based on these models is an example of focussed optimisation of one or two dimensions based on one class of variables. The parameter optimisation and schedules that are derived from these models yield good results when good quality data is available but in the context of larger global production networks, the complexity of gathering the necessary data make them ineffective and only useful in limited instances [90].
(2) Configuration models: The other class of models that feature prominently in the production system literature to deal with disruptions are those that consider the configuration of the manufacturing system as a decision variable as well as the work schedule. These include models that focus on optimal design before the occurrence of disruption [54,95] and those that focus on reconfiguration following the disruption. The latter category saw a significant growth in numbers in the aftermath of global disruptions [36,55,217].
(3) Distributed manufacturing systems: In addition to inventory models, another class of models that regularly consider disruptions and their effect on manufacturing systems are distributed systems, often expressed as multi-agent manufacturing systems with models comprised of interaction rules between the various agents [28,110,174,188,197]. This class of models, depending on the flexibility of the approach that has been utilised to create the agent framework may allow emergent behaviour to synthesise [204]; a prospect very well aligned with the daydreaming framework. In the absence of strict architecture of a pre-determined decision-making framework, an anarchic manufacturing system composed of distributed agents interacting with each other as the scenario assessment tool in the daydreaming framework may extrapolate in the exploration space [123] as seen in Fig. 8. In the anarchic manufacturing system, the different elements of the system negotiate based on a market bidding

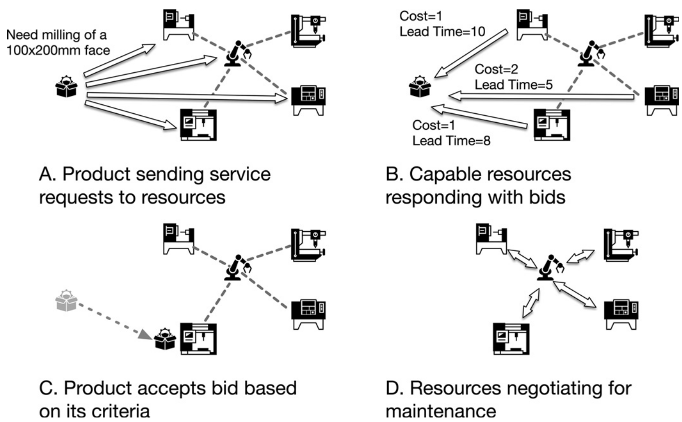

Fig. 8. Anarchic manufacturing system as a scenario exploration tool (based on [110]).

mechanism. A product announces its requirements (a), resources may send bids (b) and the product would accept the best bid based on internal criteria (c). There may be other negotiations in the same environment at the same time, for example for procuring maintenance services (d). Examples of applications of such anarchic systems have been shown in dealing with complexity [111], balancing multiple objectives [112], mass customisation [109], cloud manufacturing [113], transition to new product lines [108] and assembly [114] as well as dealing with disruptions.

These examples are representative of the types of digital models at various fidelities that would form the basis for scenario generation in a daydreaming factory. With the selection of the digital model fidelity and the choice of method for exploration of model space, a process would be desirable to automate the generation of extrapolation scenarios instead of relying on constant human input.

2.8. The theory of domain randomisation and its application in reveries in daydreaming factories – domain randomisation

Domain randomisation is consideration of all parameters, variables and even some of the constants in the exploration space and initialisation of scenarios based on random values or guestimates chosen by experts for all of these.

This is often done using a low-fidelity digital model of a physical artefact that is computationally inexpensive. Each randomised model is then simulated and the inputs from virtual sensors that mimic the sensors available on the physical system are recorded. In many of the implemented systems, the values from the virtual sensors are used to train a machine learning model, although any type of learning, human, machine or a combination of the two could hypothetically be used to establish foresights. In case of machine learning, the foresight takes the shape of the trained model.

The trained model is then connected to the physical sensors and effectors connected to the actual system. The model is then used for decision making based on the input from the real sensors.

The technique has been used with success in computer vision [193], robotic pose manipulation [164] and the control of autonomous vehicles [156]. The formal definition articulated in [152] can be adapted to daydreaming factories as follows:

Let us assume that $s_t \in S$ indicates the state of a system at time t. The strategy $\pi(a|s)$ defines one approach for investigating the exploration space E given the state s where each element samples an action a. The actions could range in scope from changing process parameters to modifications in the system architecture and structure. For example, in the state where all machines are working, the action "no maintenance" or "maintain machine 1" could be examples of such actions resulting from the "maintenance" domain associated with the manufacturing system.

The reward function $r: S \times A \rightarrow R$ denotes desirability of the action at the given stage. A higher number signifies a higher desirability.

In a manufacturing system, this function would typically be a representation of profits, whereas in a daydreaming factory it would be either a compound function or a set of rewards capturing dimensions such as environmental impact, social sustainability, and rare resource usage as well as economic returns [2,14,77,194]. For brevity, the notation $r_t = r(s_t, a_t)$ is introduced. A daydreaming system would strive to maximise the aggregate return function over the horizon T which can be defined as:

$$R_t = \sum_{t'-t}^{T} \gamma^{t'-t} r_{t'} \tag{1}$$

$\gamma \in \mathbb{R}^+$ is a discount factor that controls how important getting good rewards quickly would be in the exploration context. In pursuit of antifragility, higher values of γ are likely to be assumed. The objective is to find the best strategy π^*that yields the maximum return in the system J:

$$\pi^* = \underset{\pi}{\operatorname{argmax}}\, J(\pi) \tag{2}$$

Assuming that each planning horizon starts in a fixed initial state, the return that can be expected can be written as

$$J(\pi) = \mathbb{E}[R_0|\pi] = \mathbb{E}_{\tau \sim p(\tau|\pi)} \sum_{t=0}^{T-1} r_t \tag{3}$$

Where $p(\tau|\pi)$ is the likelihood of the given trajectory expressed as $\tau = (s_0, a_0, s_1, \ldots, a_{T-1}, s_T)$ under the strategy π. The likelihood is the product of arriving at each of the states given the actions that are taken in the preceding state:

$$p(\tau|\pi) = p(s_0) \prod_{t=0}^{T-1} p(s_{t+1}|s_t, a_t)\pi(s_t, a_t) \tag{4}$$

Note that the transition model $p(s_{t+1}|s_t, a_t)$ is determined by the dynamics of the production system and the exploration space. If unlimited experimenting was possible in the context of the dynamics of the system, good strategies could be determined. However, in the context of manufacturing systems, sampling from the real-world dynamics is infeasible economically.

In domain randomisation, therefore, an approximate dynamics model is used $\hat{p}(s_{t+1}s_t, a_t) \approx p(s_{t+1}|s_t, a_t)$. $\hat{p}$ takes the form of the reveries in daydreaming factories. An individual approximation may not be representative of the outcome in the physical manufacturing system; therefore, the approach is to decide the strategy based on a variety of dynamics models instead of just one. With the introduction of a set of parameters μ that defines the dimensions of the exploration space the possible set of dynamics can be written as $\hat{p}(s_{t+1}s_t, a_t, \mu)$. So the objective is updated to maximise the return that can be expected across a distribution (ρ_μ) of different dynamics models in the exploration space (see [210] for a discussion on selecting the parameters):

$$\pi^* = \underset{\pi}{\operatorname{argmax}}\, \mathbb{E}_{\mu \sim \rho_\mu} \mathbb{E}_{\tau \sim p(\tau|\pi,\mu)} \sum_{t=0}^{T-1} r_t \tag{5}$$

Domain randomization thus relies on the digital system reference with an instantiation of underlying engineering models to establish the dynamics of the system to randomise variables that are likely to affect the performance significantly. This makes the method useful for daydreaming as the resulting reveries may represent possible futures with a significant change in performance thus getting the factory closer to antifragility.

The investigation of the exploration space may be carried out by a variety of methods, ranging from brute-force algorithms [78] if the desired exploration space is small to heuristic strategies [56] (such as path-dependent stepping stones to parameter refinement and refining grids), using meta heuristics such as particle swarm optimisation [30] and multi agent based exploration [92] to using quantum computing techniques [51].

With appropriate engineering models, re-use of simulations would be possible, and it would be feasible to consider the simplification of common simulations (e.g. using an algorithm to approximate complex simulations in relatively stable situations). Without a stable base and a good understating of the dynamics of the system in the form of a well-articulated model, any forethought will be vain or at least unrealistic. So, the existence of the engineering model underpinning the digital representation of the production system is critical.

In addition to automated domain randomisation, an integrated conglomerate of mutually dependent simulations can be defined by expert users who have an understanding deeper than the available digital instances of the engineering model in an attempt to converge on a good answer quickly.

This paper will not enumerate all existing randomisation approaches, but rather discuss how the resulting scenarios are used in conjunction with simulation and analytics to create useful foresights.

3. Learning from simulation in reveries

In the past few decades, many advances in simulation of manufacturing systems have come about [131]. The overall purpose of the technique is to evaluate the modelled system under a set of parameters [142]. In the context of this paper, fundamentally, the set of parameters are generated based on pursuit of a planning strategy and formalise the structure of this application in the daydreaming factory framework as an enabler for investigation of the exploration space.

