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A survey of challenges in modelling and decision-making for discrete event logistics systems

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ABSTRACT

In this paper, we consider discrete event logistics systems (DELS). DELS are networks of resources through which material flow. They have been the subject of a large body of analytic research. A huge variety of specific models exists that generally require application by model and/or solution experts to answer narrowly-defined logistics questions about inventory, sourcing, scheduling, routing, etc. It has, however, proven difficult to integrate these models in any comprehensive way into information systems for logistics because of the lack of conceptual alignment between the models produced by researchers and the information systems deployed in practice with which they should be integrated. In this paper, we systematically identify several challenges for DELS research. We analyse the root of the difficulties for applying academic research results in DELS, and indicate some potential future research directions.

1. Introduction

Discrete event logistics systems (DELS) are networks of resources through which goods and people flow. The DELS notion covers logistics systems in such diverse areas as, for example, semiconductor manufacturing, health care, and freight logistics. DELS have been the subject of a large body of analytic research (cf., for example [1–3]). A large number of models exist that generally require application by model and/or solution experts to answer narrowly defined logistics questions. It has proven difficult to integrate the resultant models in any comprehensive way into information systems like Enterprise Resource Planning (ERP) systems, Advanced Planning and Scheduling (APS) systems, Manufacturing Execution Systems (MES), or Supply Chain Management (SCM) systems, because of the lack of conceptual alignment between the models produced by researchers and the information systems deployed in practice with which they should be integrated. This difficulty is magnified enormously by four factors (cf. [4]):

1. The scale and scope of global supply networks which may involve literally thousands of individual enterprises.
2. The dynamic behaviour of these networks, which are constantly changing as firms enter and leave, products change, markets evolve, etc.
3. The broad range of information and communication systems deployed.
4. The high density of decisions, partially enabled by application systems, but in many if not most cases to be made by humans, often near real-time.

There is only a small base of theory or methodology for addressing decision problems that have scope, scale, and complexity involving all four factors. This paper can be considered as an extended and refined version of the Dagstuhl Manifesto for Grand Challenges in DELS (cf. [4]). In the present paper, we especially put effort on a more systematic derivation of the various challenges for DELS, and we also discuss the related literature in more detail. A major aim of this paper is to provide a good starting point for researchers new in this area. As pointed out by Hamming [5], it is important for scientists to know the challenges in their field. Therefore, we hope to stimulate new high-quality research to tackle at least some of the challenges described in this paper.

The paper is organized as follows. In the next section, we introduce the term DELS in more detail. We discuss DELS with respect to system theory in Section 3. Then we use the perspective provided in Section 3 to identify challenges for DELS in Section 4. Finally, in Section 5 we identify future research needs arising from the challenges described.

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2. Discrete event logistics systems

Networks of resources, through which goods and people flow, are called DELS. The term logistics refers to the fact that we consider physical flows. Each node of the network corresponds to some resource or set of resources by which the materials are either converted in some way, i.e., refined, shaped, assembled, disassembled, etc., moved, i.e., transported within one facility or between facilities, or simply held for some period of time as work-in-process (WIP) or stored in a warehouse. Material handling and transportation are key components of DELS. DELS can be found in such domains as transportation, distribution, and manufacturing. DELS are discrete because they move material in discrete quantities, and because their behaviour can be characterized effectively in terms of events happening at discrete points of time, i.e., the start or end of some conversion, transport, or storage process. While logistics systems are typically discrete, the term "discrete" refers in our understanding to the fact that DELS are not related to production logistics in process industries, i.e., for example, we are not interested in manufacturing processes inside a refinery. The third present author originated the term DELS (cf. [6]).

A DELS may range from simple to complex. They may take the form of a single warehouse, a portion of a factory, a complete factory, or a global supply network. In the following, some examples for DELS are described in more detail.

