mathematics

Article

Cooperative Game-Based Digital Twin Drives Decision Making: Overall Framework, Basic Formalization and Application Case

Fuwen Hu [1,*], Song Bi [2] and Yuanzhi Zhu [1]

[1] School of Mechanical and Material Engineering, North China University of Technology, Beijing 100144, China; tozyz1@163.com
[2] School of Electrical and Control Engineering, North China University of Technology, Beijing 100144, China; bisong@ncut.edu.cn
* Correspondence: hfw@ncut.edu.cn

Abstract: The emerging progress brought about by Industry 4.0 generates great opportunities for better decision making to cope with increasingly uncertain and complex industrial production. From the perspective of game theory, methods based on computational simulations and methods based on physical entities have their intrinsic drawbacks, such as partially accessible information, uncontrollable uncertainty and limitations of sample data. However, an insight that inspired us was that the digital twin modeling method induced interactive environments to allow decision makers to cooperatively learn from the immediate feedback from both cyberspace and physical spaces. To this end, a new decision-making method was put forward using game theory to autonomously ally the digital twin models in cyberspace with their physical counterparts in the real world. Firstly, the overall framework and basic formalization of the cooperative game-based decision making are presented, which used the negotiation objectives, alliance rules and negotiation strategy to ally the planning agents from the physical entities with the planning agents from the virtual simulations. Secondly, taking the assembly planning of large-scale composite skins as a proof of concept, a cooperative game prototype system was developed to marry the physical assembly-commissioning system with the virtual assembly-commissioning system. Finally, the experimental work clearly indicated that the coalitional game-based twinning method could make the decision making of composite assembly not only predictable but reliable and help to avoid stress concentration and secondary damage and achieve high-precision assembly. Obviously, this decision-making methodology that integrates the physical players and their digital twins into the game space can help them take full advantage of each other and make up for their intrinsic drawbacks, and it preliminarily demonstrates great potential to revolutionize the traditional decision-making methodology.

Keywords: digital twin; game theory; decision making; smart manufacturing; cooperative game; composite skins; assembly planning

MSC: 91A12; 74S05

check for updates

Citation: Hu, F.; Bi, S.; Zhu, Y. Cooperative Game-Based Digital Twin Drives Decision Making: Overall Framework, Basic Formalization and Application Case. *Mathematics* **2024**, *12*, 355. https://doi.org/10.3390/math12020355

Academic Editors: Chen Jiang, Zhenzhong Chen, Xiaoke Li, Xiwen Cai and Zan Yang

Received: 22 December 2023
Revised: 14 January 2024
Accepted: 19 January 2024
Published: 22 January 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Generally, the study of decision making is a highly interdisciplinary concern that involves psychology, economy, management, neurobiology, cognitive science and others. More recently, the intelligent decision-making mechanisms of industrial fields have increasingly attracted attention under the banner of smart manufacturing or Industry 4.0. As a grand vision to improve the efficiency and responsiveness of the global industry, Industry 4.0 is a roof-type concept that comprises the integration of many enabling technologies, such as the Internet of Things (IoT), big data analytics, cloud computing, artificial intelligence (AI), additive manufacturing, augmented reality, autonomous robots and so on. Empowered by these emerging technologies, the industrial decision-making paradigm is currently undergoing transformative progress to increase the autonomy level of production systems and operational teams in complex, changeable and uncertain environments [1,2]. Obviously, outstanding opportunities appear for developing new methods to achieve high-level intelligent tasks such as understanding (i.e., why does it happen), prediction (what will happen) and prescription (what decisions should be made and implemented to select a well-grounded action) and reshaping the logical relationship between the decision process and actions [3]. According to the Industrie 4.0 Maturity Index [4], this far-reaching transformation would undergo four stages: visibility (digital shadow), transparency (semantic linking and aggregation of data), predictive capacity and adaptability (delegating certain decisions to the systems).

As a close relative of decision theory, game theory is concerned with the actions of decision makers, who are able to feel that their actions affect each other. It proposes that an agent in an interactive decision should and does take into account the deliberations of the other players involved, who, in turn, take their deliberations into account. Indeed, game theory offered social scientists, biologists, military strategists and others a common, flexible language. Enlightened by this point, this research endeavored to marry game theory with the digital twinning method to explore an autonomous decision-making methodology. The basic novelty of this work can be summarized as the following:

- In order to distinguish the asymmetry of the digital twin and its physical counterpart or its functionality, the digital twin is viewed as a virtual agent, which performs the problem-solving computational simulation. The physical entity acts as a physical agent to undertake real tasks. Both the virtual agent and physical agent improve themselves or help the other reduce the risk of uncertainty by sharing information in the Extensible Markup Language (XML) or JavaScript Object Notation (JSON) format.
- To promote the cooperation of the virtual agent and physical agent, the cooperative game framework is proposed through negotiation objectives, alliance rules and negotiation strategy to autonomously ally them. For task-centered decision making, it is supposed that the game process is purely cooperative games, where the interests of two types of agents coincide perfectly.
- As a proof of concept, a cooperative game-based digital twin planning system was developed for the assembly process planning of large-scale composite skins. In this specific interactive situation, the reconfigurable multi-point loading and multi-sensor feedback physical assembly-commissioning system was developed as the physical player, and the finite element simulation optimization of the virtual assembly system was developed as the virtual player.

That is to say, in the interactive twinning digital space and physical space, a higher-level decision-making space is set up: game space. To the best of our knowledge, this is a rare attempt to integrate a physical entity and its digital twins through game theory and help them take full advantage of each other and make up for their intrinsic drawbacks. The interesting convergence of the agent-based modeling method, the digital twin-based modeling method and the game theory-based decision-making method perhaps opens a new door to the autonomy of industrial systems' decision making.

This article is structured as follows. Section 2 reviews the decision-making paradigm under Industry 4.0 and the research status of composite assembly decision making. Section 3 methodically introduces the overall framework and basic formalization of the game-theoretic and digital-twin-based decision-making methods. Section 4 presents the development details of the cooperative game-based digital twin planning system for composite assembly. This article concludes with conclusions and forthcoming work in Section 5.

2. Research Background

2.1. Decision-Making Paradigm under Industry 4.0

First of all, the most widely accepted fact is that the massive generation and real-time flow of structured and unstructured data have become the catalyst to improve real-time decision making. To a certain extent, big data analytics is not just a technology but an entirely new epistemological approach to produce meaningful and insightful knowledge about complex phenomena without constructing hypotheses and models [5]. Data-intensive aided decision-making methods like machine learning or AI have been extensively used for predictive maintenance [6], optimizing supply chain [7], fault diagnosis [8], predictive production planning [9], autonomous robots [10] and so on. Moreover, ubiquitous connectivity and extensive integration also enable modern industrial decision making to assume a new aspect. With the perspectives of IoT, cyber-physical systems (CPSs) or digital twins (DTs), any virtual or physical entity (i.e., asset, process or system) involved in the production scenario is not isolated and immutable but involved in a dynamic continuum. As such, computer simulation that has been one of the most popular methods for analysis and decision support over recent decades is evolving into a more comprehensive and inclusive container of DTs [11].

The big reason making DTs stand out is that they can connect the physical counterpart and other related digital twins and dynamically update themselves to support more efficient and effective decision making. To this end, scholars have carried out DT-based or DT-driven decision-making studies over the years [12–15]. Drawing on the lessons from several different DT cases, it is confirmed that DTs can integrate insights from multiple stakeholders and support them to make joint decisions within the ecosystem and develop the system wisdom from the codified information [16]. More evidently, future manufacturing systems are becoming more autonomous by integrating decentralized intelligence, context awareness, high reconfigurability and proactive perception into the decision-making process [17,18]. For instance, since the complex interaction dynamics of a flexible fixturing system cannot be modeled by analytical methods or common control laws, the digital-twin-based method is proposed to generate a reference criterion for real-time process control [19]. This context-specific closed-loop decision-making paradigm allows the reconfigurable fixture system to behave more adaptably and flexibly.

Conceivably, industrial modeling and cybernetics are transcending the traditional rigid system in the digital ecosystem with the properties of autonomy, intelligence, adaptation and cooperation [20]. There are many agents like intelligent machines and problem-solving computational entities to compose collaborative production networks [21]. The agent that behaves in a simple "stimulus–response" fashion is called a purely reactive agent, which is incapable of foreseeing what will happen. The more deliberative or goal-oriented agents proactively reason about their goals to act with higher success rates. Indeed, a multi-agent system leads to a sharp increase in complexity, enabling the proper system behavior to reach the desired production goal. However, owing to the high heterogeneity and complexity of CPSs, and the lack of intelligence, interoperability and low level of cyber abstraction, holonic or agent-based industrial systems are not widely built in production systems [22]. Moreover, the nonlinear relationships between variables, irreversible processes, time delays and the asymmetry of virtual presentations and physical twins also hinder the autonomy of industrial system decision making. In addition, the new paradigm is also subject to the evolutionary changes in nature, such as organizational structure and cultural habitus [23]. Therefore, the application of emerging technologies and new ideas to industrial decision making has made inadequate progress in production systems in recent years.

2.2. Research Status of Composite Assembly Decision Making

Nowadays, composite materials are extensively used in automobile, aerospace, marine and recreational fields thanks to high specific strength, specific modulus, good fatigue resistance, high damage tolerance and good performance designability [24]. The amount of composite materials has become one of the important indicators to measure the technical level of aircraft and spacecraft. The three common existing types of composites are carbon fiber, glass and aramid-reinforced epoxy, and carbon-fiber-reinforced epoxy (CFRP) is the most widely used composite in aircraft construction. However, the wide applications of composites to meet the demand for lighter and more efficient aircraft also cause many intractable challenges due to the complexity of the composite molding process. Unlike homogeneous materials, composite parts are prone to process-induced deformation (PID) and process-induced stress during and after temperature-associated processing due to complex and unclear factors, such as thermal strains, resin cure shrinkage strains, the frictional locking between the part and the tool and so on [25]. The undesirable PIDs including geometric scaling, spring-in and web warpage could affect the final shape and dimensions of an as-formed composite part and make assembly difficult [26]. Hence, the assembly force is exerted on composite structures to ensure surfaces match in the assembly process. However, if the fit-up gap is large, or the assembly forces and positions are out of place, the forced assembly method (FAM) could lead to the assembly being out of tolerance owing to over deformation and cause high assembly stress in the component [27]. Therefore, shimming operations are involved to fill the gap with liquid shim or laminated shim [28]. Also, stress concentration may be produced in the assembly of composite structures, which may reduce the mechanical performance regarding the load capacity, fatigue, residual strength and damage tolerance of the component. Specifically, the riveting, screwing and other connection operations in the regions with assembly-induced stresses could produce unacceptable damage such as delaminations or cracks [29]. For a long time, the assembly process for composite components has always been based on manual experience. Only highly skillful operators are capable of these challenging assembly operations. However, it is still difficult to guarantee the quality and efficiency of the assembly, i.e., the one-time pass rate of the product is relatively low. In brief, the decision-making tasks of composite part assembly are full of high complexity and uncertainty and still remain highly relevant both in engineering practices and scientific research. There are three main research methodologies as follows.