3.1. Simulation and its use in foresighting

Simulation [172], in general, covers a large arsenal of techniques, technologies and tools, the focus of the paper is on manufacturing systems, so the interpretation of the term simulation here refers to the focus on factory simulation. Simulation of manufacturing systems is a well-documented field [141]. This paper will not contemplate all of the details and instead focus on providing the working definition and highlighting related fields that fit in the daydreaming framework including factory control (intervention based on digital representation on the physical factory), bi-directional communication (twinning) and product development (scenario generation and assessment).

According to the VDI (Verein Duetscher Ingenieure – The Association of German Engineers) guideline 3633 [10], simulation is the imitation of a dynamic process within a system employing an experimental model. The aim of this simulation is to receive results that may be transferred to real systems. In addition, simulation defines the preparation, execution and evaluation of directed experiments within a simulation model. Including these basic steps, the execution of a simulation study is a cyclical and evolutionary process. Typically, the first draft of the model will frequently be altered to make use of in-between results and in general the final model can only be achieved after several cycles. The aim of such traditional simulation studies is to arrive at objective decisions by dynamic analysis and support the user in the decision-making process.

Modelling is regularly considered as a powerful tool for visualising systems and enabling both quantification and observation of their behaviour. Manufacturing system modelling may use different formalisms and modelling methods, depending on the field addressed by the considered problem and aspects to be described.

Building a model is rarely an end in itself. The goal of most analyses is to be able to make a 'good' decision. Whether the system is a production line, a distribution network, or a communication system, modelling can be used for gaining knowledge of the system at different life-cycle phases, for evaluating a certain feature in the system, for prediction of system performance, for comparison between several alternatives, for problem detection, for evaluating and improving system performance.

3.2. Simulation modelling techniques

Restricting the scope to simulation-based modelling of factories, essentially three major simulation techniques shall be considered: Discrete-Event Simulation (DES) [199] which has been the quasi-standard for modelling complex system in operations research communities for many decades; Agent-Based Simulation (ABS) a newer approach in factory modelling [176]; and, system dynamics which has attracted limited attention in manufacturing systems [44].

Multimethod approaches combining some of these methods have been used. A complex DES model, for example, may be utilised online for short term rescheduling of the factory while agent-based technology is applied for modelling the behaviour of the human operators in the shop-floor [154]. In another example, system dynamics and agent based modelling are combined for a remanufacturing study [139]. Nevertheless, DES remains the most popular modelling methodology in manufacturing system simulation, especially for discrete parts manufacture and thus important in the context of daydreaming factories.

3.3. Simulation models and factory control

This section covers the applications of simulation on different levels of a production system modelled at various fidelities. The different roles of simulation in production planning and scheduling and production control systems, and the corresponding fidelities are shown in Fig. 9.

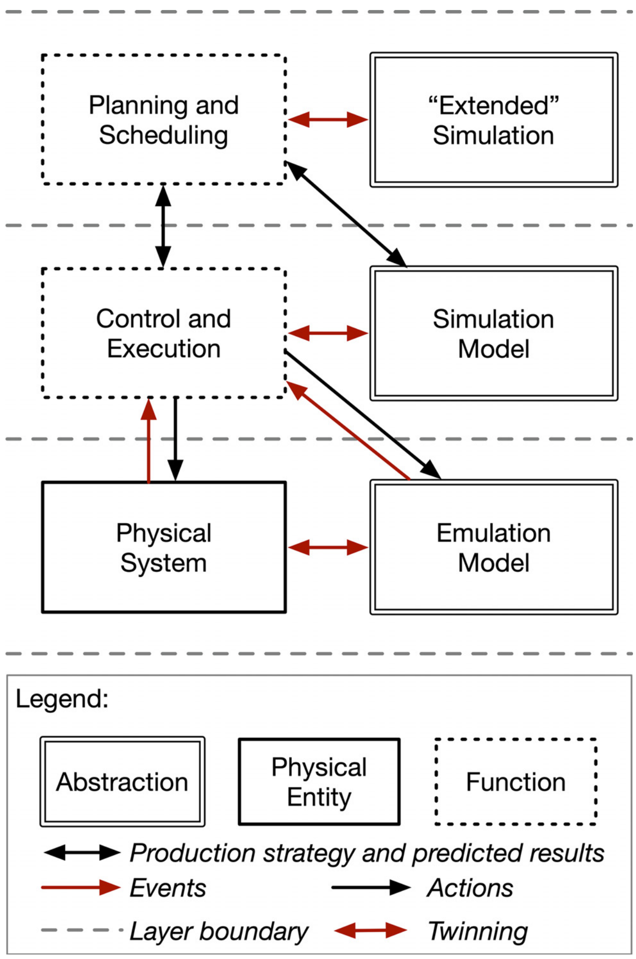

Fig. 9. Various fidelities of simulation models and information exchange between the systems involved (adapted from [71]).

To make the categorization easier, three main levels are defined. A real production environment is presented on the left side of the figure. The physical system constitutes the lowest level that includes the real manufacturing facilities of the factory.

The middle level corresponds to the control and schedule execution system and generally, this is the Manufacturing Execution System (MES) of the production system and the link between the simulation model and this system mirrors the "intervention" connection between the digital representation and physical factory in the daydreaming framework. It controls the physical system, i.e. propagates the scheduled tasks as commands to the physical system and receives reports about the execution state of the plan. This level, normally, does not have any complex planning or decisions-making function but it has a close connection to the resources at a lower level. Any change in the state of the lowest level is described by events, and these events will cause reactions in the control system.

The highest level represents the integrated planning and scheduling system, where complex decision-making and scheduling processes are carried out. At this level, the simulation models tend to be combined with additional components such as optimisation algorithms and sensitivity analysis resulting in "Extended" simulations. The resulting plans from such simulations are executed by the physical system under the control of the second level. The planning and scheduling system gets feedback information about the plan from the second level. Both, new planning and scheduling tasks and feedback information are received from the production database. About production systems, the third level is usually very complex. In order to eliminate the technical problems in the design phase, the modelling and simulation of the whole system is needed. However, in order to model the three levels in one framework substantial compromise is needed due to the different fidelities required. A solution that is often used is to use separate models of the system at various fidelities as shown in Fig. 9. This manifestation of the planning functions on different levels of operational, tactical and strategic have been explored by researchers in this area [45,179]. Daydreaming, being a top-down exploration, starts at the highest level (i.e. strategy) which would circumvent the challenges of consistency between the current state of the physical system and the digital representations. With availability of computational power and good data, daydreaming can extend to the more operational layers, where possible and appropriate.

Generally, a simulation model is developed, for modelling the overall behaviour of the system, including control methods and reflecting the physical system by modelling the resources [69]. Mainly this kind of simulation model (simulation model in 9) is applied for testing and validating production plans and collecting statistical data. To use the terminology from section 2.8, simulation is used to generate foresight in the form of $E_{\tau\sim p(\tau|\pi,\mu)}$. The detail, the granularity and the time-horizon of the simulation model depend on the system to be modelled, or more accurately, the fidelity with which the state and the actions are modelled. In the daydreaming framework, these features are chosen to enable fast simulation runs, thus ensuring great number of model runs, to allow a robust calculation across the entire ρ_μ distribution. Fig. 10 shows the diagrammatic view of the detailed process of reveries in the context of simulation. In this context, the explo-ration domain is used to parametrise many

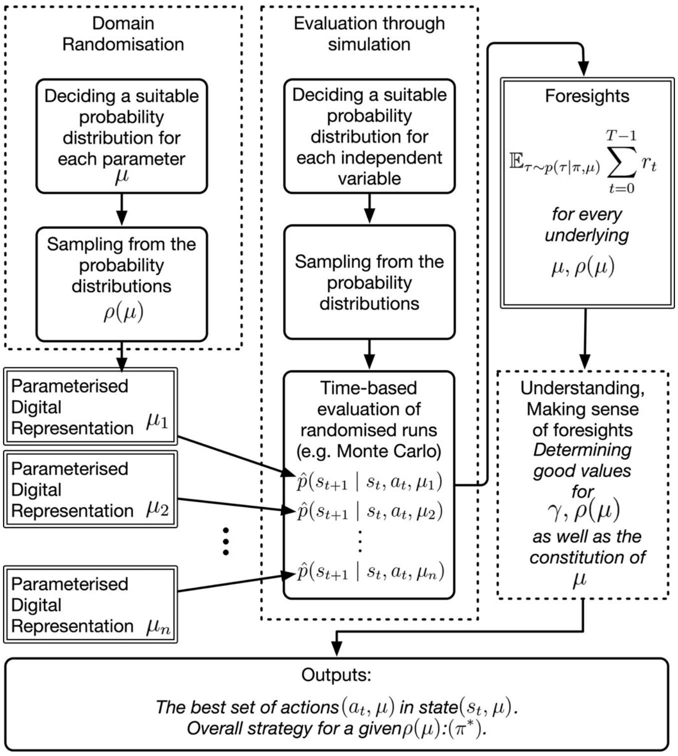

Fig. 10. Reveries and generation of foresights using simulation.

simulation models. The probability distribution assumed for the parameters can control how much the reverie would favour exploration of black swan events. For each set of values for the selected parameters, a simulation is used to estimate the dynamics of the system and predict the future state. The aggregate results from the foresights which are then used to form the strategy and a catalogue of actions with the best expected outcomes given any state of the system. These outputs may be used, as shown in Fig. 2, to update the strategy, change and update engineering models or modify the digital representation to enable operational intervention in line with the daydreaming paradigm.