As a first example, we consider the production of integrated circuits, also called chips. A semiconductor chip is a highly miniaturized, integrated electronic circuit consisting of thousands of components. Semiconductor manufacturing starts with thin discs, called wafers, made of silicon or gallium arsenide. A large number of usually identical chips can be produced on each wafer by fabricating the electronic circuits layer by layer in a wafer fabrication facility. Such a facility is commonly called a wafer fab. It consists of hundreds of machines (cf. [7]) and a sophisticated automated material handling system (AMHS) (cf. [8]). Lots are the moving entities within wafer fabs. The routes of the lots contain several thousands of processing steps. Consequently, the cycle time of the lots is between four and six weeks. Wafer fabrication is widely considered to be amongst the most difficult of all manufacturing environments (cf. [9]).

The second example is related to electronics supply networks. They consist of wafer fabs, assembly and test facilities, distribution centres, printed wiring assemblies, and finally customers. While wafer fab related operations are often performed in highly industrialized nations, assembly and test related operations are typically carried out in countries where labour rates are cheaper (cf. [7]). The global supply chains in the electronics industry are formed itself by a large number of subsystems that are also DELS.

The next example is given by the company UPS. The key services are logistics and distribution, transportation and freight using air, sea, ground, and rail transport, with services for freight forwarding, international trade management, and customs brokerage (cf. [10]). UPS is the leading provider of less-than-truckload services coast-to-coast in US. It has 400,600 employees worldwide. The daily delivery volume is 15.1 million packages and documents. UPS runs over 800 facilities in more than 120 countries.

The last example is from the health care domain. The Mayo Clinic is one of the largest service providers in this domain. More than 55,000 doctors, scientists, students and allied health staff work and study at Mayo Clinic campuses at different locations in US (cf. [11]). Mayo Clinic cares for more than half a million people each year.

3. System theory point of view on discrete event logistics systems

This aim of this section is to unify the diverse picture of DELS presented in Section 2. We use insights from system theory to reach this goal. According to Grochla [92], an enterprise can be decomposed into the following subsystems:

- Base system.
- Operative system.
- Control and monitoring system.
- Planning system.

Note that the enterprise interacts with its environment. The functionality provided by the different subsystems is sketched in Table 1.

The obtained decomposition of a single enterprise is shown in Fig. 1.

It is possible to associate a corresponding process with each of the subsystems. The base process, for example, transforms raw materials into final goods in a manufacturing related context. The base process is characterized by its use of the resources of the base system in activities related to the working objects. In a manufacturing context, these activities correspond to operations performed on jobs. The planning and the control process describe the circumstances in which the planning and the control and monitoring systems are used. The planning, control and monitoring system, the operative system, and finally human actors form the information system of the enterprise. Fully automated parts of the information system are called application systems. According to Anthony [12] it is differentiated between *strategic planning*, i.e., management activities regarding overall goals, *management control*, i.e., middle management guiding the organization towards meeting the goals, and finally *operational control*, i.e., first line supervisors directing specific goals (cf. [13]). In our framework, the planning system supports strategic planning and parts of the management control, while the control and monitoring system supports management control and also parts of the operational control. The operative system finally supports the operational control that is closely related with base system and base process related decisions. It should be pointed out that according to Simon [94] the decisions that are treated by the planning system are typically ill-structured or semi well-structured, while the decisions made by the control and monitoring system often are well-structured. Therefore, planning decisions are typically less automated than control decisions.

Note that a similar decomposition into subsystems can be derived for logistics networks. We obtain a system of systems.

Table 1
Decomposition of an enterprise into subsystems.

Subsystem	Description
Base system	Responsible for transferring commodities into products in course of rendering goods and services. Represents the resources and also the working objects.
Operative system	Immediate planning, control, and monitoring of the base system
Control and monitoring system	Calculation of control instructions to connect the operative system with the planning system. Because of the longer horizons in the planning system, aggregation and disaggregation functionality is provided by the control and monitoring system.
Planning system	Calculation of plans that are used to fulfil the goals of the enterprise taking information from the environment and the remaining subsystems into account.