The first methodology for composite assembly decision making is quasi-physical simulation assembly. The finite element method (FEM) based on the physical properties, FEM-based Monte Carlo simulation and FEM-based method of influence coefficients (MIC) are all quasi-physical assembly simulations of assemblies of composite parts [30]. In order to reduce the dimensional errors when joining two composite parts, Yue et al. [31] presented an automatic optimal shape control method by introducing the surrogate model considering uncertainties in a feedforward control algorithm. For the simulation of assemblies of composite parts, Roulet et al. [32] proposed an efficient computational strategy for the resolution of multiple nonlinear problems, especially when these problems involve damage. Corrado et al. [33] presented a comparison on the applicability of two methods to predict geometrical deviations in composite assemblies: the virtual numerical model and the MIC. The presence of adhesive and assembly sequence are also suggested to be considered to foresee the geometrical distortions in composite laminate assembly [34]. Yang et al. [35] proposed an enhanced spring–mass stiffness model to predict the stiffness of the single-lap single bolt composite joint considering assembly gap and gap shimming. For the variation propagation problems with local delaminations, Liu et al. [36] presented a methodology based on MIC that is proposed to analyze the influence relationship between delamination defects and manufacturing deviations. Jonsson et al. [37] proposed to assemble a semi-compliant aircraft component with multiple surfaces using an industrial robot equipped with force feedback. Ramirez et al. [38] presented a flexible automated assembly system for large CFRP structures, which was not only able to hold and manipulate the CFRP structures in three-dimensional space but also able to have an influence on its shape, as needed for panel assembly. Zhang et al. [39] proposed an optimization method for the layout and magnitude of assembly forces to effectively improve the distribution of assembly gaps between components and avoid the damage of composite structures caused by stress concentration simultaneously. Quasi-physical assembly simulations could reduce the high cost of large-scale quantitative physical experiments by simulating complex assembly behaviors and provide a priori insights into uncertainties during assembly based on the produced simulation data. However, there are still many technical difficulties in the simulation of composite part assembly, for instance, the complex contact interactions among matching components, the anisotropic properties and damage behaviors of materials and the granularity limit of model refinement. There are indeed challenges left to fully replace physical assembly activities with virtual tools and simulation methods. These remaining limitations of simulation mechanisms determine that the "front-running" simulation results are predictive and they cannot be directly regarded as deterministic and reliable in reality.

The second methodology for composite assembly decision making is measurement-assisted assembly (MAA). From beginning to end, the assembly of composite components is inseparable from measurement. As a bridge or an interface throughout the assembly process, measurement and test planning have been the key content of assembly decision making, including the control and management of geometrical variation, gap and accuracy compensations, assemblability analysis, traceable quality assurance and control and the closed-loop control of flexible automation systems [40,41]. At the very start, the real models of as-built composite components need to be measured by a 3D optical scanner for the assembly decision making. During the part-to-part assembly, the distribution of strain field and displacement on the panel surface and fit-up gaps also need real-time monitoring. The dimension errors, stress level and joint quality of finalized assembly components need inspection. As the surface of a part and assembly product is a 3D free-form surface, the key characteristics for describing assembly quality are decomposed into key control characteristics (KCCs), such as fit-up gaps, deflections and stresses at specified critical points, assembly pose and assembly forces. A closed-loop control of assembly processes could be realized by feeding back the assembly quality parameters to refine the process control parameters. To meet the demands for enhanced production capability, efficiency and product performance, measurement planning is responsible for the determination of measurement methods, instruments, sensors and data analysis. As highly accurate measurements become increasingly affordable, measurement technology has become a bridge connecting the real world and the digital world. Liang et al. [42] presented a real-time full-field displacement perception method for a component digital twin in aircraft assembly by the combination of online multi-point displacement monitoring and matrix completion theory. MAA generates new chances for the automation of fitting processes and the active closed-loop control of onsite assembly processes. However, owing to the poor real-time, unreachable deployment of sensors and complex interactions of KCCs, MAA could not directly drive the assembly process of composite components.

In the wake of Industry 4.0, the assembly issues of composite parts demand a broader methodology to represent the coupling of the product, physical processes and digital computations. The concept of CPSs [43] and the emerging vision of digital twins [44] undoubtedly suggest a new opportunity to change how the assembly process is viewed. The perspective of digital-twin-embedded cyber-physical assembly system inherits the advantages of virtual assembly and quasi-physical virtual assembly and combines the advantages of advanced technologies such as computing technology, AI and data measurement. The creation of sophisticated virtual models, or digital twins, can reflect the as-built geometry of physical products and generate new chances for the management of geometrical deviations [45]. Polini et al. [46] developed a digital twin tool to manage geometric variations from manufacturing to assembly based on simulation and a skin-based approach. Li et al. [47] proposed a general framework for twin data and knowledge-driven intelligent process planning of aviation parts and analyzed four standard procedures that support the framework, namely a mechanism–data fusion process digital twin model, dynamic process knowledge base, process decision making and evaluation, machining quality prediction and process feedback optimization. Based on the digital information model and driven by the twin data of the assembly-commissioning context, Sun et al. [48] provided a solution for accurate performance prediction and commissioning decision making of a complex assembly. Conceptually, the digital-twin-embedded CPS helps to reduce the unpredicted undesirable behaviors that arise as the assembly operates and augment the adaptability, reliability and smartness of the decision making of complex assembly tasks [49]. Digital-twin-based assembly methodology suggests a new paradigm to change how we deal with the complexities of composite assembly. It is grounded in big and accessible data and the information fusions that are produced in cyber-physical spaces. Sufficient interaction information feedback between the physical world and virtual space helps to upgrade the success rate so that "the whole is greater than the sum of its parts". Digital-twin-based decision making is likely to reveal the high-level system properties of CPSs to deal with the scenario of complexity, uncertainty and dynamism that reality generates.

3. Method

3.1. Overall Framework

As illustrated in Figure 1, above the split line is the concept of digital twin modeling, and below the split line is the game theory modeling. As stated previously, the core of the presented approach is to marry the physical agent and its digital twin in the game space. Since the first introduction of DT from the aerospace industry, it has been an emerging terminology that has attracted the attention of experts in various fields. Although its definition is wide and vague, the basic consensus on it is that DT is a dynamic and comprehensive container including models, simulation or other digital representation, which can update itself through bidirectional data exchange and learn to respond better to any change that may occur [50]. Properly, the "truth" of DT is an evolving and holographic modeling process rather than a dogmatic solution [51]. The benefits of applying digital twins in manufacturing cover a large scope [52]: predictive maintenance, virtual commissioning of production line, process traceability, accurate scheduling of production, real-time optimization of running systems, agile operation of supply chain and low-carbon production. The core value of DT lies in the on-demand aggregation of multi-source data, multi-disciplinary models, subject matter expertise and ubiquitous computation powers. Essentially, the DT is a partial replacement for wasted physical resources, i.e., time, energy and material, to perform repetitive and complex tasks in the exact way that minimizes those resources [53]. To date, many different frameworks or methods of digital twinning have been presented [54–57], but there is no one-size-fits-all architecture to guide all digital-twin-based development. Generally, a DT system contains at least three basic components: observable physical entity in the physical world, digital representation in the virtual space and the fusion domain that merges the two worlds. Furthermore, some researchers attempted to combine the agent-based method and DT method to build intelligent systems [58,59], which could empower the DT system to show high-level behavior such as proactiveness and social ability. Therefore, in the presented method, the DT model is encapsulated as a virtual agent that is capable of autonomous action in the digital twin environment to meet objectives assigned to it. Accordingly, the physical counterpart is viewed as a physical agent that performs goal-oriented behavior in the real world. Meanwhile, the twin agents can work cooperatively for a commonly agreed-upon goal by information sharing.

To transfer the above-mentioned concepts into a federated system, game theory is introduced to achieve interaction, mutual coordination and cooperation among the agents. Generally, game theory is viewed as a branch of economics of modeling and evaluation of the behavior of decision-making systems, in which the individual's success in the choosing process depends on the choice of others [60]. Game theory is closely related to decision theory and optimization methods for the solution to make optimal choices in decision-making problems with multiple conflicting goals or complex uncertainty [61,62]. More recently, the game theoretic approach has been adopted to deal with the complex issues within the context of industrial fields and information systems that involve multiple decision makers [63,64]. Moreover, games can be categorized into many branches, such as noncooperative games, cooperative games and evolutionary games. A coalitional model is distinguished from a noncooperative model primarily by its focus on what groups of players can achieve rather than on what individual players can do and by the fact that it does not consider the details of how groups of players function internally. In this research, the digital twin agent and the physical twin agent cooperate with each other via the joint strategy within the context of complete information sharing. Briefly speaking, this game theoretic and digital-twin-based decision-making method would bring about the following benefits:

- Ideally, the attractive metaphor of DT emphasizes the perfect mirroring or exact mapping to the physical entity. However, neither the sensor data-driven update nor the aggregation of multi-domain models has changed its essence as a virtual model. First, the spatial distribution and temporal sampling frequency of the sensor are limited or partially reachable, in particular, not all desirable attributes can directly be measured by applying advanced IoT technologies [65,66]. Secondly, the time-consuming expense associated with large multi-physics simulations of complex systems means that real-time updating, which may be required in the real system, is not possible [67]. Moreover, the physical processes are compositions of many things occurring at the same time, while the DT essentially depends on formal and procedural continuous computation in a relatively ideal framework [68]. In other words, the DT in the cyberspace and the physical counterpart in the real world cannot behave exactly the same in response to changes. Therefore, from the decision-making perspective, it is naturally beneficial to regard digital twins and physical twins as agents with different behavioral patterns in different spaces, cooperating and complementing each other.
- The behavior encapsulations of twins agents in the game space enable them to act in a social way via cooperation, coordination and negotiation and perform specific tasks according to a common goal. Without this high-level abstraction, in the cyberspace and the real world, the twins agents can only respond to the context changes in a reactive way or perform goal-driven actions in a proactive way. In other words, the introduction of game space helps to develop a generic decision model representing the decision-making process instead of the physical process.