There are numerous examples of this method in the recent literature in simulation-based improvement of manufacturing systems that implement, partially, the daydreaming framework: [183] deployed the framework together with reinforcement learning to enhance the operational efficiency of a production control system. They showed that a reinforcement learning based adaptive order dispatching algorithm, in this framework, can outperform existing rule-based heuristic approaches.

On a similar basis, [226] who use environment simulation rather than reveries and daydreaming, proposed a tool for generalised conversion of production control decisions based on discrete events simulation to reinforcement learning environments that can use the basis of the simulated system to approximate control outcomes and determine strategies that are shown to perform better than the heuristics that are typically used.

[173] show that for single unit transfer, an online reinforcement learning based scheduling method utilising many simulation results competes with heuristic methods and verify that such strategy is robust to stochastic processing time.

The concept of using discrete events simulation in this manner has attracted sufficient attention to encourage researchers to investigate means to automate the integration of the simulation and learning tools. As exemplars: [52] proposed a framework for integration with a commercial off-the-shelf simulation software system and [227] articulated the workflow for converting a smart manufacturing context into one where reinforcement learning based on simulation could be achieved automatically.

In the absence of full digital representations of Fig. 3, digital twins provide a good source of information as the basis for reveries. These have been used in the context of production control to assess the rewards for a reinforcement learning approach [150]. The applicability of this approach in dynamic production scheduling problems has also been demonstrated with the data coming from various elements of the cyber-physical system being utilised to form and run the simulations [72]. The paper also demonstrated the benefits of the tight integration between the simulation framework and the learning framework as underpinned in daydreaming.

Another alternative for foresight generation in the context of automated machine learning from synthetic data generated from simulation (or indeed other computational sources) is data farming [53]. This term has roots in the military [103] and has gained more and more attention with the fact that computing capabilities constituting information storage, information processing and information transmission speed have increased more than a trillionfold since the 1950s making such approaches feasible. Researchers have articulated how data generated from such approaches is not “big data” but “better data” that could yield better information [167].

Simulation has been used as means to optimise parameters in a production system. Generally, in a system like this, the simulation module is applied as a fitness evaluation function of an optimization algorithm [86,163]. These algorithms may reside outside the simulation software in a separate solver system [16] or in the simulation system as an integrated sub-module [66].

The boundary layers between the different levels in mapping the simulation and emulation model (in Fig. 9) and the daydreaming framework (in Fig. 2) are not always well defined. For example, researchers have made distinction between simulation where the control layer is replicated and emulation (emulation model) which lacks the control elements [58] but may incorporate parts of the hardware in the model. Despite this difference, the applied modelling techniques across the two levels are the same. Instead of validating production plans, emulation is applied for testing and evaluating control systems. Emulation models are not generally used for experimentation in the same manner as simulation models. As an emulation model reflects the physical system more precisely, it can be used to carry out a constrained series of verification procedures to ensure the performance or reaction of the control system [125]. In other words, regardless of the layer at which the interaction between the simulation (or emulation) model and the physical factory is taking place, a corresponding link mirrors the relationship in the daydreaming framework. Actions are, in fact, the interventions carried out on the physical factory based on the digital representation and production strategy and predicted results form the learning and strategy in the daydreaming framework.

3.4. Learning beyond the model used for simulation and verification

One of the fundamental hazards in using synthetic data generated based on a model is the speculation that any learning, be it by human or machine, will only result in the rediscovery of the model that was used to generate the said synthetic data [145]. However, for any non-trivial discrete manufacturing system, the number of nonlinearities that permeate in the generation of the system model diminish the probability of such an event. The virtual environment generation that takes place in daydreaming factories, generally involves a shift in perspective between the original engineering model used as the basis of generating the parameterised digital representations and the data that is gathered. The functions generating the data, in general, are nonlinear and hard to invert. Considering these properties the chances of rediscovery of the initial model is not high [198].

The other consideration which is often a major issue in the use of simulation is the validation and verification of the model before it can be used to reliably predict the behaviour of the system [131]. However, one of the main advantages of using the results of many simulations as synthetic data for learning is that there is less need for verification of each individual model to match reality. There is research that shows that if the parameters that describe the exploration space are reasonably realistic the aggregate learning achieved could be of good quality [156].

4. Learning from analytics in reveries

While digital simulations and purely numerical methods have played an increasingly important role in evaluation of engineering models; analytic methods still have a pivotal role in generative models and find good use in evaluative assessment of systems of higher orders of complexity [24,49,57]. For example, consider the case of an engineering model such as Markov Chains applied to several workstations in a hybrid serial and parallel configuration in an attempt to evaluate performance [25]. These techniques have provided a good balance between performance and precision with many of them allowing iterations to get more precise answers. The use of parallel computing including graphical processing unit (GPU) based ones allow analysis of many iterations of many models at the same time. The iterations in methods such as those that set thresholds and resolve them until the overall best answer is obtained [116], can thus be carried out in parallel instead of running consecutive iterations one after another. This allows a significant increase in speed and hence applicability of the methods for generating foresights about the possible changes in and around the production system.

The time saving offered by these techniques which allow mass analysis of similar models with different parameters may be significantly beneficial for models that consider different objectives in an integrated manner [3]. One of the relatively recent advances in this area is the use of consumer graphical processing units to allow parallel computing using accessible and inexpensive hardware [144]. For an example see Fig. 11 where the source paper proposes an iterative process where the parameters are continuously modified and rounds of optimisation are carried out until the threshold for the desired throughput is met. In mass analytics, the alternative approach of considering many different values for the parameters (drawn from the probability distribution $\rho(\mu)$) at the same time and then comparing and selecting the best outcomes is utilised.

The application of such methods is still emerging in manufacturing systems and is in early stages of research and development. However in other fields that have similar computational needs, the use of GPUs has shown excellent promise and speed ups [101,166].

The performance gain from mass parallelisation allows rich datasets that can be used to achieve high quality learning to be produced

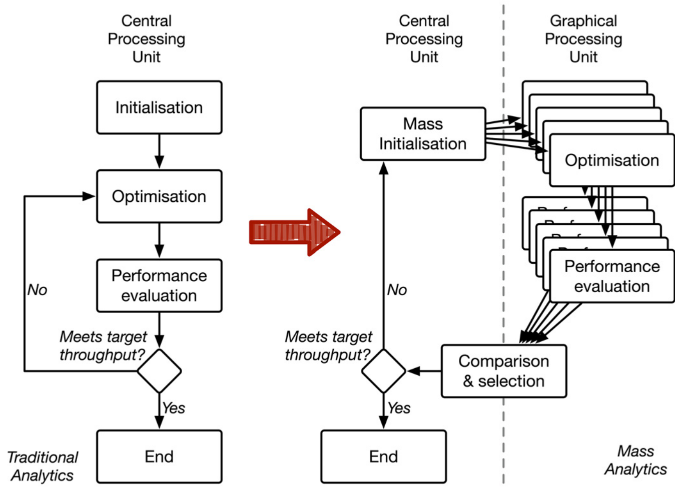

Fig. 11. Mass analytics with a GPU (based on approach in [116]).

using analytic techniques. In the context of daydreaming, this enables extrapolation in the exploration space in reasonable times.

In addition to simulation and analytics, the third class of techniques that can be used to predict the trajectory of the system are those that are based on data analytics and machine learning applied to the data that is gathered from the physical factory (e.g. [9,50,97]). However, these have been excluded from the scope of the paper as Gao et al. provided a comprehensive overview of these techniques [48]. Combinations of these methods have also been explore by researchers (e.g. simulation and learning [153], analytics and learning[57], and simulation and analytics [27])

5. Transferring learning and twinning for foresighting

Completing the dynamics loop in daydreaming factories requires the ability to transfer learning from the synthetic world of the reveries to the physical system. In the proposed framework in Fig. 2, it is shown that the intervention in the physical system is through the digital representation of the factory and no direct action is taken based on the achieved learning. This approach is based on that proposed around the development and operation of digital twins [181]. Twinning or mirroring which is the cycle between the physical and digital counterparts of the system would allow a controlled implementation of interventions [68].

In the vast majority of production systems, a proportion of interventions will be reliant on human action based on the produced foresights. A number of frameworks have been proposed to formalise the process of such action in the context of smart manufacturing [5,6].

The necessity for human intervention often brings with it a desire for explainability for the generated foresights. Most machine learning approaches are still "black box" and while automated systems follow adjustment instructions, the humans interacting with such systems often seek an explanation. A deep exploration of explainable artificial intelligence [29] is outside the scope of this paper; examples of application in manufacturing can be found in [59,85,170,221]

5.1. Transferring learning from the physical space to the cyberspace

The prospect of automated transferring of learning from one context to another is one that has gained significant attention from the machine learning researchers [148]. In the context of daydreaming, the transfer from the physical space to cyberspace may take place at different levels. The complexities of the hardware configuration of physical sensors and network connections is addressed under internet of things [134] and 5G enabled manufacturing [19,215] and will not be considered.

At the lowest level of abstraction, what is transferred is data. Depending on the context, this may already constitute learning (e.g. direct measurement of a pre-defined quality indicator i.e. surface roughness in a polishing process), but in most cases higher levels of abstraction are required for learning to take place. Many different protocols allow data from physical manufacturing resources to be captured, transferred, and linked with a digital representation [48]. At higher levels of abstraction, information and knowledge [218] become the subject of transfer.