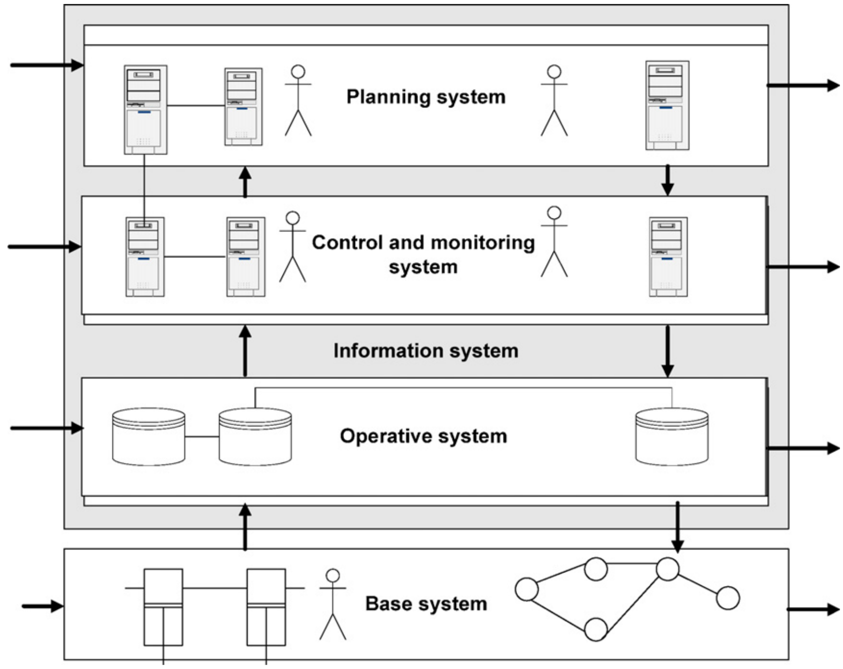

Fig. 1. Decomposition of an enterprise into subsystems.

However, in this situation the different subsystems that correspond to different nodes of the network are typically distributed. We will later use the resultant decomposition of the networks to identify challenges.

Because application systems are the fully automated parts of the information system, they can be considered as adaptive systems. A system is called adaptive if the planning and control instructions are generated automatically, i.e., without disposition of human decision-makers (cf. [14] for a discussion of adaptive systems within the context of feedback-control systems). It is important that adaptive systems maintain internal models of the base system and process to adapt to the environment. Such models are necessary to derive decision models. These models are typically computational models (cf. [15]). Each application system for planning or control consists of two components. There is an active component that is used to derive planning or control instructions, and there is a passive component that represents the underlying base system and process.

Next, we briefly discuss how different systems can interact within a distributed hierarchical system. According to Schneeweiss [16], the decision-making provided by a single planning and control system can be formalized using a decision model

$$M_t := (C, A, I_t), \tag{1}$$

where we denote C as preference structure (criterion), A as decision field (action space), I_t as information status at time t, where the decision is made.

The preference structure is given by single or multiple objectives of the decision-making entity, whereas the decision field describes the set of feasible actions with respect to the constraints to be fulfilled. The decision field is given implicitly by sets of constraints. Finally, the information status of a decision-making entity is provided by information of its own internal and external situation [16]. Furthermore, it contains information about the internal and external situation of other decision-making entities and also information about the information status of other decision-making entities, although this information may be more aggregated and less reliable than information about its own internal situation and external situation. The later point means that it is also important for a decision-making entity to know what other decision-making units can know in principle. It is clear that the information status contains the internal model of the base system and process as a subset.

Based on the notion of decision models given by expression (1), there are different possibilities for the decision-making behaviour of an application system for planning and control to be impacted or changed by some other system, for example, when two systems are in a hierarchical relationship. It is possible to change the preference structure C. Moreover, we can also change the decision field A. These two possibilities are also called goal modification in the literature. The last possibility is given by changing the information status, for example, by providing a different internal model. The term image modification is common for this kind of change. Note that in organization theory goal modification is called management-by-objectives, while image modification is called management-by-exception (cf. [14]).

The preference structure can be interpreted as a principal-agent relationship (cf. [16,17]) between the intervening entity, the top-layer in the hierarchy, as principal and the changed system as agent. Principal-agent type relationships are well studied in organization theory. The principal concludes a contract with an agent. The preference structure transferred from the principal to the agent can be seen as some specification of a contract. The agent provides the principal with services. But the principal has usually incomplete information about the behaviour of the agent. This type of inherent information asymmetry is typical for decision-making in DELS.