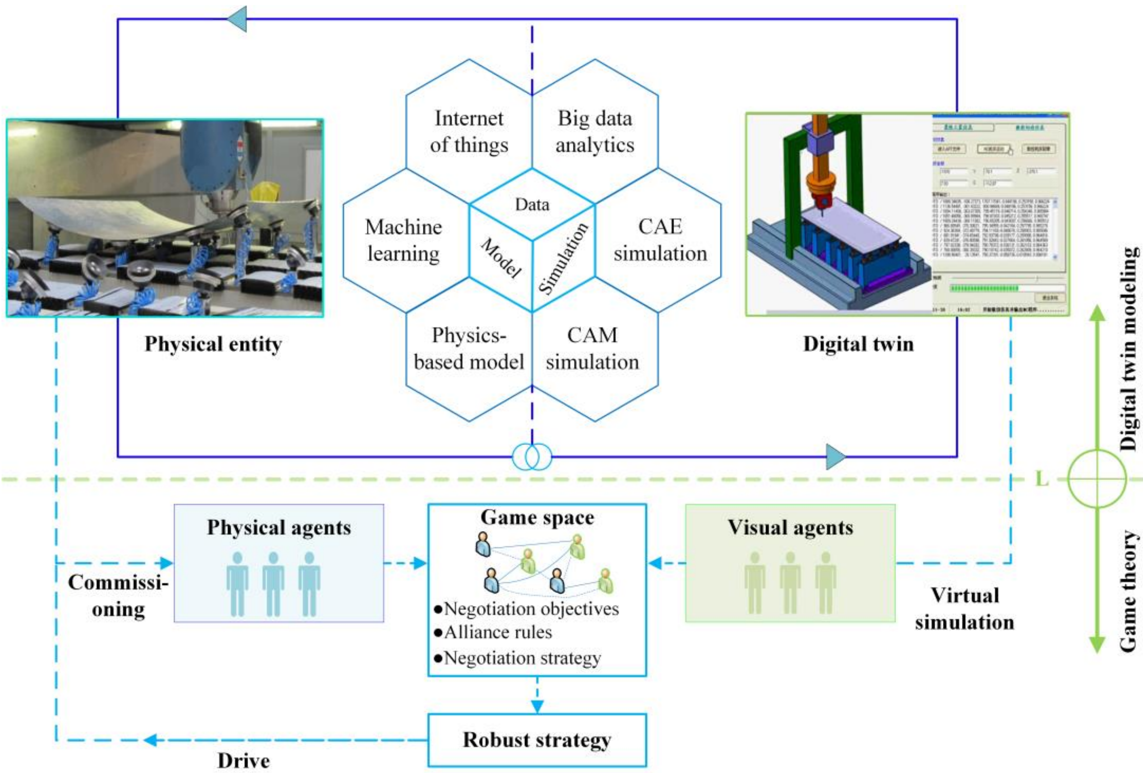

Figure 1. Schematic of the marriage between digital twin concept and game theory.

3.2. Basic Formalization

To transform the above-mentioned concepts into general applications, the formalization method is further given below.

Given a decision-making space X with the variable vector $(x_1, x_2, x_3, \cdots, x_p)$, the decision-making tasks are defined as a set of negotiation subjects that are denoted by Nt in the game space. Generally, the negotiation subjects Nt include the issues Nt_g of the decision-making goals and the attributes Nt_c of the decision-making constraints, that is,

$$Nt = \{Nt_{g1}, \cdots, Nt_{gn}, Nt_{c1}, \cdots, Nt_{cm}\} \tag{1}$$

where n is the number of the decision-making goals, and m is the number of decision-making constraints.

Let $Pa(X)$ represent a set of players that are produced in the real system, and $Da(X)$ represents a set of players that are produced in the digital twin environment. In this stage of the decision-making task, the physical agents and digital twin agents are only predictive according to the available information. Moreover, owing to the differences in their behavior or their time of birth, the physical agents and the digital twin agents are not exactly aligned in the decision-making space–time. This means, for any agent in $Pa(X)$ and $Da(X)$, it can only determine partial subjects in the Nt, while the other decision subjects are full of uncertainty. Therefore, they are supposed to further validate themselves and obtain more decision gains by seeking an alliance partner in the game space. The rules that possibly enable the physical agents $Pa(X)$ and the digital twin agents $Da(X)$ to obtain more decision gains are called alliance criteria that are denoted by Ac. Here, in the same space X of the decision-making variables, the standardized Euclidean distance (SED) is adopted to couple a physical player with a digital player. If the SED is small enough, the coalition will approximate to a twin pair with supplementary information. For this reason, the coalition can help to focus on feasible strategies with high efficiency.

If the decision-making space X has the variables $(x_1, x_2, x_3, \cdots, x_p)$, the standardized Euclidean distance $Dseu(Pa_i, Da_j)$ can be calculated by

$$Dseu(Pa_i, Da_j) = \sqrt{\sum_{k=1}^{p} \left(\frac{x_{Paik} - x_{Dajk}}{s_k} \right)^2} \tag{2}$$

where s_k is the standard deviation of the dimension k. If $Dseu(Pa_i, Da_j)$ is less than the SEDs of other combinable pairs, they form a coalition $\langle Pa_i, Da_j \rangle$. Therefore, the alliance rule can be expressed by

$$\begin{gathered} \forall Pa_i \text{ in } Pa(X),\ \forall Da_j \text{ in } Da(X), \\ \text{if } Dseu_{ij} < Dseu_{kj},\ k \neq i, \\ \text{then } At_{ij} = \langle Pa_i, Da_j \rangle \end{gathered} \tag{3}$$

where At_{ij} is a coalition that is composed of the physical agent Pa_i and digital agent Da_j. If the SED is small enough, the coalition will approximate to a twin pair with incremental information. For this reason, the coalition can help to focus on feasible strategies with high efficiency.

Academically, the mathematical model of a cooperative game in characteristic function form is described by a finite nonempty set N and a real-valued function v on the family 2^{N} of subsets of the player set N, satisfying $v(\varnothing) = 0$. A subset S of N is called a coalition and $v(S)$ the value of coalition S. Here, the characteristic function of the game is the decision certainty that any agent S carries, that is, the ratio of determined subjects to all the negotiation subjects.

$$v(S) = \frac{Ds}{m+n} \tag{4}$$

where Ds is the number of determined subjects for the agent in $Pa(X)$ or $Da(X)$. Obviously, for any player pair At_{ij},

$$v(Pa_i \cup Da_j) \geq v(Pa_i) \cup v(Da_j) \tag{5}$$

Coalitional game model scenarios are where players can collaborate by forming coalitions in order to obtain higher a value than by acting in isolation. Although the coalitions have formed and earned the value defined by the characteristic function, their utility is nontransferable because their decision parameters are not the same vector. However, the coalition is yielded by the SED, so the decision-making variables of the player pairs are close, and if the SED is small enough, the utility can be viewed as transferable in engineering. For a further step, their twin models are generated, and two twin sets $\langle Pa_j(X_j), Da_j(\mathrm{X_j})\rangle$ and $\langle Pa_i(X_i), Da_i(X_i)\rangle$ will have the transferable utility because they have the same decision parameters. In the transferable utility (TU) setting, coalition utility can be freely distributed among agents, while in the nontransferable utility (NTU) setting coalitions are allowed to distribute utility only in some specified configurations, called consequences. In other words, in the digital-twin-based cooperative game space, three two-player coalitions can be obtained, and by comparing their cooperative utility, the optimal player capable of accomplishing the given tasks can be clearly identified.

If the twinning cost is considered, the above coalition strategies can be achieved by the negotiation strategy Ns,

$$Ns(Pa_i, Da_j) = \begin{cases} \text{If } Ct_{Pa} > Ct_{Da}, \text{and } v(Pa_i \cup Da_i) = 1, \text{stop the game and output the solution;} \\ \text{If } Ct_{Pa} < Ct_{Da}, \text{and } v(Pa_j \cup Da_j) = 1, \text{stop the game and output the solution;} \\ \text{Otherwise, seek a new alliance.} \end{cases} \tag{6}$$

where Ct_{Da} denotes the cost of digital twinning, and Ct_{Pa} is the cost of physical twinning. Firstly, if $Ct_{Pa} > Ct_{Da}$, the digital twin variant with the cooperative variable vector is produced first. The new decision certainty $v(Pa_i \cup Da_i)$ with the support of cooperative twins is calculated, and if the utility value reaches 1, the twins with the variable vector X_i are accepted to achieve the agreed-upon goal. Conversely, if $Ct_{Pa} < Ct_{Da}$, the physical twin variant with the cooperative variable vector is produced first. The new decision certainty $v(Pa_j \cup Da_j)$ with the support of cooperative twins is calculated, and if the utility value reaches 1, the twins with the variable vector X_j are accepted to achieve the agreed-upon goal. If neither of the two new utility values reaches 1, the agents with the variable vectors X_i and X_j are cleaned out from the game space.

Table 1 gives the utility analysis of the digital-twin-based cooperative game strategies. For more clarity, the chief flow chart of the presented method is shown in Figure 2. In the next section, as a proof, the presented method is adopted to generate the assembly plan of large-scale composites skins.

Table 1. Utility analysis of digital-twin-based cooperative game.

Twinning-Based Cooperative Game $\langle Pa_i(X_i), Da_j(X_j)\rangle$		**Digital Domain**	
		Without Twinning $\langle Pa_i(X_i), Da_j(X_j)\rangle$	**Coalition-Based Twin Variant** $\langle Pa_i(X_i), Da_i(X_i)\rangle$
Physical domain	Without twinning $\langle Pa_i(X_i), Da_j(X_j)\rangle$	$v(Pa_i \cup Da_j)$	$v(Pa_i \cup Da_i)$
	Coalition-based twin variant $\langle Pa_j(X_j), Da_j(X_j)\rangle$	$v(Pa_j \cup Da_j)$	$v(Pa_j \cup Da_i)$

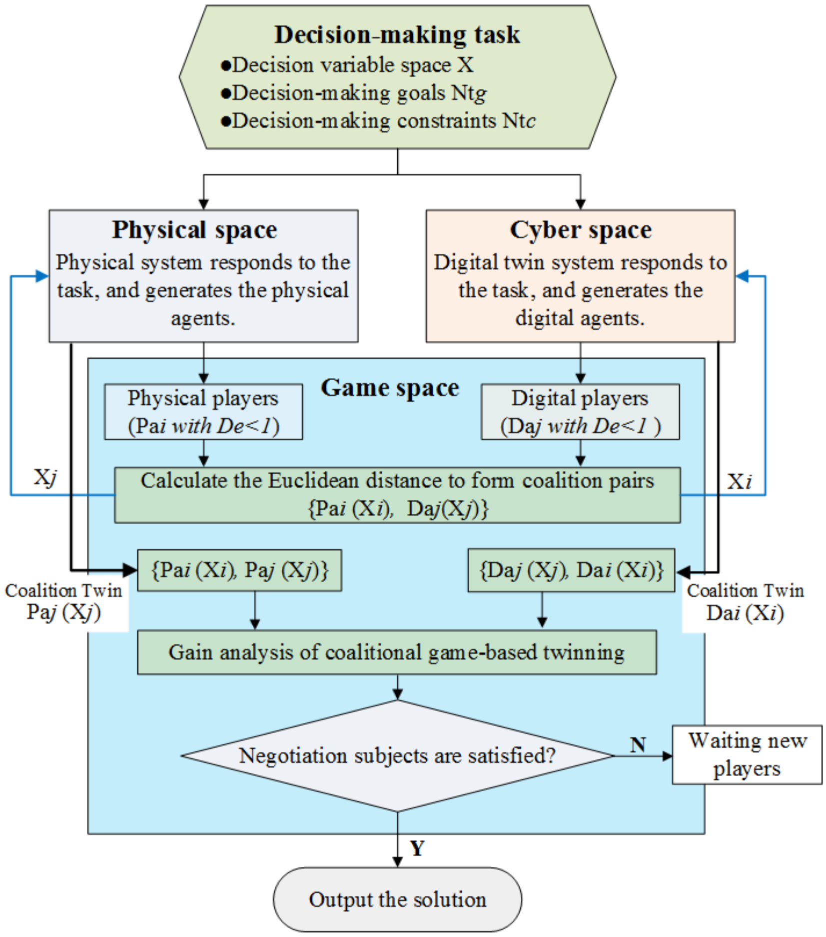

Figure 2. Flow chart of the game theoretic and digital-twin-based decision-making method.