Setting aside the automated transfer of learning, the human initiated transferring of learning has long been a generalisation mechanism for extrapolating from limited experiences to make changes towards achieving a goal in a larger system.

In consideration of the automated transfer of learning, generalisation of limited learning from the physical system is of significant interest. The core idea here is to devise a generator that creates synthetic data and then the learning from the synthetic data is compared to that achieved from the physical data. The generator is adjusted until there is no discernible difference between the learning resulting from the physical data and that from the synthetic data. The generator can then be used to generate more generalised data that maintains the core attributes of the data generated by the system [43].

The learning is thus transferred from the physical system to a calibrated cyber system that can be adjusted and on which experimentation can be conducted through means like simulation [137].

Fig. 12 shows this approach in diagrammatic form with simulation as the generation technique using the terminology introduced in section 2.8 based on the work presented in [20]. The strategy π_θ is initially selected with the parameters μ_θ and the probability distribution of $\rho(\mu_\theta)$ for the parameters. The strategy is then carried out in the real system and data is gathered to establish the trajectory based on observed system states. Simultaneously, the strategy, the parameters and their distribution are used to simulate trajectories. Afterwards, the discrepancy between the two are calculated and the parameters and their distribution are updated over time to minimise the discrepancy. The updates stop when the discriminator is not able to distinguish between the synthetic learning and the learning achieved from the physical system.

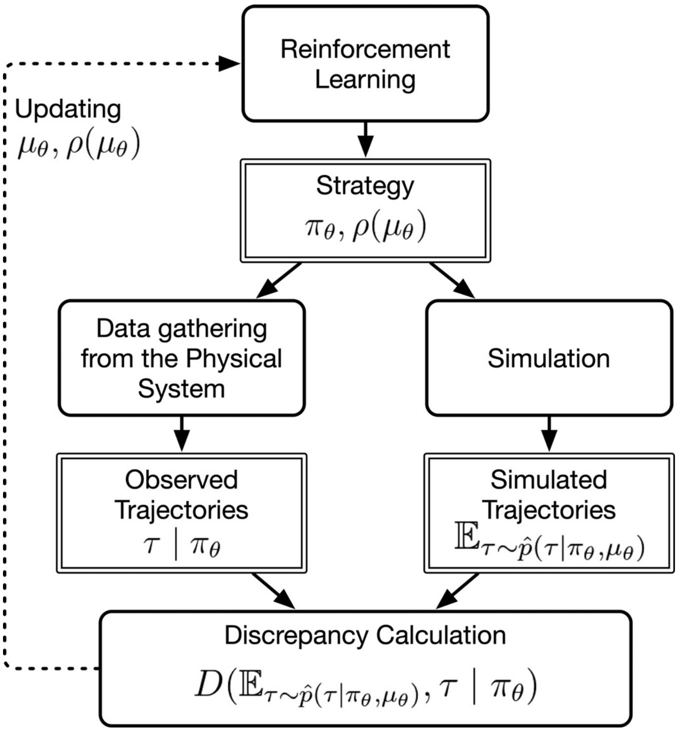

Fig. 12. An approach for transferring learning from the physical system to cyberspace (adapted from [20]).

5.2. Transferring learning from the cyberspace to the physical space

The main method of transferring learning from the cyberspace to the physical production system has been manual intervention. For example, an engineer considering various scenarios in a simulation model would make the decision on how to change the parameters in a physical system to implement the results learned from considering the overall outcome of all simulation.

The more recent research in digital twins and associated technologies has allowed a consideration for automated transfer of learning from the cyberspace to the physical space [81].

The general approach for transferring learning from the cyberspace to the physical space based on foresights (as shown in Fig. 10) would be to use physical sensors to establish the state of the system (s_t) and implement the best set of actions (a_t) under the circumstances (with a given μ) in the control structure of the digital representation. This would then get replicated in the physical system automatically through the bi-directional information transfer expected in a digital twin or through manual intervention. As a good example of bi-directional information transfer, a virtual-physical scheduler system based on offline training at different fidelities using this approach was demonstrated in [214].

In some cases, utilising an interim virtual model created with a different perspective would allow intermediate learning that is easier to transfer to the physical space. In such cases first the learning is attempted by considering a synthetic data and mapping it to another set of synthetic data. The learning is then transferred to allow mapping between data from the physical space and the second set of synthetic data, which, in turn is used for learning and determining strategy [65].

One area in manufacturing systems where this aspect of transferring learning has been used prominently is in human robot collaboration. For example, an investigation into deep learning for recognising the motions of the human and the context to infer the intention of the operator has shown great promise in the method [212]. A proof of concept for adaptive path planning for human robot collaboration based on a digital twin was presented in [31]. The authors showed how the learning in the digital twin could be used to effect control in the physical system to avoid the human operator during operation of the robot.

5.3. Combining learning from cyberspace with learning from physical space

While transferring learning from physical space to cyberspace and vice versa is used to great effect in the manufacturing systems domain, it is also necessary to consider the cases where the learning from both domains is combined. This is usually through an extension of the generalisation method explored in section 5.1. Some information from the physical system is used to create and train a synthetic data generator which then can be used to generate larger datasets that have attributes similar to those exhibited by the physical system [43] where the general approach to create the synthetic data generator and calibrate it based on learning from the physical system (see Fig. 13). Generative adversarial networks are a particular implementation of this approach and have been used successfully in a range of applications in production systems [87,98]. In these approaches, a generator is used with initial parameters to create synthetic learning. A discriminator is then used to find measurable differences between learning gained from data from the physical system and synthetic data. The differences can be used to update the parameters in the generator and the loop can iterate until calibration is achieved to the require accuracy. The generator is then used to create the necessary data for the purpose of the system.

As examples of this approach, its use in establishing the root cause of quality issues as demonstrated in [120] is noteworthy. In this case, the automated learning is combined with expert knowledge using Bayesian techniques. In contrast, the sensitivity of the success of the approach to the quality of the utilised model has been highlighted in [177]. It was shown that if the underlying model for creating of the synthetic data is not calibrated well with the physical system the quality of the learning will not be high.

Despite this sensitivity, the effectiveness for fused learning between physical and cyberspace has been shown in domains as varied as knitted garment manufacture [74], detection of industrial

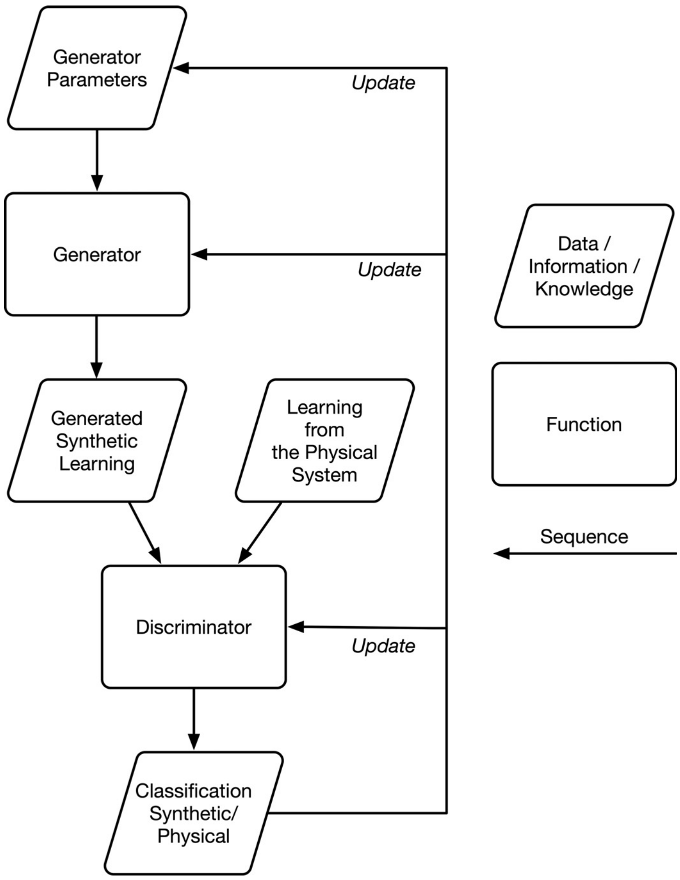

Fig. 13. Initialisation and calibration of synthetic data generator for fused learning between physical and cyber systems (adapted from [43]).