4. Identification of challenges

Our identification of challenges is based on the different subsystems shown in Fig. 1. We differentiate between modelling and decision-making related issues. In the next section, we discuss modelling issues for DELS. Then, we continue with challenges related to the deployment of DELS models. Finally, we also discuss challenges related to decision-making in DELS.

4.1. Modelling issues for DELS

4.1.1. Introduction to modelling problems

We start by describing modelling problems for DELS. Taking a simulation point of view, the term modelling refers mainly to modelling the base system and operative system and to a lesser degree, to modelling the planning system and the control and monitoring system. However, the decision-making perspective of a DELS is derived from the planning and control system. Of course, we need decision models for decision-making in DELS. A decision model is defined as a formal description of a decision problem according to expression (1). In this sense, we associate the terms decision model and optimization model. Decision models, for example a linear programming model, can be populated with data using the internal model of the base system that is maintained by the planning system and by the control and monitoring system. When we talk about building a DELS model, we have to address models for the base system, the operative system, the control and monitoring system, and finally the planning system. However, often it is impractical to model all these subsystems at the same level of detail. For example, when we are interested in studying the impact on cycle time of a certain sophisticated dispatching rule in a wafer fab, we may assume that the job release times or rates are given. Of course, job releases are a result of a decision made by the planning system. Thus, in this case, the planning system is not modelled in detail, but is represented by a relatively crude approximation. On the other hand, when we are interested in assessing product mix decisions in a wafer fab, we model the part of the planning system, i.e., a specific planning algorithm that is responsible for these decisions, but dispatching may be modelled by a simple First-In-First-Out (FIFO) dispatching rule that is already included in the simulation package. Note that we have to model the base system and process in both situations. The different submodels that have to be taken into account are summarized in Fig. 2. Typically more than one decision model is available.

4.1.2. Multiple levels of abstraction

We start by describing simulation modelling efforts to represent the base system. These models are usually descriptive by nature, i.e., we are interested in understanding the system behaviour. At this stage of identifying challenges, we are explicitly not interested in the planning system and the control and monitoring system.

Over the past two decades significant progress has been made with regard to simulation modelling of single nodes of a DELS. For example, in 1990 it was considered quite a challenge to build a simulation model for an entire wafer fab, or for the automated material handling within a wafer fab (cf. [18]). Today, developing these models is much easier and almost standard (cf. [7]). There are a couple of reference models for single wafer fabs available on the web (cf. [19]). However, it is still challenging to integrate simulation models for job processing with simulation models for automated material handling.

There are approaches in the literature that address the modelling of entire supply chain networks (cf. [20–23] amongst others). Various simulation paradigms that are appropriate for simulating entire supply chains are described by Kleijnen [24]. The paradigms discussed include discrete-event simulation and system dynamics (SD). However, the studies described in the literature typically consider only an extract, i.e., often a very small part, of real supply chains. Therefore, it is rather challenging to build simulation models of supply network at various levels of abstraction of various level of detail from a common data description. This modelling step has to include the time-dependent and/or stochastic behaviour for several stakeholders. The ability to create such models is essential for achieving horizontal integration