4. Application Case

4.1. Generalization of Composite Part Assembly Task

Generally speaking, the decision making of complex assembly tasks is essentially to generate a feasible and robust solution to the assembly process (positioning, closing, fastening and releasing, namely PCFR), which belongs to a highly coupled design of product–process–resource (PPR). Manifold methodologies should be involved, such as the joining method of part–fixture–tooling, dimensional error control and compensation method, assembly sequence and process parameter optimization method and testing and measurement-planning method. In this work, the composite part assembly is generalized by Figure 3.

The as-built composite panel with free-form surfaces cannot correctly conform to the as-designed model owing to the geometrical deviations. These nonlinear geometrical deviations at component level tend to propagate along the assembly process, which further likely produces fit-up gaps, shape errors and undesired stress level. This type of part-to-part assembly without interchangeability tolerances is likely to present significant costs and technical challenges. In particular, as more and more flexible tooling, fixtures and robotic systems are adopted to replace manual operations, the support of assembly decision-making systems becomes more important to ensure that the assembly is finished right first time and with improved accuracy of aerodynamic profiles.

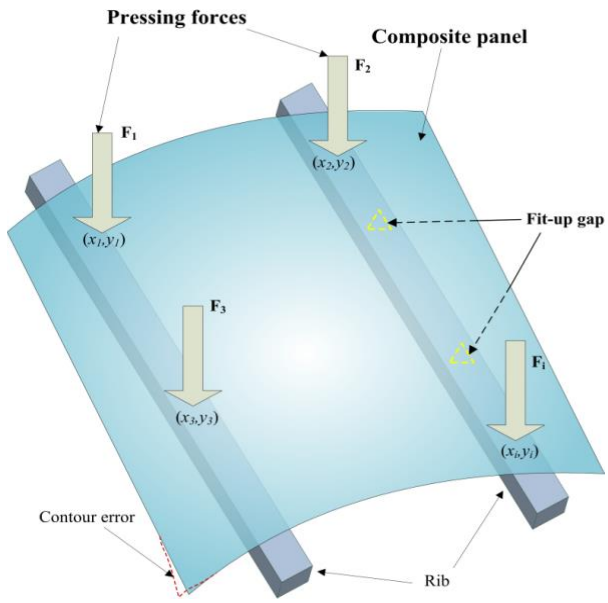

Figure 3. Large thin composite skin added to the frame components (stringers and ribs).

4.1.1. Decision Variables of Assembly Planning

For large composite components, force-controlled multi-point reconfigurable flexible tooling or robotic actuators are usually used during assembly to impose over-constraints on the positioning surface to complete the positioning and clamping work and eliminate the gap between the components. For assembly objects with different component configurations, different assembly methods or different loading mechanisms, the stress-coupling methods are also different, and the poor layout of the compression force can easily lead to uneven stress distribution inside the component, especially at the geometric discontinuity and with the application of external force. Stress concentrations are prone to occur, which may cause damage and defects, including at assembly locations, free edges, bonded joints and cut edges. In addition, the gaps generated by the assembly of large-scale composite structures have large spans and wide distribution, and the effect of multi-point pressing force on the elimination of gaps varies depending on the arrangement. It can be seen that the poor distribution of the pressing force will not only lead to stress concentration and cause internal damage to the components but also cannot effectively eliminate the assembly gap between the components to complete high-quality assembly.

Therefore, the manipulated variables of the assembly process are the positions denoted by (x, y) and the intensity denoted by f of multi-point pressing forces. Here, the decision-making variable vector is expressed by

$$X = \{(x_1, y_1, f_1), (x_2, y_2, f_2), \cdots, (x_m, y_m, f_m)\},\ (x_i, y_i, f_i) \in \Omega,\ \mathrm{m} \leq \mathrm{M} \tag{7}$$

where $\Omega \in \mathrm{R}^3$ is the feasible region of the positions and pressing forces. m is the maximum allowable quantity of the loading and closing actuators.

4.1.2. Goals and Constraints of Assembly Planning

Composite skins are an important guarantee for maintaining the aerodynamic shape of high-speed-flight vehicles (e.g., aircraft and space shuttles). The geometrical accuracy of their contour surfaces and boundary edges directly affects the aerodynamic performance. Besides the geometrical errors of the part itself, during the assembly process, the composite panel may undergo translation, rotation and other pose changes and may also experience elastic–plastic deformation (e.g., secondary bending) due to nonlinear interactions. However, as the surfaces of the part and assembly product are continuous, the assembly accuracy is usually evaluated by the dimension error field of characteristic points on part surfaces. Additionally, the gaps (noncontact status) perhaps occur between the framework and the skin due to the shape distortions of the skin and the machining error and the assembling error of the framework. For most of the assembly gaps that appear in the assembly process, the positions of the gaps are usually randomly distributed, that is, it is difficult to predict the positions of the gaps. Moreover, the fit-up gaps have an influence on load transfer and assembly-induced stress and even assembly-induced delaminations, thus gaps in composite structures are risk factors. In some cases, shimming is therefore used to compensate for bad fitting [69].

Let Δ_s represent the allowable contour error (here 1.0 mm), and Δ_g represents the allowable maximum gap value (here 0.2 mm). $\delta_{si}(X)$ represents shape error at the ith KRP. $\delta_{gi}(X)$ represents the gap clearance at the ith KRP. Furthermore, a Boolean variable $g_i(X)$ is used to judge whether the gap state meets the technical requirement at the ith KRP, and a Boolean variable $s_i(X)$ is used to judge whether the shape error at the ith KRP meets the technical requirement. As such, they can be expressed by

$$g_i(X) = \begin{cases} 1,\ if\ \delta_{gi}(X) \le \Delta_g, \text{ the gap of KRP is allowable;} \\ 0,\ otherwise \quad \text{the gap of KRP still exists.} \end{cases} \tag{8}$$

$$s_i(X) = \begin{cases} 1,\ if\ \delta_{si}(X) \le \Delta_s, \text{ the shape error of KRP is allowable;} \\ 0,\ \text{otherwise the shape error } of \text{ KRP still exists.} \end{cases} \tag{9}$$

Therefore, the decision-making goals are to maximize the indicator function $f(X)$ of external clearance (gap) and internal clearance (shape error) distributions. Consequently, the agreed-upon goal attributes Nt_g can be defined as

$$Nt_g = \{Nt_{g1} = \frac{1}{N}\sum_{i=1}^{N} g_i(X) = 1, Nt_{g2} = \frac{1}{M}\sum_{i=1}^{M} s_i(X) = 1\} \tag{10}$$

During the assembly process, the fit-up gaps and assembly-induced stresses are prone to cause initial defects expanding to form secondary damage [70]. Assembly stress and secondary damage can cause the aircraft to be damaged without warning during service, seriously affecting the reliability of the service performance of composite load-bearing components, and even causing disasters [71]. Here the mixed-mode fracture criterion is adopted, which assumes that damage initiation can be predicted using the quadratic failure criterion:

$$\left(\frac{\langle\sigma_1\rangle}{\sigma_n^{max}}\right)^2 + \left(\frac{\sigma_2}{\sigma_s^{max}}\right)^2 + \left(\frac{\sigma_3}{\sigma_t^{max}}\right)^2 = 1 \tag{11}$$

where σ_1 is the normal traction, and σ_2 and σ_3 are the transverse tractions. σ_n^{max} is the nominal normal tensile, σ_s^{max} and σ_t^{max} are shear strengths. The Macauley operator $\langle\cdot\rangle$ is defined as x if $x > 0$ and 0 otherwise.

Further considering the constraint of the restricted minimum distance denoted by L between loading actuators and the prevention of assembly-induced secondary damage, the attributes Nt_c of the decision-making constraints are subjected to

$$Nt_c = \{Nt_{c1} = S(X) < 1, Nt_{c2} = |P_iP_j| > L\} \tag{12}$$

where $|P_iP_j|$ represents the distance between two neighboring loading actuators P_i and P_j. $S(X)$ represents the value of the mixed-mode fracture criterion as in Equation (10).

To sum up, the decision-making task of composite assembly can be formalized by

$$\begin{cases} \text{In the decision making space}: (x_i, y_i, F_i) \in \Omega,\ i = 1\ to\ m \le M \\ \text{By the cooperative game}: \text{ digital twin agents and physical agents} \\ \text{To satisfy}: Nt = \{Nt_{g1} = \frac{1}{N}\sum_{i=1}^{N} g_i(X) = 1, Nt_{g2} = \frac{1}{M}\sum_{i=1}^{M} s_i(X) = 1, Nt_{c1} = S(X) < 1, Nt_{c2} = |P_iP_j| > L\} \end{cases} \tag{13}$$

4.2. Digital-Twin-Driven Decision-Making System for Composite Assembly

4.2.1. Digital Twin System

Regarding the process to assemble the large thin composite skin onto the frame components (stringers and ribs), the presented digital-twin-driven assembly process decision-making framework is illustrated by Figure 4. The overall framework comprises four functional domains: physical assembly-commissioning domain, virtual assembly-commissioning domain, cross-space data fusion domain and game theoretic twinning and optimization. Their details are introduced in the following subsections. The objective is to determine the optimized decision variables of the assembly process, as said, the layout and intensity of pressing forces. In this research, we did not distinguish the onsite specific operation manners, for example, the actual manners of loading actuators, and mainly provide a digital-twin-driven assembly process decision-making methodology. The optimized decision variables of the assembly process could be transferred to an automatic tooling system or used to instruct manual operations and inspections. Furthermore, the following prerequisites or assumptions are defined:

- Owing that the rigidity of frame structures is much higher than the rigidity of large thin composite skins, the frame structures are treated as rigid bodies.
- The geometrical tolerances of frame structures are prone to reach, so the probability of dimensional variation is ignored.