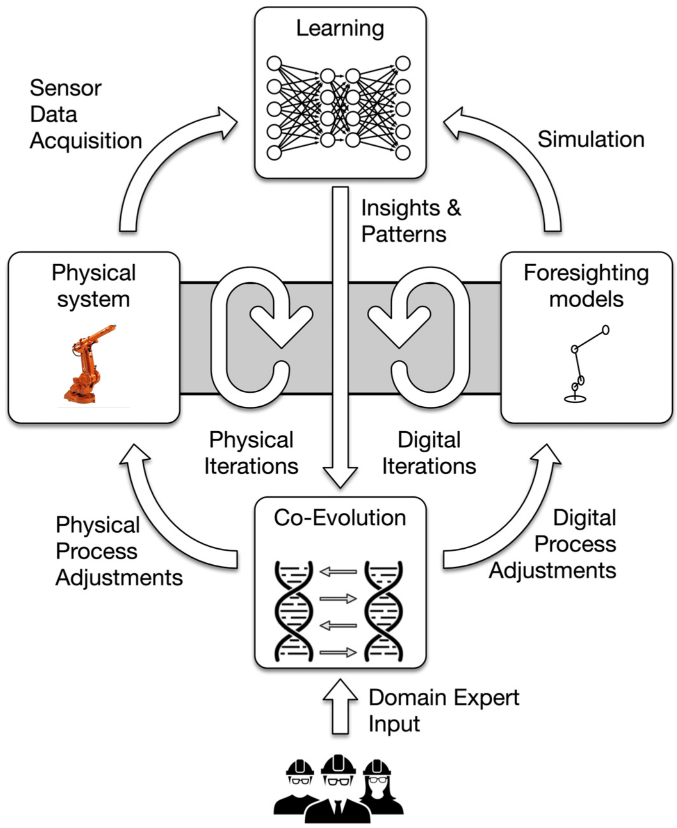

Fig. 14. Co-evolution of physical and digital entities for foresighting.

components in various environments [94], categorisation of fatigue in materials [67], and, surface defect detection [64].The advantages and challenges in combining learning from the synthetic and real data in the context of manufacturing have been articulated in [96]. Fig. 14 shows the framework for co-evolution of physical and cyber systems in a daydreaming factory with a combination of machine and human learning. This framework is proposed based on the amalgamation of the presented research with the consideration of the potential advantages of understanding that is gained from domain expert knowledge.

Sensor data acquisition over the use phase of the factory generates data that will be used in learning (sensor data acquisition in the figure). Algorithms such as deep learning, deep Q learning, reinforcement learning or any of the other algorithms that have been presented over the years of machine learning research in manufacturing may be used for this purpose [41,129,155,213]. From the learning insights and patterns emerge which are scrutinised by the domain experts (insights and patterns in the figure). As a result of this scrutiny both the physical system and the digital counterpart that is the foresighting model will be updated (physical and digital process adjustments in the figure). Depending on the exploration space, the foresighting may be a digital twin or a different digital representation.

This is used in conjunction with a randomised set of generative parameters to explore different possibilities in the production system in a diverging space (simulation in the figure). This exploration which can use the same learning techniques as those used with the physical system will generate additional insights which are then fused with those generated through learning from the physical system.

The digital and physical learning loops thus coincide and enable a co-evolution of both the physical system and the digital counterpart (co-evolution in the figure). It is important to note that in conjunction with the daydreaming reveries or iterations, the operation of the physical system and tactical simulations on the digital counterpart continue to deliver the objectives of the manufacturing system.

The co-evolving framework is demonstrated in [38] where the notion of *digital closeness* is used to track how different the digital twin and a robotic system are and starting with a basic model of a robotic workcell and an iterative approach is used to bring the two together.

The controlled fusion of automated learning together with incorporation of domain expertise in parallel to the normal operation of the production system forms the daydreaming framework. As noted above, various subsets of the interweaving loops in the daydreaming framework have already been implemented by researchers. Nevertheless, an integrated holistic implementation with the specific, identified aim of achieving antifragility is only identifiable through combining outcomes of various research efforts and yet to emerge in full.

The co-evolution of digital and physical counterparts of a production system reinforces the paradigm of co-evolution of products, processes and production systems as articulated in [195]. This enables positive dynamics in interactions between the company strategy, the manufacturing strategy and the understanding and anticipation of the effects of external driving forces and is in line with co-creative value as defined in [203]. Fig. 15 identifies how daydreaming factories provide an enabler for parts of the co-evolution framework.

They allow the effect of external stimuli as well as the possible interactions between the manufacturing strategy, the products, the processes and the production system to be explored and foresights generated that can be used to change the production system directly, or provide information to enable a change in product design, process design or company and manufacturing strategy.

6. Outlook for foresighting AI-augmented factories

The presented framework for daydreaming is the consolidation of a number of partial paradigms that brings together learning from synthetic data, transferring learning from the digital domain to the

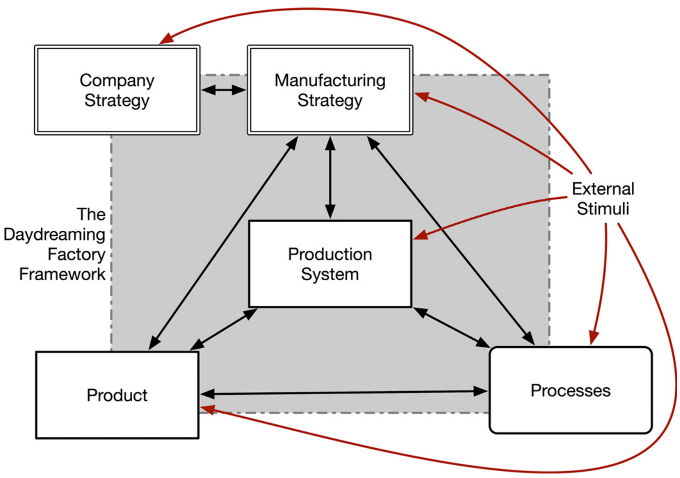

Fig. 15. Daydreaming factories in the context of coevolution of products, processes and production systems (adapted from [195]).

physical, virtual environments, human-led maching learning, human-machine collaboration and digital twinning together. Partial implementations of the framework have been presented throughout the paper to demonstrate individual aspects and in this section various examples, together with their mapping onto the framework are enumerated and the future prospect of the emergence of holistic implementations to achieve resilience, robustness and antifragility are explored.

Section 1 relayed how daydreaming based on human learning has existed in some form throughout the history of the development of production systems. Therefore, the main focus of this section is on daydreaming where the human learning is augmented by artificial intelligence. It is acknowledged that significant computational power would be required to implement such a framework. However, considering that daydreaming takes place in parallel to the factory carrying out its normal operation, it is conceivable that the spare computing capacity in a cyber physical factory can be repurposed for daydreaming. Furthermore, even with limited computational power, imprecise but useful foresights may be produced that could lead to abstract level solutions. Daydreaming is a continuous process that is conducted with no direct interference with the physical factory and as time goes by the accuracy and precision of the foresights will increase without critical requirement for additional computational resources.

6.1. Partial implementations of daydreaming across different applications in production systems

In order map the partial implementations of daydreaming to the proposed framework, a simplified abstract diagrammatic version of the framework is used as shown in Fig. 16. The simplified version of

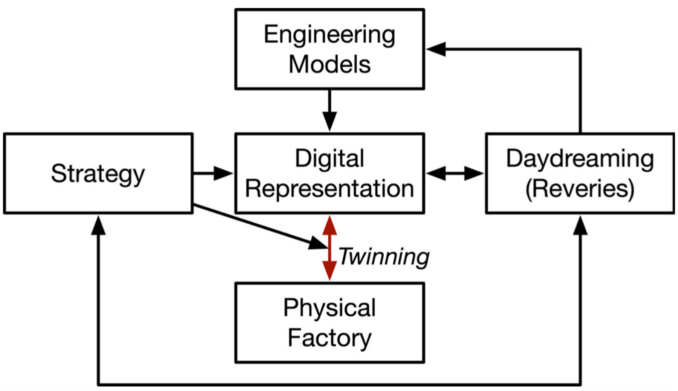

Fig. 16. Simplified daydreaming framework.

the framework is useful for marking which aspects of the daydreaming framework in a particular research work without presenting unnecessary complexity. Twinning between the digital representation and the physical factory is conducted according the requirements of the strategy. Daydreaming then generates information that updates the digital representation – and consequently the physical factory -, the engineering models that are used to generate the digital representation and, ultimately, the strategy for designing, running, maintaining, upgrading, and dismantling the factory.

Human in the loop systems

Several researchers have considered the human decision maker as an active part of the production system [83]. This view resonates well with the daydreaming framework as many of the higher cognitive functions required for the reveries are traditionally carried out by humans and in this strand of research, they are formalised. See Fig. 17 for an example from [17].

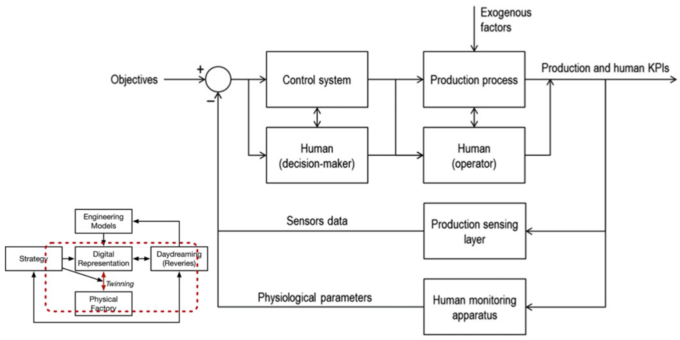

Fig. 17. Human-in-the-loop factory adaptive automation and mapping to daydreaming (from [17]).

Combining human and machine learning is a powerful construct to go beyond optimisation and explore unlikely tangents in the exploration space.

The daydreaming and digital representation loop

Learning from the synthetic data and updating the digital counterpart based on calibration with the real system has been shown to be an effective approach for achieving resilience in the digital twin [209]. Fig. 18 shows the mapping of this introvert application of reveries where the overall goal is to have better digital representations based on the rever-ies and comparison with observables from the real system. The resilience in the digital twin is achieved here by continually detecting anomalies, evaluating their effect, deciding on responses, and self-adapting the digital twin.