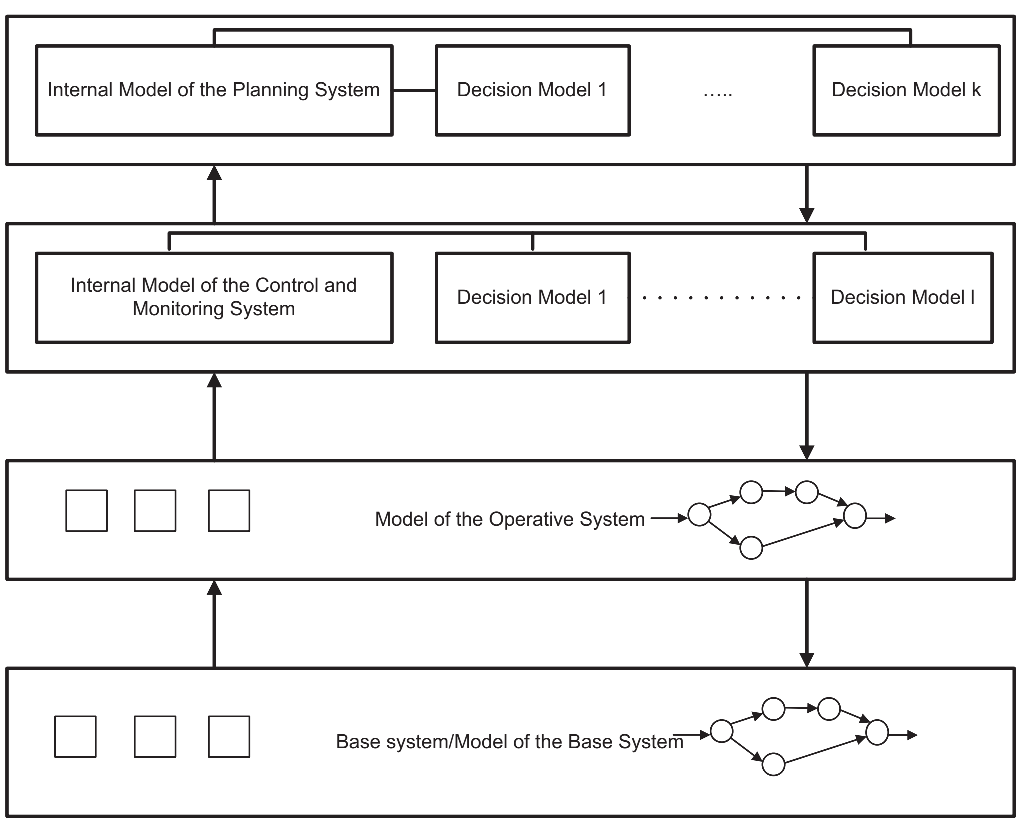

Fig. 2. Subsystems/submodels of a DELS model.

of various submodels. The integration across the material flows from initial supplier to final customer, including any closed loop recycling, can be achieved by doing so. An interesting approach to combine SD and discrete-event simulation to model supply chains is presented by Venkateswaran et al. [25].

Often it is necessary from a computational point of view to deal with aggregated or reduced simulation models. Such models are often intended to answer more strategic questions. They have to be derived from available operational data. The capability of model reduction is essential for achieving vertical integration of models, i.e., integration from the strategic decision level down to the real time operational level.

The criticality of detailed modelling in a supply chain simulation context is discussed by Jain et al. [26]. An interesting approach for a compact representation of an entire wafer fab using empirical cycle time and throughput distributions is presented by Duarte et al. [27]. However, an extension of this approach to networks of nodes is not available so far. In contrast to the situation of single wafer fabs, reference models for entire supply networks are not available in semiconductor manufacturing, although their need has been recognized (cf. [28,29]).

Apart from vertical integration, there is often a need for a horizontal integration of simulation models. Such an integration must be accomplished, for example, in distributed simulations. Examples for the simulation of supply networks in semiconductor manufacturing are described in [30–32]. However, applying distributed simulation is itself a challenge as described by Lendermann et al. [33].

Therefore, when considering a supply network in semiconductor manufacturing that typically consists of dozens of wafer fabs and dozens of backend facilities, a reduction of each single node is necessary to run the model from a computational time point of view.

4.1.3. Unified DELS language

Another fundamental challenge is the creation of a unifying language for the description of DELS models. Several attempts have been made in the ontology community to create ontologies related to DELS. An ontology is defined as a model of a particular field of knowledge, the corresponding concepts and their attributes, as well as the relationships between the concepts (cf. [34]). An ontology always includes

1. A conceptualization of a domain, i.e. how to view and model a domain.
2. A specification of this conceptualization, i.e. basically a formal description.

We refer for example to the Enterprise ontology (cf. [35]), the OZONE ontology for scheduling systems [36], CEO, a core enterprise ontology (cf. [37]), and the FABMAS ontology for production control of wafer fabs [38]. The development of ontologies for manufacturing from an IT point of view is discussed in [39]. However, a widely accepted universal ontology for manufacturing is still not available.