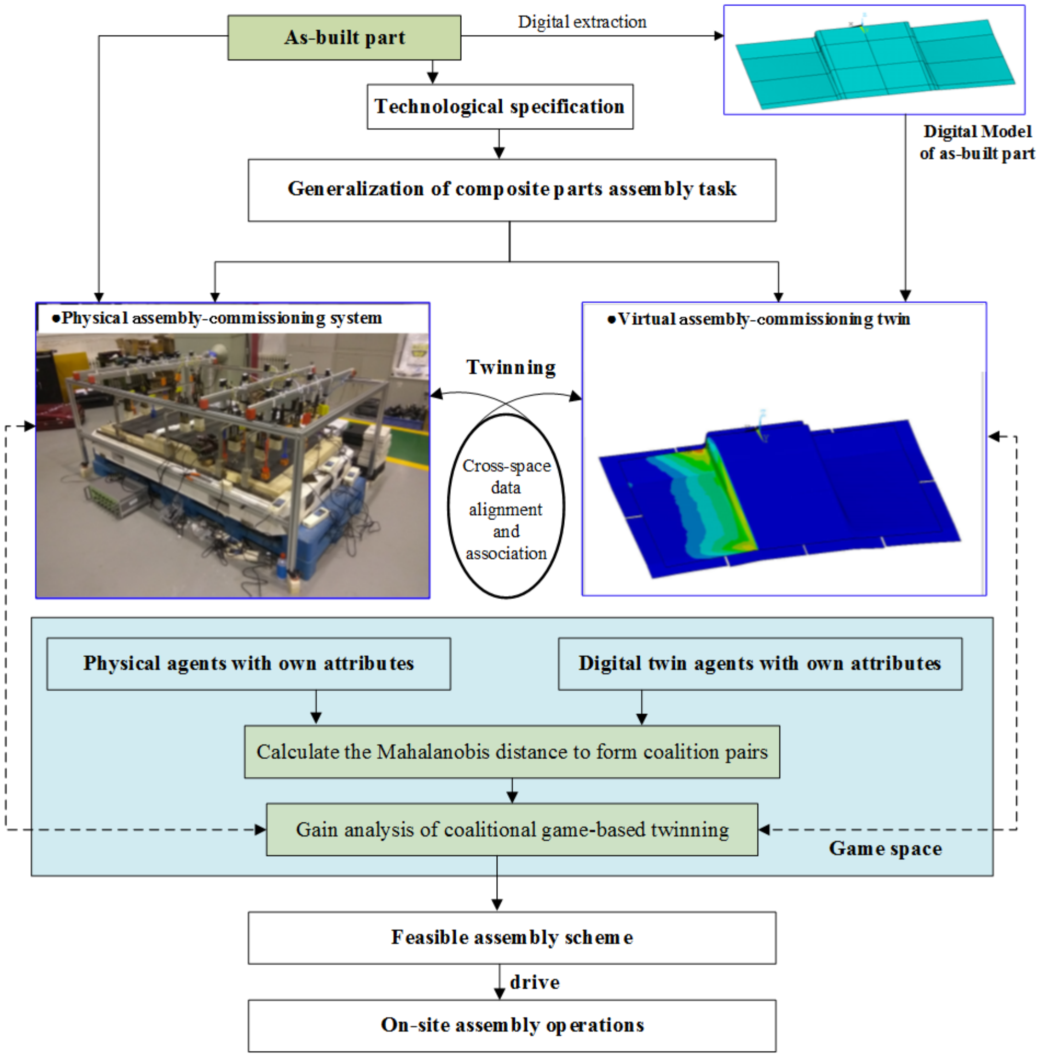

Figure 4. Overall framework of digital-twin-driven assembly process decision making.

4.2.2. Physical Assembly-Commissioning Domain

In the physical assembly, the physical entities mainly include components, tooling, fixtures, robots, measuring instruments and sensors, persons, environments and processes. If the behavioral influences of operators and the environment are temporarily ignored, then there are mainly four parts: assembly force loading tooling, deformation strain and stress measurement instrument, assembly precision measurement instrument and should-be fitted components. As illustrated in Figure 5, a 4 × 4 array of loading actuators and a 4 × 4 array of deformation sensors are mounted on movable guide rails of the X-axis and Y-axis, and their Z-axis positions can also be adjusted by screwing mechanisms. Therefore, the reconfigurable multi-point loading and multi-sensor feedback tooling has good adaptability to the assembly deformations of the as-built composite part. Furthermore, the dynamic resistance strain instrument is employed to measure the surface strain field, and the strain gauge is generally adhered to the location prone to deformation, such as chamfer and saddle-backing.

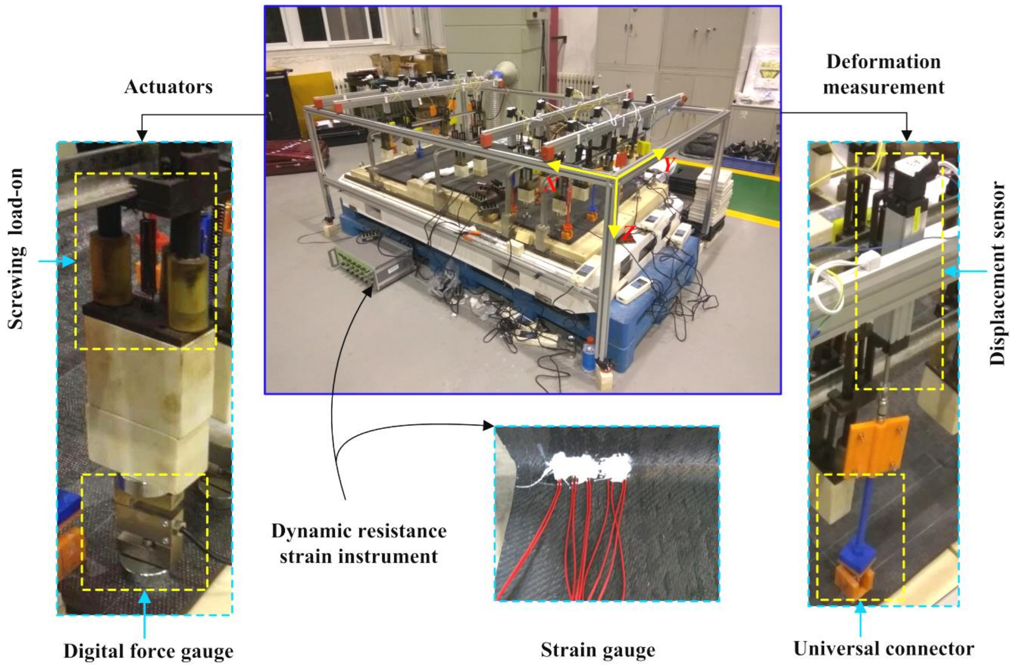

Figure 5. Physical assembly-commissioning system.

As is known to all, the precision of the virtual simulation assembly is susceptible to many factors like the accuracy of material parameters, convergence accuracy or calculation time. Consequently, the optimization solutions generated in the virtual space can only be regarded as "recommendation" rather than "determination". Therefore, in the closed loops of digital twinning or decision making, the physical assembly-commissioning system is a reactive entity, which can implement product assembly activities according to the specifications and feedback instructions from the virtual space and further provide some deterministic information (e.g., fit-up gaps and surface strains) to verify the probabilistic optimization solutions that are generated by the virtual assembly-commissioning system.

Conversely, even without the recommended manipulated variables, the measurement-assisted and rich sensor-connected physical assembly system can also generate alternative solutions through the experimental method. In this situation, the physical assembly-commissioning system can be viewed as an entity with some autonomy. However, this method is inefficient and costly, and it also brings out probabilistic information or unpredictable and undesirable results, such as assembly-induced secondary damage and nonmarginal fit-up gaps that cannot be easily measured. Therefore, the nonoptimal but validated solutions generated in the physical system should be transferred to the virtual space to further minimize unpredictable and undesirable risks.

To summarize, the physical assembly-commissioning domain is the physical foundation to construct the digital-twin-driven assembly process decision-making system, which is prerequisite for accurate operation, precise measurement and reliable confirmation of the product assembly process.

4.2.3. Virtual Assembly-Commissioning Domain

The virtual assembly space is the digitally geometrical, physical, behavioral and logical information-mirroring models of the physical assembly entities. In this work, empowered by the powerful computing capability, FEM simulation tools, data analysis methodology and visualization methods, the conflicts and clashes during assembly could be discovered cheaply and quickly, and the potential optimization solutions can be identified and recommended. Here, the FEM-based virtual simulation domain is built in the software ANSYS 2020R1 to simulate the nonlinear contact behavior, delamination formation and propagation behavior and the deformation behavior that occur in assembly operations. The as-designed model of a composite panel and the 3D point cloud model could not be used in FEM simulation. For the virtual replacement of the as-designed part, see Figure 6, and the geometrical model of the as-built composite panel is firstly built by three steps: 3D point cloud acquisition by a laser 3D scanner, data processing and abstract modeling. As the material propriety definition of composites and the contact analysis are well known, they will not be covered here.

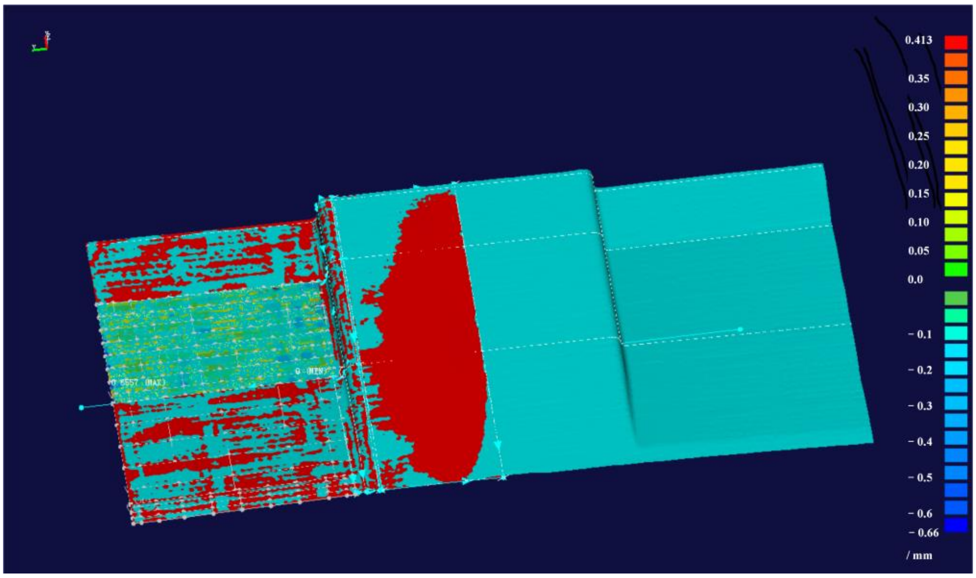

Figure 6. Error distribution between 3D point cloud and the abstract model of the as-fabricated composite panel.

The simulation of delamination formation and propagation is modeled by the method of cohesive zone material (CZM). CZM has the ability to model delamination formation and propagation by adopting softening relationships between tractions and the separations without defining the initial defect, unlike fracture mechanics methods. In the software ANSYS, it is built into special so-called interface elements that model a thin adhesive layer (potentially zero thickness) and are located inside the area of potential defect propagation [72]. The cohesive zone can be defined using both interface or contact elements. Interface elements can only be used to connect solid body elements, while contact elements can work for shells too. Modeling using contact elements is preferred, because it enables the delamination analysis of thin-walled complex structures [73]. Finally, the multi-constrained nonlinear optimization problem (see Equation (13)) is solved by the built-in penalty function method and by programming using the ANSYS Parametric Design Language (APDL) in the Windows 10 (64-bit) operating system with the configuration of 64 GB random-access memory (RAM) and 1 TB solid state disk (SSD).

Under the umbrella of the digital twin concept, the virtual assembly commissioning is no longer purely visual simulation and computation, but it can generate more optimized alternatives and more details (e.g., nonlinear contact status and process-induced delamination) to alleviate the interaction complexity and uncertainty of the actual assembly activities. The simulation accuracy, sampling period and other uncertainties of virtual assembly commissioning should be validated by a small amount of assembly experiments before formal adoption.