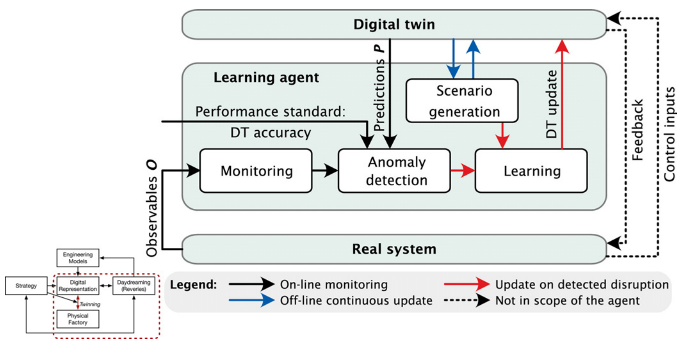

Fig. 18. Using reveries as a means to achieve resilience in digital twins (from [209]).

Shopfloor level learning

The use of synthetic data in manufacturing is not limited to manufacturing systems and is used for process level decision making

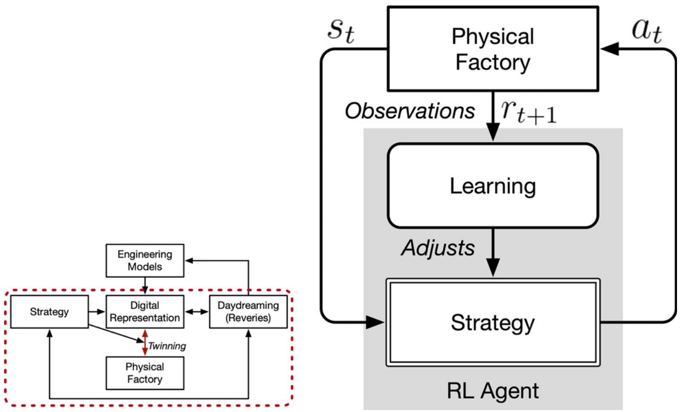

Fig. 19. Adaptable production control through the use of reinforcement learning (adapted from [84]).

as well. Researchers have used such data to tune the performance of individual machines carrying out controlled processes.

Using a physics based model to train a chatter detection algorithm as demonstrated in [21] fits in the daydreaming framework. In the context of the daydreaming framework, the engineering model is the physics based model used to generate multiple data points to train a neural network and determine the representation of chatter and inform the strategy to avoid chatter in the course of machining. This is an example of how learning from reveries can be achieved with other techniques in artificial intelligence, in this case, the use of supervised learning to train a neural network.

Adaptive production control

The use of learning to achieve better control is another application pattern that matches the daydreaming framework. For example, the reinforcement learning system proposed in [84] provides a good demonstration of how the adjustment of strategy based on learning achieved from observations from sensors in a physical production system constitutes a partial implementation of a daydreaming factory (see Figure 19). The strategy, in this case, is the set of actions that the agent will take in response to observations. This affects and is affected by the company strategy in the long term as the learning is combined across different layers of the system.

6.2. Daydreaming as a means to achieve resilience, robustness and antifragility

The research presented in section 6.1 shows that aspects of daydreaming have already been implemented in research settings and, occasionally, in the industry for plethora of purposes. However, the authors believe that the key differentiator between a daydreaming factory and other systems that learn from a combination of synthetic and real data is the pursuit of antifragility. To construct the context for measuring the antifragility of a system, quantitative measure is required. While quantitative measurement of antifragility has not been the topic of exploration in the manufacturing domain, researchers have produced measures to ascertain the resilience of production system.

Fig. 20 shows some simple definitions. The recovery time (1) is the time that it takes from the time of the occurrence of the disturbance for the system to recover its performance measure to a number within the historical boundaries of that measure. The disrupted time (2) is the time that the system spends with the performance measure outside the established bounds. The disruption volume (3) is the integration of the performance measure over the disrupted time from the basis of the lower historical bound. Using similar considerations as those presented for resilience, a definition of robustness measures in production systems can also be achieved [184].

In perfect availability of data, all these measures provide good insights. However, in a production system certain data is only available for the present and the past. Albeit suitable indicators for future

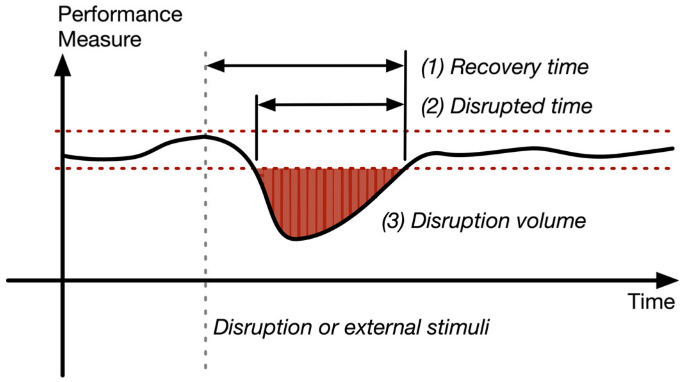

Fig. 20. Simple measures for resilience of a production system (modified from [54]).

conditions may be available, any statement on future circumstances originates from conjectures, and as such stems from extrapolation of a certain state. This immediately leads to several challenges; for example, if the disruption is external and the occurrence of the event is not known the only way to know about it would be to continuously calculate the performance measure and track it to estimate the disruption. One challenge here is how to decide the frequency of calculation for the performance measure. Too frequent and the costs associated with the data gathering may become significant. Too infrequent and the disruption may be entirely missed (assuming the system will, at some point, recover).

Another challenge is the choice of measure in a given scenario. For example, consider the scenario where the performance measure is the throughput of the production a medical product used in treatment of a pandemic. Initially, disruption volume may seem like the best measure as it correlates with the number of treatments missed.

However, as proven in the case of the COVID pandemic in 2020, recovery time is just as important. The damage caused by a long recovery time with a smaller disruption volume could lead to the health system being incapacitated whereas a short recovery time with a larger disruption volume may be absorbed better.

Consideration of such challenges shows that the concept of selecting a quantification framework for resilience and robustness is complicated. This is even more difficult for antifragility due to the time that is required for it to manifest.

Exploration of the notions of resilience and robustness is not limited to manufacturing and many other fields rely on good definitions and measures [171].

One of the definitions that resonates well with daydreaming is the capacity approach proposed in [13]. This approach relies on the fundamental understanding that resilience (and evidently robustness and antifragility) can be described as a dynamic construct that allows an entity to manage stressors and shocks using three mechanisms with varying capacities: the absorptive capacity, the adaptive capacity and the transformative capacity.

The absorptive capacity allows a system to absorb the impacts of shocks in the short term. The adaptive capacity enables the system to gain a good understanding of the post disruption environment and adjust its parameters to function well in the new setting. The transformative capacity denotes the ability of the system to influence its environment to change. With this definition and relating back to Fig. 4, a production system with a high absorptive capacity would be resilient, one with a high adaptive capacity would be robust and one with a high transformative capacity would be antifragile.

A daydreaming factory will thus be one that is pursuing a high transformative capacity. This would entail an outward looking investigation of an exploration space with interactions with the external environment. It should be noted that in many cases, as those covered in section 6.1, the learning techniques and the daydreaming framework achieve good results in increasing the absorptive and adaptive capacity of the system, however many other frameworks including prognostics [47], big data analytics [48], reinforcement learning [149] and optimisation [182] may be better contenders for improvement of adaptive capacity. The absorptive capacity often requires very quick action making heuristics a more suitable option for improvement, in general. Table 1 summarises the information in an easy to access format.

Table 1
Resilience capacity approach in production.

Capacity measure	Time focus	Environment focus	Improvementmethods
Absorptive	Short	Internal	Heuristics
Adaptive	Medium	Int. & ext. input	Optimisation
Transformative	Long	External	Daydreaming

6.3. *Key performance indicators for daydreaming*

With the primary purpose of daydreaming having been identified as improvement of the transformative capacity of a production system in pursuit of antifragility, it is important to define key performance indicators that can be used to measure how well the daydreaming process is working.

ISO22400 [62] provides a standardised methodology for detailed definition of KPIs. Since its advent, the standard has been used by researchers for monitoring discrete manufacturing systems [162], considering the challenges of human centred manufacturing in the industry 4.0 era [15], and, providing a consistent definition for overall equipment effectiveness (OEE) [169].

Although the approach proposed for defining KPIs in the standard are universal and are designed to be sector agnostic, the pre-defined KPIs are not necessarily suitable for all industries. For example, using the pre-defined KPIs for the process industry requires several modifications [225].

The standard provides a unified modelling language based class diagram (see Fig. 21) to identify the entities and relationships that need to be defined in a non-ambiguous manner to specify a KPI. In section 6.2, the difficulty of establishing a quantifiable measure for resilience, robustness and antifragility was established. Using an extensible standard allows a common baseline for defining such measures for daydreaming and making sure that they are universally understood.