Creating a high-level but universally useful abstraction of DELS that addresses resources, working objects, physical flows, and interactions amongst subsystem and is applicable across a broad range of industries, organizations, geographic, and temporal scales is highly desirable because it would be allow to reduce the efforts for simulation modelling to a large extent. We refer to [6] where such an abstraction is provided for warehouses. At the same time, the enterprise application integration would be significantly easier. Such an abstraction might be applied in two steps:

1. Using these abstractions to identify domain-specific attributes of particular classes of DELS, such as transportation networks, warehouses, wafer fabs, assembly factories.
2. Exploiting the universal abstraction and the domain specific models to create modelling libraries for decision-based application development.

Clearly, the model-driven architecture approach from software engineering provides an example of how this challenge might be approached. The model-driven architecture approach has been applied to developing simulation models using SysML (cf., for example, [40] for continuous simulation, and [41] for discrete simulation), a modelling language that is based on the Unified Modelling Language (UML). However, while the base system and process can be modelled by means of SysML, there are still challenges with regard to universal representation of the control logic, and more generally, with regard to the representation of time and time-dependent issues within SysML models. However, dealing with the time-dependency is necessary when we are interested in modelling appropriate representations of the different processes in a DELS.

Another challenge is modelling collaborative processes in DELS. Here, traditional modelling techniques like Integrated DEFinition for Process Description Capture Method (IDEF3), Petri Nets, and UML are often not appropriate. In [42] a collaborative process modelling technique is proposed. The resultant models can be transformed into marked graph models, and Petri nets techniques can be used to analyse them.

4.1.4. Non-DELS specific modelling issues

A simulation model of a DELS often does not represent simply the base model and process of the DELS (see Fig. 2), rather it also represents certain parts of the planning and the control and monitoring systems because, for example, capacity expansion decision or product mix decisions have to be made or jobs have to be released. Note that we are not interested in describing challenges that occur when designing a new planning or control and monitoring system in this subsection. Rather we are interested in assessing an existing DELS. Even in such a situation, several challenges need to be addressed. These issues are typically important to a domain broader than DELS.

One challenge is the development of modelling approaches that can cope with systems when there is incomplete or even conflicting knowledge of logistics policies, or logistics participant information, or incomplete data in very large-scaled networks.

Another challenge arises when combining lumpy, i.e., discrete, and continuous systems. For example, lumpy decisions are associated with capital expansion while the more continuous decisions are associated with real time control. Developing approaches for the integration of different modelling techniques, even hybrid approaches seem to be important in this context. The integration of IDEF3 and queuing models is discussed by Jeong et al. [43]. There are also approaches that combine discrete-event simulation and SD. Another interesting example is the incorporation of cluster tools in simulation models of full wafer fabs. A cluster tool is a mini wafer fab with a sophisticated control logic (cf. [44]). Often Petri nets are used to model such a control logic. While the number of cluster tools is increasing, up to now there is no technique known to model these tools in a reasonable way within large-scale simulation models of wafer fabs.

An additional challenge how to incorporate non-technical aspects, i.e., contracts, behaviours, principal agent issues, of DELS operations within a simulation model (cf. [45–47]).

Finally, modelling approaches for portraying human involvement and decision-making in using decision support tools are also rather challenging. Here, the main goal is to understand human-decision making and to improve the quality of simulation models. A combination of simulation and artificial intelligence techniques is used (cf. [48–51], amongst others). Much more research is needed in this area as well.

4.1.5. Modelling related to operative systems for DELS

We continue by discussing the models that are contained in operative systems. These systems serve as container for data models that are updated in an event-driven manner whenever changes in the base system occur. However, it often turns out to be difficult to deal with a large number of products, often variants of a relatively small number of different base products because product modelling is still hard (cf. [52]). A customer who orders a computer can choose different combinations of monitor, CPU, keyboard, and memory. Because of the combinatorial explosion not all variants can be stored directly in an operative system. Characteristic based planning (cf. [53]) tackles this problem by using characteristics to describe a certain product family. These characteristics can refer to the structure of the product based on the bill of material and different possibilities to produce a certain product expressed by different routes. Finally, it is also possible to process several products within one production run, taking into account the values of the characteristics. The first two possibilities are called variant configuration, while the latter one is called batch management. Although the concept of characteristic based planning turns out to be rather interesting, it seems that is not widely accepted in both research and real-world applications (a rare exception is [54]). Hence, it seems necessary to look for different ways to deal with complex configurable products.