4.2.4. Cross-Space Data Fusion Domain

The bidirectional information flow and sharing between the physical and virtual spaces is also no longer traditional data communication and conversation, because the cross-space data of different dimensions, multiple heterogeneous sources and multiple scales need correct alignment and coupling. For example, for the fit-up gaps that occur in the physical and the virtual spaces, their measured data of positions and scopes and their simulated counterparts should be aligned to make sense. Therefore, the cross-space domain should be built based on the deep understanding of physical assembly activities and their virtual representations.

The cross-space data fusion domain is responsible for the correct alignment and coupling of the data produced both in the physical assembly and the virtual space [74]. Firstly, the datum frame should be built according to the datum holes or regular lines and surfaces on the abstract model of the as-built component in the virtual space, then depending on the corresponding features on the as-built component to build the datum frame in reality, to ensure that the positioning poses stay the same between the physical assembly and virtual assembly. Secondly, the variables of KCCs in the physical assembly domain should align with the counterparts in the virtual simulation domain.

Generally, referring to the datum frames, see Figure 7, some key reference points (KRPs) are selected to characterize the assembly-induced deformations, assembly-induced stresses and assembly-induced strains. The alignment of manipulated variables of the assembly process is simple, mainly to limit the range of values and significant digits of precision.

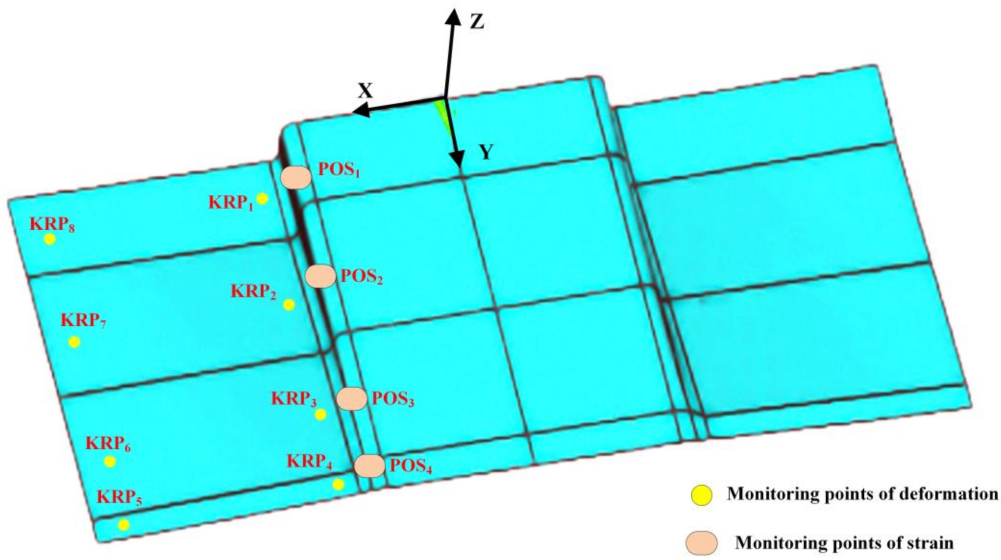

Figure 7. Monitoring points of deformation and strain.

4.3. Experiment

The digital twin agent that has the simulation ability and the physical agent that can measure the assembly deformation have been generated. Next, a specific case is demonstrated to achieve the final assembly parameters using the presented game theoretic and digital-twin-based decision-making method.

4.3.1. Composite Skin

The composite component is carbon fiber/epoxy composite laminate with a stacking sequence of [45/−45/0/90/0/90/0/45/90/−45/0/90/0/90/90/0/90/0/−45/90/45/0/90/0/90/0/−45/45], for a total of 28 plies, whose nominal cured thickness of 1 ply is 0.389 mm. The overall material properties of the composites are shown in Table 2.

Table 2. Material properties.

Density	1920 kg/m^3
Elasticity	Ex = 84.3 GPa; Ey = 80.0 GPa; Ez = 8 GPa; Gxy = 10.0 GPa; Gyz = Gxz = 4.0 GPa; PRxy = 0.15; PRyz = PRxz = 0.05
Strength	Xt = 2800 MPa; Xc = 1600 MPa; Yt = 880 MPa; Yc = 1600 MPa; Zt = 880 MPa; Zc = 1600 MPa; Sxy = Sxz = 420 MPa; Syz = 820 MPa

As stated previously, the digital model of the as-fabricated composite panel is built by three steps, first 3D point cloud acquisition by the laser 3D scanner, then data processing and finally abstract modeling by the commercialized software. Figure 6 shows the error distribution between the as-processed 3D point cloud model and the as-built abstract model, and the root mean squared error (RMSE) is less than 0.1 mm. In the cross-space domain, the datum frame is built firstly and the KRPs are selected to monitor their KCCs such as deformations or strains as shown in Figure 7.

4.3.2. Digital-Twin-Driven Decision Making of Assembly

According to the presented FEM-based optimization model, after about 600 iterations, five solutions are generated by the virtual assembly-commissioning method. Meanwhile, two solutions are generated by the physical assembly-commissioning method. Their attributes are listed in Table 3.

Table 3. The positions and pressing forces of loading actuators through optimization.

Agents	Attributes in the Variable Space (x_i, y_{ij}/mm; F_{ij}/N)																		Decision Certainty *De*
	x_1	y_{11}	f_{11}	y_{12}	f_{12}	y_{13}	f_{13}	y_{14}	f_{14}	x_2	x_{21}	f_{21}	y_{22}	f_{22}	y_{23}	f_{23}	y_{24}	f_{24}	
*Da*1	561	50	656	280	774	530	820	780	857	781	51	645	281	748	531	855	782	750	0.90
*Da*2	360	81	500	320	650	440	783	800	751	651	60	240	180	350	380	600	700	550	0.90
*Da*3	241	181	701	351	200	551	652	653	501	601	120	654	201	450	400	801	655	656	0.90
*Da*4	451	61	602	182	502	352	702	580	802	703	45	560	202	807	390	581	752	680	0.90
*Da*5	503	62	552	250	452	361	885	753	900	740	81	290	190	681	300	890	720	880	0.90
*Pa*1	353	80	803	220	850	391	603	721	754	755	50	453	260	553	381	804	657	658	0.40
*Pa*2	261	121	851	301	682	420	756	806	805	582	63	554	282	785	354	683	704	504	0.40

As said, owing to the intrinsic drawbacks in the methodology, their decision certainties are all less than 1.0, and they are 0.9 and 0.4, respectively. Further, according to Equation (2), the standardized Euclidean distances among the physical and digital agents are calculated as shown in Figure 8. Obviously, $\mathrm{Dseu}(Pa_1, Da_4)$ is less than the distances between other pairs, therefore they form a coalition twin. Next, according to the gain analysis method of the coalitional game-based twinning strategy and the negotiation strategy defined by Equation (6), the virtual agent Da_4 is preferentially selected to generate its physical twin Da_4'.

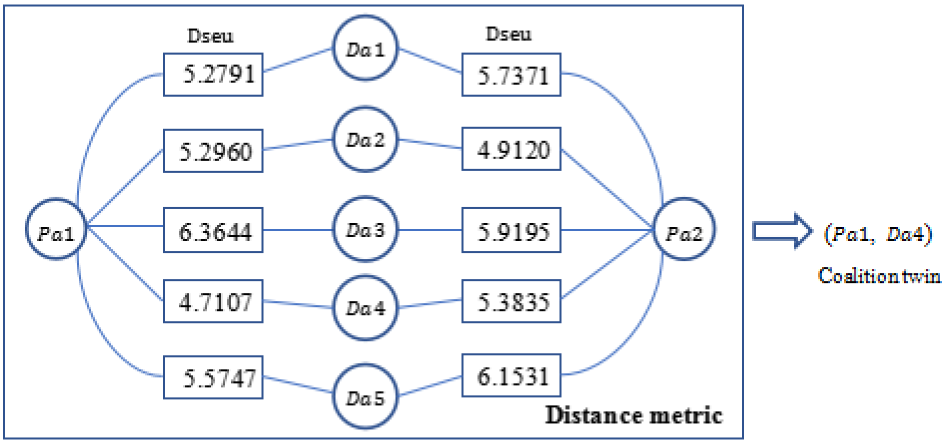

Figure 8. Generation of coalitional twins.

Figure 9 presents the comparisons of strains on the KRPs between the virtual agent Da_4 and its physical twin Da'_4. Figure 10 presents the comparisons of deformations at the KRPs between the virtual agent Da_4 and its physical twin Da'_4. According to the data, it is clear that all the KCCs in the physical space are less than the counterparts in the virtual space. Meanwhile, the shape deformation errors are within the allowable tolerances. Therefore, the allied players (Pa_1, Da_4) have solved all negotiation issues, and the decision-making variables are accepted as a deterministic and reliable solution.

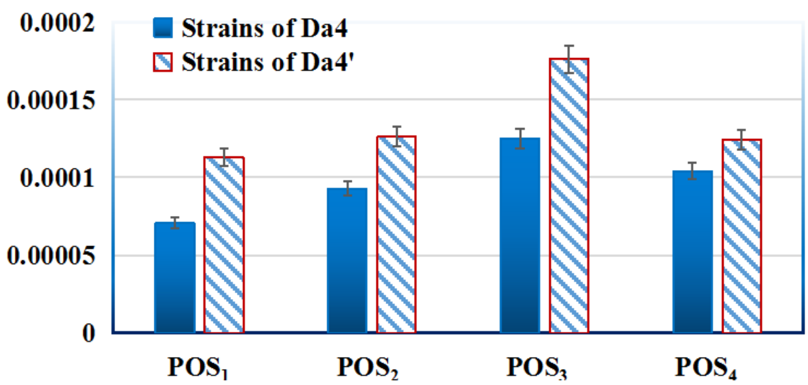

Figure 9. Comparisons of strains between physical assembly and virtual simulation.

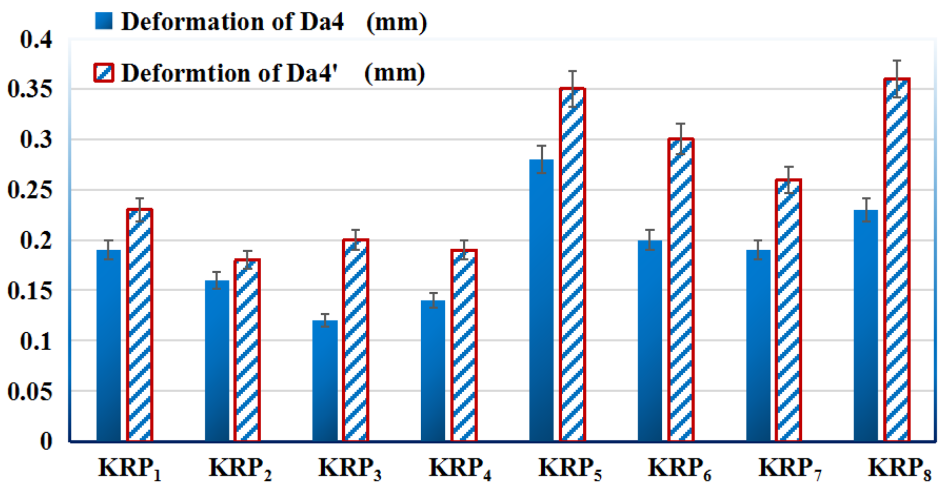

Figure 10. Comparisons of deformations between physical assembly and virtual simulation.