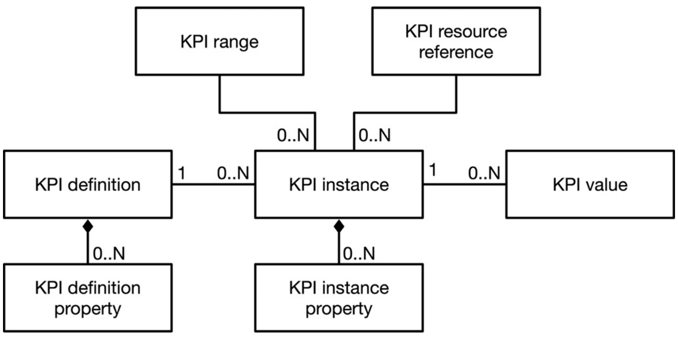

Fig. 21. UML model for defining a KPI (Adapted from [61]).

As indicated in the figure, each KPI definition can be used to generate many instances of the KPI, each with many values. The references and ranges are associated with individual instances of KPIs to allow granular definition. In addition the standard specifies a tabular format for the definition of KPIs as shown in Table 2.

The tabular format has the advantage of presenting the information in an easy to access format recognising multiple stakeholders. This makes sure that the chances of misinterpretation of the KPI is minimised [147].

In addition, with the notion of standardised KPI definitions the prospects of using generic meta models for automated computer aided analysis of productions sytems becomes more attainable [23].

Table 2
Tabular structure of a KPI (Adapted from [43]).

Row	Description
Content:	*Primary data related to a KPI*
Name	*The long name and abbreviation*
ID	*The ID used in the enterprise*
Description	*A textual description of the KPI*
Scope	*Related elements in the system*
Formula	*Mathematical formula for calculation*
Unit of measure	*SI Unit of measure*
Range	*Minimum and maximum values*
Trend	*Higher or Lower better*
Context:	*Secondary data to understand KPI*
Timing	*Frequency of calculation*
Audience	*Who would be interested*
Production methodology	*Discrete, batch or continuous*
Effect model diagram	*Links with other KPIs as a diagram*
Notes:	*Additional notes*

In order to quantify the anticipated benefits of a daydreaming factory, it is essential to define an effective KPI. The operational KPIs such as throughput or work in progress will not be affected by whether the daydreaming process is formalised or left to the traditional ad-hoc processes of previous generation. By definition, the daydreaming happens in parallel to the production system generating the usual value on an ongoing basis so this is expected.

A better class of KPIs for measuring the effectiveness of daydreaming, would be those designed to assess the robustness, resilince and antifragility of the system.

While a good starting point, this KPI would not measure any attribute uniquely associated with a formally articulated daydreaming system. In other words, any system that incorporates means for achieving resilience, including but not limited to the use of formal semantics [223], designing the system configuration for resilience [54], open manufacturing [88], the use of distributed control systems [127], data oriented approaches [11], or the use of strategies from biological systems [118] would produce good results for this KPI without daydreaming. Table 3 shows such an example KPI.

Table 3
A proposed time based KPI for resilience.

Row	Description
Content:	
Name	*Recovery time*
ID	*The time between an external stimulus and recovery of the system performance to within pre-established bounds.*
Description	
Scope	
Formula	*The entire system*
Unit of measure	$R_t = N_t - D_t$ *where* N_t *is the time the system re-achieves the normal performance and* D_t *is the time the disturbance took place.*
Range	
Trend	
Context:	*seconds*
Timing	$[0, +\infty)$
Audience	*Lower is better*
Production methodology	*Research needed*
Effect model diagram	*Investors, planners, engineers*
Notes:	*Discrete, batch and continuous*
	Selection of the timing of the calculation depends on the likely disturbances and recovery times. The calculation frequency should be selected such that the probability of completely missing disturbances is close to zero.

This KPI is defined for measuring the resilience of the system on a time basis. This definition is similar to the throughput underproduction time (TUT_ε) in [54] but calculates the time from the start of the disruption rather than the start of the underproduction. Here, the assumption is that there are natural variations in the performance metric and therefore boundaries for normal performance are defined.

For daydreaming to be measured, a different class of KPI that could measure antifragility of the system is needed. The authors propose that the performance measures for antifragility in manufacturing should take the form of a set of KPIs linked to the critical success factors (CSF) [63] of the enterprise as antifragility needs to be viewed as a multidimensional measure with no obvious linearisation approach for the various dimensions.

So to define the success criteria for daydreaming, the UML model in the ISO22400 (Fig. 21) needs to be augmented to add the notion of CSF as a linking entity. This is shown in Fig. 22 where the entity CSF is added as an aggregation of KPI instances.

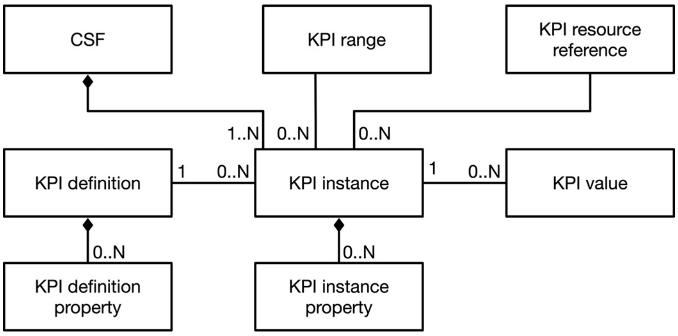

Fig. 22. Augmenting the ISO22400 class model to add CSF.

While domain specific research is required to identify the minimal optimal set of KPIs that could form an effective CSF for measuring the daydreaming ability of a manufacturing system, the set is likely to include: measures of number of innovations in the system as defined by changes in configuration, measures of discrete increases in throughput, measures of discontinuous increases in output value, the time that it takes to double the output of the production system, long term trajectory of traditional KPIs, rate of adoption of new technologies, delay in adaptation to new strategic goals, long term job satisfaction changes for human workers and improvement in involvement of stakeholders.

The timing for the measurement of the KPIs is another aspect that requires further research. While some could be measured before and after each intervention resulting from reveries, others would require careful selection of timing to capture long-term effects of strategies.

6.4. An illustrative example of a daydreaming factory

To bring the overall picture for the daydreaming factory together, it would be useful to consider a practical example of one such factory in action. The example involves a small production line of two machines and two operators (see Figure 23). The line is attempting to make low-volume, very high value, very high-quality products. At the beginning of the exemplar scenario, highly skilled operators are using the machines with frequent adjustments to maintain quality. The yield is low but the quality is excellent and one of the operators is considering retirement. Deploying the daydreaming framework results in the following events:

(1) A lightweight digital representation of the line (see section 2.2). At this stage, very little effort is put into this twinning activity and the resulting digital entity is only partially representative of the system at a very high level.
(2) The digital model is used to identify a potential set of parameters that can be set on the machine to maintain quality with fewer adjustments. On this occasion, due to the differences between the behaviour of the non-identical digital entity and the physical line, the intervention is not successful, and more actions become necessary on behalf of the operators.
(3) The skilled operator sees a new highly costly, “connected and sensorised” machine in a machine tool show and proposes that purchasing one would be beneficial to the company in the long term. The digital representation of the factory is used for the traditional simulation analysis, assessing the impact of the introduction of the new machine. Based on the trust in the expert operator and the encouraging results from the simulation, the company invests in one such machine. The machine works and improves the quality and the throughput. The backlog starts to go down and the company starts thinking about replacing the other machines with more expensive connected equivalents (see section 3.1).
(4) Observations from the physical factory and the “guesses” of the expert operators are used to recalibrate and improve the digital representation. At this stage, the accuracy of the representation has improved but may not yet capture all of the dynamics of the real system (see section 5.3).
(5) This is the critical step where daydreaming makes the difference. The digital representation is used to assess many different scenarios. The representation is connected to external sources of data and analyses very many possible combination of technology upgrades. Technologies such as text mining [7,115], the quality backward chain [12] and interoperability enablers like the asset administration shell [189], customer purchasing data [222], and MTconnect [99,100,205] provide the sources for the information. As the result of these reveries (which happen on a relatively low cost computing system, using a GPU for parallel processing), a solution based on retrofitting sensors on the existing machines is identified. This brings all of the pertinent benefits of the new machines to the existing line at a fraction of the cost (see sections 3 and 4).
(6) The solution is procured and installed; enabling the operator with less expertise to upskill and deliver the quality and throughout, capture the expertise of the retiring operator and maintain an up to date digital representation that can be used for future reveries. The performance of the system is monitored using effective KPIs to ascertain the short and long term effects of daydreaming (see section 6.3)

6.5. An industrial example of daydreaming in a factory

At the beginning of section 6, it was identified that complete implementations of the full daydreaming factories are arguably yet to emerge. However, there are examples that implicitly implement most of the framework. In this section, the case of a tyre manufacturer attempting to improve their warehousing solution, only to discover unexpected foresights is presented.

Tyre manufacturing is a complicated process involved the processing of natural rubber to get compounds with various properties. The compounds are then processed and cut to various shapes and sizes, which are then assembled into a *green tyre* on a drum, green referring to the uncured status of the rubber. The green tyre is then cured under pressure and heat on a press to create the finished product.

Typically, a large tyre manufacturing plant would have hundreds of these presses and produces different sizes and types of tyres simultaneously. After production, the quality of tyres is ascertained through numerous inspection and test procedures. Once the quality control is complete, the tyre can be sent to the warehouse. The tyres arriving at the warehouse are subjected to sorting before they can be stacked in iron racks or pallets.

Apollo Tyres in Hungary use the energy efficient solution of gravity channels. The produced tyres are moved through a single conveyor to the warehouse. A barcode scanner scans each individual tyre to determine its details and allocates a storage space, designated by a gravity channel for each unique type of tyre. A lift then takes the tyre to the identified location. This is similar to the luggage handling mechanism used in airports.

At any given time, each gravity channel can only accommodate one type of tyre. Since the length of the channel is fixed, the tyre-carrying capacity for each channel would only depend on and is inversely proportional to the size of the tyre that is stored in the channel.

Sorted tyres are palletised and a pre-set number of tyres of the same type are packaged on the same pallet to be shipped to customers. For each type of tyre, there is an ideal number of tyres that need to be stored on a pallet. Tyres are stored in various gravity channels

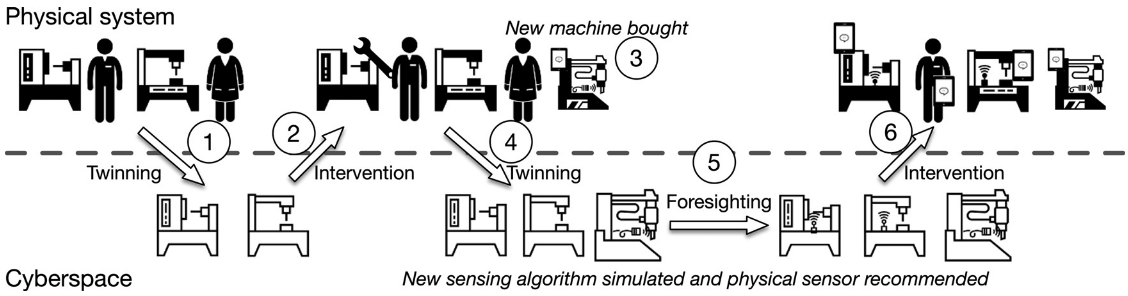

Fig. 23. A daydreaming factory in action.

until the total number of available tyres of a specific type reaches the ideal number, at which point a palletisation order is generated and the tyres are gathered from the various channels, packaged on the pallet and shipped. If the system is waiting for a specific type of tyre for a long time (longer than a timeout period), it may decide to palletise fewer tyres than the ideal number and ship the partial pallet.

Apollo wanted to know if the existing facility could cope with additional complexity in their product portfolio or if the infrastructure would be overwhelmed and additional capacity should be procured. The company set up a digital representation of the sorting and storage facility (see Fig. 24) and generated many scenarios with various parameters. The scenarios were simulated using the digital representation allowing for associated uncertainties.

The original intent for setting up the scenarios was to establish optimum values for parameters such as timeouts and ideal pallet sizes. The learning from the simulation of numerous scenarios, however, went much beyond this and showed that the static approach to deciding the rules was a limiting factor in capacity usage. Further investigation of the exploration space and mapping it to the solution space allowed the company to design a dynamic decision-making logic for deciding timeouts and ideal pallet sizes which increased the overall capacity by 15% at no cost and reduced the predicted cost of investment in expansion by 33% through better alignment of the proposed future solution with the needs of the factory. Using scenario generation, reveries and learning, Apollo tyres implemented a daydreaming factory that, according to the company, allowed them to go beyond optimisation and “to identify what they did not know” they needed.

There are other examples of successful implementation of solutions that closely match the daydreaming factories in the literature. For example, in [70] the authors implemented an automated scenario generation that autonomously created discrete events simulation models. The models were automatically populated with the data from the manufacturing execution system and the enterprise resource planning system and then the simulations were run in an automatic manner. The generated models showed that replacing the static dispatching rule used in the factory with a dynamic dispatching rule that took maintenance into account improved the KPIs and allowed the company to not only meet their production targets but also to deliver 2% of their products early in the final month of the study. Again, the initial purpose for setting up the automated platform was to optimise the parameters, but the generated knowledge went beyond the original intention and gave the company the confidence to try and use a completely new production release mechanism.

The work in [18] shows how scenario generation and reveries across different layers can allow new product development to accelerate. Here scenario generation for reveries at one level were selected from the pareto optimal front of the higher level using a workflow automation system. The learning outcome that transcended the initial premise of the platform that was set up for optimisation, in this case, was the knowledge that joint optimisation of two aspects of the process would yield better results as reported in [37].

6.6. Challenges and future research directions for daydreaming

While daydreaming is a flexible framework which can fit a wide variety of production systems as shown in previous sections, there are challenges to make it work effectively in a manufacturing scenario.

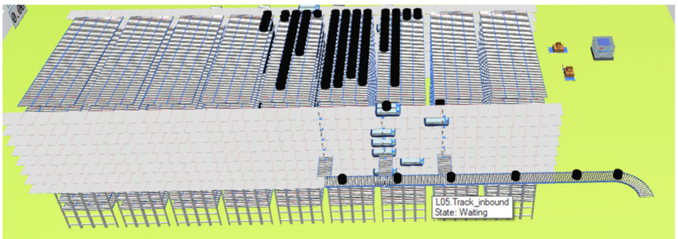

Fig. 24. The simulation model for Apollo Tyres.

The main challenge for the reveries is defining the exploration space. Fig. 25 shows the selection of the probability distribution for shaping the exploration space. The selection of the distribution can affect the behaviour of the reveries. (1) Selecting a probability distribution similar to the observed historical data will result in prognosis and an attempt to predict the behaviour of the existing system. (2) In order to pursue robustness in performance, a “wider” probability distribution can be chosen to allow more anticipation of outlying values.

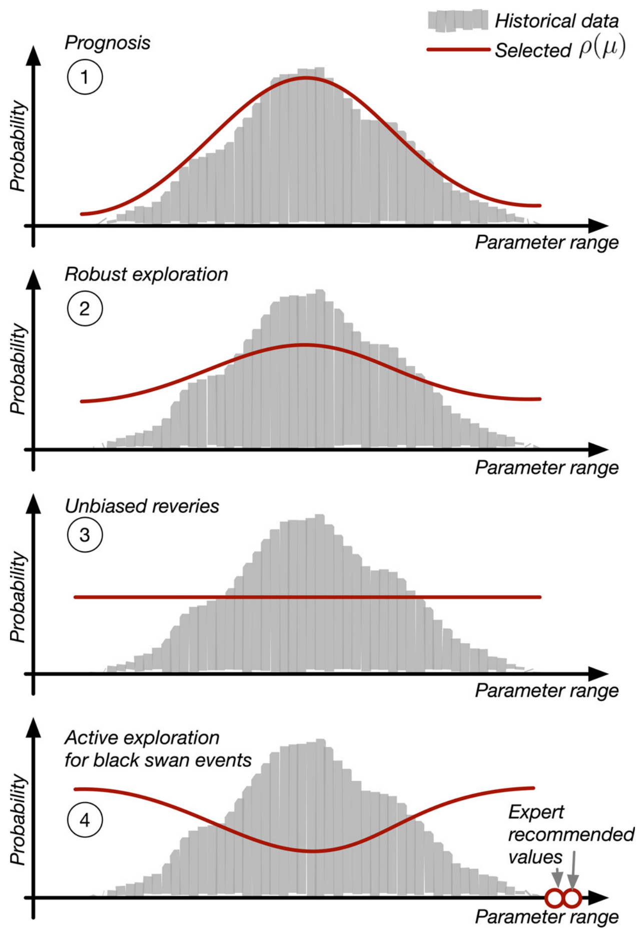

Fig. 25. Selection of parameter probability distributions in pursuit of antifragility in a production system.

(3) Unbiased reveries can be generated by exploring the entire exploration space with a uniform probability distribution. In many scenarios this would be desirable as, daydreaming will be conducted in parallel to the value generating function, and as such, it can gently explore the space while the production continues. (4) A probability distribution that actively tests less likely scenarios based on historical data is one that is likely to identify the black swan events. This adventurous strategy can be combined with specific values for parameters based on expert "guestimates". It may even be the case of actively seeking points of failure to better prepare the system [93].

The other challenge for a daydreaming system is that it is reliant on trust of the humans involved in the production system. A good way of building this trust would be to start with prognosis and over time explore more adventurous probability distribution for the reveries.

7. Conclusions

In this paper, a framework was proposed for achieving antifragility in production systems. The term "daydreaming" was chosen to refer to this framework. Daydreaming in a factory occurs when imagination about possible futures of the system, with some credibility, is used to explore interesting interventions; and, when a change, that is likely to produce additional value is identified it is investigated to predict the effects. The change is implemented if seen appropriate, lessons are learned, and a new cycle starts.

In considering the advances in manufacturing systems over the past 60 years, it can be argued that efforts have been representative of an evolution toward what Merchant envisioned as a unified, coordinated, and automated manufacturing system with the caveat that the desire to completely automate systems has morphed into human enabling systems instead.

The questions that led to the genesis of daydreaming factories is "What is the pattern of industrial evolutions that when take place without anticipation they seem revolutionary?" and "Can the hitherto human based step changes be assisted by computers?".

The presented framework shows that researchers have already been working in this area for many years without a unifying vision. Based on reverie enabled foresighting, the use of computers to enable and assist breakthroughs can be pursued in a formal and definitive manner. With a full implementation of the entire daydreaming cycle as outlined in this paper, even the most unexpected changes are likely to be considered in reveries assisted by artificial intelligence and implemented with good foresight, making it possible to better prepare for future industrial revolutions and transition to new production paradigms more rapidly.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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