5. Conclusions

In Industry 4.0 or smart manufacturing, the deep integration and interaction of virtual and real worlds are profoundly reshaping the decision-making paradigm of complex industrial production systems. The most important contribution of this paper is to push the digital twin modeling, which captures the similarity of reactive behavior, to a higher-level model with proactive and social ability by introducing game theory. The digital twin model is not only the digital representation of reality but is also a virtual agent that can perform goal-driven actions in a proactive way. The twin virtual system and physical reality system carry out cooperative games on the basis of fully sharing information to improve the autonomy of complex decision-making tasks. This work presented the general framework, basic steps, formalization method and an application proof of the methodology.

Undeniably, some limitations of the current work also indicate future research opportunities. As for the basic formal model of the presented method, the stability and the fairness criteria of the coalition are not formalized. That is to say, the general solution concepts like core or Shapley value are not covered. Implicitly, the stable coalitions are formed by the negotiation of subjects and coalition rules. In future, the formal model of multi-attribute coalitional games [75] may help to improve the formal model. In addition, in the formalization of our method, the complexity and cost of the twinning method are not measured by a standard method. Therefore, the impacts of the intrinsic complexity of engineering modeling and computation on the overall complexity and convergence of the presented method are not demonstrated [76]. Moreover, some concepts of game theory in economics are not suitable for engineering problems, hence formalizing the procedure of applying game theory methods in engineering problems needs further research to reveal the connection between game theory and traditional methods for optimal decision making [63].

In future research, we can try to introduce more game theory models into the field of digital twin modeling, such as the noncooperative game, the incomplete information game and the large-language-model-driven game. In the game space, in addition to the virtual twin agents and real agents of a single system, more heterogeneous agents can also be introduced to participate in decision-making tasks, such as customers or attackers with virtual glasses, and the digital twin agents of higher-level or peer-level systems. In this case, the game will undoubtedly make the decision making of the huge and complex system more robust, so that the twin system has a greater ability to deal with the uncertainty. It is conceivable that this socialized digital twin modeling idea has great potential in the decision-making fields of digital twin cities, digital twin medical care, digital twin battlefields, digital twin transportation and other super digital systems. Hopefully, one day this exploration will be applied to the emerging metaverse.

Author Contributions: Conceptualization, F.H.; methodology, F.H.; software, F.H. and S.B.; validation, F.H. and Y.Z.; formal analysis, F.H.; investigation, F.H.; resources, F.H.; data curation, F.H. and S.B.; writing—original draft preparation, F.H., S.B. and Y.Z.; writing—review and editing, F.H., S.B. and Y.Z.; visualization, F.H., S.B. and Y.Z.; supervision, F.H.; project administration, F.H.; funding acquisition, F.H. and Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: The project was funded by the National Key Research and Development Program of China, grant number 2023YFB3406300.

Data Availability Statement: All data generated or analyzed during this study are included in this article.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

APDL	ANSYS Parametric Design Language
AI	Artificial Intelligence
CFRP	Carbon-Fiber-Reinforced Epoxy

CZM	Cohesive Zone Material
CPS	Cyber-Physical System
FEM	Finite Element Method
FAM	Forced Assembly Method
JSON	JavaScript Object Notation
KCC	Key Control Characteristics
KRP	Key Reference Point
MAA	Measurement-Assisted Assembly
MIC	Method of Influence Coefficients
PID	Process-Induced Deformation
PPR	Product–Process–Resource
RMSE	Root Mean Squared Error
TU	Transferable Utility
NTU	Nontransferable Utility
XML	Extensible Markup Language

References

1. Rosin, F.; Forget, P.; Lamouri, S.; Pellerin, R. Enhancing the Decision-Making Process through Industry 4.0 Technologies. *Sustainability* **2022**, *14*, 461. [CrossRef]
2. Romero, D.; Stahre, J. Towards the Resilient Operator 5.0: The Future of Work in Smart Resilient Manufacturing Systems. *Procedia CIRP* **2021**, *104*, 1089–1094. [CrossRef]
3. Hu, F. Mutual information-enhanced digital twin promotes vision-guided robotic grasping. *Adv. Eng. Inform.* **2022**, *52*, 101562. [CrossRef]
4. Schuh, G.; Anderl, R.; Gausemeier, J.; ten Hompel, M.; Wahlster, W. (Eds.) *Industrie 4.0 Maturity Index: Managing the Digital Transformation of Companies (acatech STUDY)*; Herbert Utz Verlag: Munich, Germany, 2017. Available online: https://www.acatech.de/publikation/industrie-4-0-maturity-index-die-digitale-transformation-von-unternehmen-gestalten/download-pdf?lang=en (accessed on 20 April 2020).
5. Kitchin, R. Big Data, new epistemologies and paradigm shifts. *Big Data Soc.* **2014**, *1*, 2053951714528481. [CrossRef]
6. Bousdekis, A.; Lepenioti, K.; Apostolou, D.; Mentzas, G. A Review of Data-Driven Decision-Making Methods for Industry 4.0 Maintenance Applications. *Electronics* **2021**, *10*, 828. [CrossRef]
7. Sanders, N.R. How to use big data to drive your supply chain. *Calif. Manag. Rev.* **2016**, *58*, 26–48. [CrossRef]
8. Huo, Z.; Mukherjee, M.; Shu, L.; Chen, Y.; Zhou, Z. Cloud-based data-intensive framework towards fault diagnosis in large-scale petrochemical plants. In Proceedings of the 2016 International Wireless Communications and Mobile Computing Conference (IWCMC), Paphos, Cyprus, 5–9 September 2016; pp. 1080–1085.
9. Ma, S.; Zhang, Y.; Lv, J.; Ge, Y.; Yang, H.; Li, L. Big data driven predictive production planning for energy-intensive manufacturing industries. *Energy* **2020**, *211*, 118320. [CrossRef]
10. Xu, J.; Zhu, S.; Guo, H.; Wu, S. Automated labeling for robotic autonomous navigation through multi-sensory semi-supervised learning on big data. *IEEE Trans. Big Data* **2019**, *7*, 93–101. [CrossRef]
11. Santos, C.H.D.; De Queiroz, J.A.; Leal, F.; Montevechi, J.A.B. Use of simulation in the industry 4.0 context: Creation of a Digital Twin to optimise decision making on non-automated process. *J. Simul.* **2020**, *16*, 284–297. [CrossRef]
12. Granacher, J.; Nguyen, T.V.; Castro-Amoedo, R.; Maréchal, F. Overcoming decision paralysis—A digital twin for decision making in energy system design. *Appl. Energy* **2022**, *306*, 117954. [CrossRef]
13. dos Santos, C.H.; Gabriel, G.T.; do Amaral, J.V.S.; Montevechi, J.A.B.; de Queiroz, J.A. Decision-making in a fast fashion company in the Industry 4.0 era: A Digital Twin proposal to support operational planning. *Int. J. Adv. Manuf. Technol.* **2021**, *116*, 1653–1666. [CrossRef]
14. Hu, F.; Wang, W.; Zhou, J. Petri nets-based digital twin drives dual-arm cooperative manipulation. *Comput. Ind.* **2023**, *147*, 103880. [CrossRef]
15. Sierla, S.; Azangoo, M.; Rainio, K.; Papakonstantinou, N.; Fay, A.; Honkamaa, P.; Vyatkin, V. Roadmap to semi-automatic generation of digital twins for brownfield process plants. *J. Ind. Inf. Integr.* **2022**, *27*, 100282. [CrossRef]
16. West, S.; Stoll, O.; Meierhofer, J.; Züst, S. Digital twin providing new opportunities for value co-creation through supporting decision-making. *Appl. Sci.* **2021**, *11*, 3750. [CrossRef]
17. Marques, M.; Agostinho, C.; Zacharewicz, G.; Jardim-Gonçalves, R. Decentralized decision support for intelligent manufacturing in Industry 4.0. *J. Ambient Intell. Smart Environ.* **2017**, *9*, 299–313. [CrossRef]
18. Rosen, R.; Von Wichert, G.; Lo, G.; Bettenhausen, K.D. About the importance of autonomy and digital twins for the future of manufacturing. *Ifac-Pap.* **2015**, *48*, 567–572. [CrossRef]
19. Hu, F. Digital Twin-Driven Reconfigurable Fixturing Optimization for Trimming Operation of Aircraft Skins. *Aerospace* **2022**, *9*, 154. [CrossRef]
20. Leitão, P. Agent-based distributed manufacturing control: A state-of-the-art survey. *Eng. Appl. Artif. Intell.* **2009**, *22*, 979–991. [CrossRef]

21. Marik, V.; McFarlane, D. Industrial adoption of agent-based technologies. *IEEE Intell. Syst.* **2005**, *20*, 27–35. [CrossRef]
22. Morgan, J.; Halton, M.; Qiao, Y.; Breslin, J.G. Industry 4.0 smart reconfigurable manufacturing machines. *J. Manuf. Syst.* **2021**, *59*, 481–506. [CrossRef]
23. Schuh, G.; Anderl, R.; Dumitrescu, R.; Krüger, A.; ten Hompel, M. (Eds.) *Industrie 4.0 Maturity Index: Managing the Digital Transformation of Companies-UPDATE 2020-(acatech STUDY)*; Herbert Utz Verlag: Munich, Germany, 2020. Available online: https://www.acatech.de/publikation/industrie-4-0-maturity-index-update-2020/download-pdf?lang=en (accessed on 20 January 2021).
24. Mrazova, M. Advanced composite materials of the future in aerospace industry. *Incas Bull.* **2013**, *5*, 139–150.
25. Kappel, E. Forced-interaction and spring-in–relevant initiators of process-induced distortions in composite manufacturing. *Compos. Struct.* **2016**, *140*, 217–229. [CrossRef]
26. McEwan, W.; Butterfield, J.; Price, M.; Murphy, A. Development of a digital methodology for composite process & manufacture in aerospace assemblies. In Proceedings of the 10th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference, Fort Worth, TX, USA, 13–15 September 2010; p. 9070.
27. Zhang, T.; Zhang, C.; Zhao, J.; Guo, A. Analysis of Allowable Assembly Forces for Composite Laminates. IOP Conference Series: Materials Science and Engineering. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *647*, 012011. [CrossRef]
28. Gao, G.; An, L.; Zhang, W.; Ge, E.; Yue, X.; Yun, Y.; Han, N. Shimming effect on the mechanical behaviors of composite assembly structures of aircraft. *Proc. Inst. Mech. Eng. Part G J. Aerosp. Eng.* **2019**, *233*, 851–860. [CrossRef]
29. Greco, A.; Caputo, F.; Caterino, M.; D'Ambra, S.; Fera, M.; Laudante, E. Composite parts assembly operational improvements. *Macromol. Symposia* **2020**, *389*, 1900098. [CrossRef]
30. Jareteg, C.; Wärmefjord, K.; Cromvik, C.; Söderberg, R.; Lindkvist, L.; Carlson, J.; Larsson, S.; Edelvik, F. Geometry assurance integrating process variation with simulation of spring-in for composite parts and assemblies. *J. Comput. Inf. Sci. Eng.* **2016**, *16*, 031003. [CrossRef]
31. Yue, X.; Wen, Y.; Hunt, J.H.; Shi, J. Surrogate model-based control considering uncertainties for composite fuselage assembly. *J. Manuf. Sci. Eng.* **2018**, *140*, 041017. [CrossRef]
32. Roulet, V.; Boucard, P.A.; Champaney, L. An efficient computational strategy for composite laminates assemblies including variability. *Int. J. Solids Struct.* **2013**, *50*, 2749–2757. [CrossRef]
33. Corrado, A.; Polini, W.; Moroni, G. Comparison between two numerical tools for geometrical deviation analysis in composite assemblies. *Procedia CIRP* **2020**, *92*, 100–105. [CrossRef]
34. Corrado, A.; Polini, W.; Sorrentino, L.; Bellini, C. Geometrical deviation analysis of CFRP thin laminate assemblies: Numerical and experimental results. *Compos. Sci. Technol.* **2018**, *168*, 1–11. [CrossRef]
35. Yang, Y.; Liu, X.; Wang, Y.Q.; Gao, H.; Bao, Y.; Li, R. An enhanced spring-mass model for stiffness prediction in single-lap composite joints with considering assembly gap and gap shimming. *Compos. Struct.* **2018**, *187*, 18–26. [CrossRef]
36. Liu, J.; Li, Z.; Liu, T.; Li, X. Variation Analysis for Composite Parts with Considering Local Delamination Defects. In *ASME International Mechanical Engineering Congress and Exposition*; American Society of Mechanical Engineers: New York City, NY, USA, 2019; Volume 59384, p. V02BT02A061.
37. Jonsson, M.; Murray, T.; Robertsson, A.; Stolt, A.; Nilsson, K. Force feedback for assembly of aircraft structures. In Proceedings of the 2010 SAE Aerospace Manufacturing and Automated Fastening Conference, Wichita, KS, USA, 28–30 September 2010.
38. Ramirez, J.; Wollnack, J. Flexible automated assembly systems for large CFRP-structures. *Procedia Technol.* **2014**, *15*, 447–455. [CrossRef]
39. Zhang, W.; An, L.; Chen, Y.; Xiong, Y.; Liao, Y. Optimisation for clamping force of aircraft composite structure assembly considering form defects and part deformations. *Adv. Mech. Eng.* **2021**, *13*, 1687814021995703. [CrossRef]
40. Muelaner, J.E.; Maropoulos, P.G. Design for measurement assisted determinate assembly (MADA) of large composite structures. *J. CMSC* **2010**, *5*, 1–10. Available online: https://www.cmsc.org/autumn-2010-design-for-measurement-assisted-determinate-assembly-mada-of-large-composite-structures (accessed on 18 January 2024).
41. Maropoulos, P.G.; Muelaner, J.E.; Summers, M.D.; Martin, O.C. A new paradigm in large-scale assembly—Research priorities in measurement assisted assembly. *Int. J. Adv. Manuf. Technol.* **2014**, *70*, 621–633. [CrossRef]
42. Liang, B.; Liu, W.; Liu, K.; Zhou, M.; Zhang, Y.; Jia, Z. A displacement field perception method for component digital twin in aircraft assembly. *Sensors* **2020**, *20*, 5161. [CrossRef] [PubMed]
43. Müller, R.; Hörauf, L.; Vette, M.; Speicher, C. Planning and developing cyber-physical assembly systems by connecting virtual and real worlds. *Procedia Cirp* **2016**, *52*, 35–40. [CrossRef]
44. Sun, X.; Bao, J.; Li, J.; Zhang, Y.; Liu, S.; Zhou, B. A digital twin-driven approach for the assembly-commissioning of high precision products. *Robot. Comput.-Integr. Manuf.* **2020**, *61*, 101839. [CrossRef]
45. Grégorio, J.L.; Lartigue, C.; Thiébaut, F.; Lebrun, R. A digital twin-based approach for the management of geometrical deviations during assembly processes. *J. Manuf. Syst.* **2021**, *58*, 108–117. [CrossRef]
46. Polini, W.; Corrado, A. Digital twin of composite assembly manufacturing process. *Int. J. Prod. Res.* **2020**, *58*, 5238–5252. [CrossRef]
47. Li, J.; Zhou, G.; Zhang, C. A twin data and knowledge-driven intelligent process planning framework of aviation parts. *Int. J. Prod. Res.* **2021**, *60*, 5217–5234. [CrossRef]
48. Sun, X.; Liu, S.; Bao, J.; Li, J.; Liu, Z. A Performance Prediction Method for a High-Precision Servo Valve Supported by Digital Twin Assembly-Commissioning. *Machines* **2022**, *10*, 11. [CrossRef]

49. Cohen, Y.; Faccio, M.; Galizia, F.G.; Mora, C.; Pilati, F. Assembly system configuration through Industry 4.0 principles: The expected change in the actual paradigms. *IFAC-Pap.* **2017**, *50*, 14958–14963. [CrossRef]
50. Qi, Q.; Tao, F. Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access* **2018**, *6*, 3585–3593. [CrossRef]
51. Hu, F.; Qiu, X.; Jing, G.; Zhu, Y. Digital twin-based decision making paradigm of raise boring method. *J. Intell. Manuf.* **2022**, *34*, 2387–2405. [CrossRef]
52. Singh, M.; Fuenmayor, E.; Hinchy, E.P.; Qiao, Y.; Murray, N.; Devine, D. Digital twin: Origin to future. *Appl. Syst. Innov.* **2021**, *4*, 36. [CrossRef]
53. Grieves, M.; Vickers, J. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems*; Springer: Cham, Switzerland, 2017; pp. 85–113. [CrossRef]
54. Shao, G. *Use Case Scenarios for Digital Twin Implementation Based on ISO 23247*; National Institute of Standards: Gaithersburg, MD, USA, 2021. [CrossRef]
55. Qi, Q.; Tao, F.; Hu, T.; Anwer, N.; Liu, A.; Wei, Y.; Wang, L.; Nee, A.Y.C. Enabling technologies and tools for digital twin. *J. Manuf. Syst.* **2021**, *58*, 3–21. [CrossRef]
56. Wang, H.; Li, H.; Wen, X.; Luo, G. Unified modeling for digital twin of a knowledge-based system design. *Robot. Comput.-Integr. Manuf.* **2021**, *68*, 102074. [CrossRef]
57. Redelinghuys, A.J.H.; Basson, A.H.; Kruger, K. A six-layer architecture for the digital twin: A manufacturing case study implementation. *J. Intell. Manuf.* **2019**, *31*, 1383–1402. [CrossRef]
58. Croatti, A.; Gabellini, M.; Montagna, S.; Ricci, A. On the integration of agents and digital twins in healthcare. *J. Med. Syst.* **2020**, *44*, 1–8. [CrossRef]
59. Stary, C. Digital twin generation: Re-conceptualizing agent systems for behavior-centered cyber-physical system development. *Sensors* **2021**, *21*, 1096. [CrossRef]
60. Madani, K.; Lund, J.R. A Monte-Carlo game theoretic approach for multi-criteria decision making under uncertainty. *Adv. Water Resour.* **2011**, *34*, 607–616. [CrossRef]
61. Parsons, S.; Wooldridge, M. Game theory and decision theory in multi-agent systems. *Auton. Agents Multi-Agent Syst.* **2002**, *5*, 243–254. [CrossRef]
62. Sohrabi, M.K.; Azgomi, H. A survey on the combined use of optimization methods and game theory. *Arch. Comput. Methods Eng.* **2020**, *27*, 59–80. [CrossRef]
63. Mei, S.; Wei, W.; Liu, F. On engineering game theory with its application in power systems. *Control Theory Technol.* **2017**, *15*, 1–12. [CrossRef]
64. Hernandez, G.; Mistree, F. Integrating product design and manufacturing: A game theoretic approach. *Eng. Optim. + A35* **2000**, *32*, 749–775. [CrossRef]
65. Yazan, D.M.; Yazdanpanah, V.; Fraccascia, L. Learning strategic cooperative behavior in industrial symbiosis: A game-theoretic approach integrated with agent-based simulation. *Bus. Strategy Environ.* **2020**, *29*, 2078–2091. [CrossRef]
66. Tomko, M.; Winter, S. Beyond digital twins—A commentary. *Environ. Plan. B Urban Anal. City Sci.* **2019**, *46*, 395–399. [CrossRef]
67. Kim, S.; Pérez-Castillo, R.; Caballero, I.; Lee, D. Organizational process maturity model for IoT data quality management. *J. Ind. Inf. Integr.* **2022**, *26*, 100256. [CrossRef]
68. Wright, L.; Davidson, S. How to tell the difference between a model and a digital twin. *Adv. Model. Simul. Eng. Sci.* **2020**, *7*, 1–13. [CrossRef]
69. Derler, P.; Lee, E.A.; Vincentelli, A.S. Modeling cyber–physical systems. *Proc. IEEE* **2011**, *100*, 13–28. [CrossRef]
70. Söderberg, R.; Wärmefjord, K.; Lindkvist, L. Variation simulation of stress during assembly of composite parts. *CIRP Ann.* **2015**, *64*, 17–20. [CrossRef]
71. Topac, O.T.; Gozluklu, B.; Gurses, E.; Coker, D. Experimental and computational study of the damage process in CFRP composite beams under low-velocity impact. *Compos. Part A Appl. Sci. Manuf.* **2017**, *92*, 167–182. [CrossRef]
72. Liu, J.; Li, Z.M.; Liu, T.; Qiao, P. Influence of Local Delamination on Assembly Variation Modeling of Laminated Composite Beams. *J. Aerosp. Eng.* **2020**, *33*, 04020064. [CrossRef]
73. Glud, J.; Christensen, E.T.; Lindgaard, E.; Bak, B.L.V. Implementation of a state-of-the-art cohesive zone element for ANSYS Mechanical. In Proceedings of the 26th Nordic Seminar on Computational Mechanics, Oslo, Norway, 23–25 October 2013.
74. Lindgaard, E.; Bak, B.L.; Christensen, E.T.; Glud, J. Cohesive Zone Modelling of Wrinkle Defects in Glass-Epoxy Laminates Using User Finite Element Feature. In Proceedings of the 11th World Congress on Computational Mechanics (WCCM XI), 5th European Conference on Computational Mechanics (ECCM V), 6th European Conference on Computational Fluid Dynamics (ECFD VI), Barcelona, Spain, 20–25 July 2014.
75. Ieong, S.; Shoham, Y. Multi-attribute coalitional games. In Proceedings of the 7th ACM Conference on Electronic Commerce, Ann Arbor, MI, USA, 11–15 June 2006; pp. 170–179.
76. Greco, G.; Malizia, E.; Palopoli, L.; Scarcello, F. On the complexity of core, kernel, and bargaining set. *Artif. Intell.* **2011**, *175*, 1877–1910. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.