4.2. Deployment issues for DELS related models

Next, we consider challenges that are related to deployment of DELS models. Deploying models in real-world applications requires adaptation of the models to a particular application in two different ways:

1. Populating the models with available data.
2. Adapting the models to the decision-making process.

Because models have to be based on data to be useful they must be integrated with application systems. This presents challenges on several levels, from understanding clearly what data should be available in the application system, to the details of the specific software interfaces needed to access the data that is available to populate the models.

On the other hand, decision models and internal models are intended to support decision-making (see Fig. 2), but the decision-making process itself is often somewhat ad hoc, especially with regard to strategic planning decisions. A model that can only answer one very specific and/or narrowly defined question may have limited utility if the strategic decision-making processes require addressing of other related questions. Considering these factors, several challenges associated with model deployment for DELS can be identified.

4.2.1. Dealing with the inherent distributed nature of DELS

First, we discuss challenges that are a result of the inherent distributed nature of DELS. It is necessary to establishing standards for re-usable plug-and-play model components and data structures in application systems and their interoperation. It is increasingly important that the different application systems and also the corresponding models are able to quickly communicate with each other and with their environment (cf. [55]). One partial solution to this challenge is the High-Level-Architecture (HLA). It is a general-purpose architecture, mainly for simulation model interoperability. Each simulator or other application system forms a separate federate, i.e., is executed as a separate process. All the different federates form a federation. Federates can be implemented individually using different software technologies and hardware (cf. [55]). However, the number of successful applications is limited (cf. [31,56]; amongst others). There is still an ongoing controversy whether distributed simulation and HLA especially are useful or not (cf., for example [33,57]).

Another challenge is the design and development of better methods and tools for distributed modelling of supply network operations and control to solve the "System of Systems" problem for DELS.

It is necessary to close the gap with respect to modelling the system state between the base system and the planning and control and monitoring system. These challenges coincide with challenges that were identified by the US NSF Commission for Visionary Manufacturing Challenges for 2020 (cf. US [58]). They published a report where they identified "Grand Manufacturing Challenges". Amongst these challenges are the instantaneously transformation of information gathered from diverse sources into useful knowledge for making effective decisions.

This is hard for DELS because the base system and also the information system itself are distributed systems. Therefore, we have to deal also with interoperability problems on the information system level. As in any distributed system, we have to determine how much data redundancy is allowed to reduce the communication effort between the different horizontal and also vertical subsystems of the information system. It seems that web services can help to reduce this kind of interoperability problems (cf. [59] for applications in manufacturing).

4.2.2. Model persistency issues

It is also required to shorten the cycle time for model generation and maintenance. It is well known that the development of a simulation model is very time consuming. This leads to a smaller number of experiments that can be performed using this simulation model. Therefore, we need a technology to keep models persistent, i.e., to maintain them so that they are always consistent with the system being represented [55]. While there is some experience for automatically building simulation models from operative systems in simulation-based scheduling (cf., for example [60]), little is known for modelling entire supply chains.

There is also a need for approaches and methodologies to support the evolution of planning and control and monitoring systems, leading to the creation of models to design systems with the ability to learn – so they do not break abstractly because they are able to adapt to the current situation. Base models for learning agents are proposed by Bierwirth [14]. Zimmermann [61] discusses adaptive multi-agent-systems for production control using machine learning techniques. However, considerable human intervention is still required.

Finally, approaches, methods, and tools are required that allow us to take into consideration the fact that there are soft boundary conditions in a model that can be violated, up to some unknown limit.

4.2.3. Data availability and quality

Methods and tools are needed to take advantage of the wealth of empirical data that are collected during the operation of DELS; these data should inform the design of future DELS, even if future requirements are different from past experience.

Furthermore, theories, methods, and tools are needed for dealing with multiple data sources, high-density data streams, errors, uncertainty, conflict, etc. These problems are long lasting (cf. [62]), but it seems that a transfer of academic research into real-world applications is still made difficult by missing data or low data quality (cf. [63]). It seems necessary to do more research on data mining techniques to deal with missing or wrong data in enterprises (cf. [64]).

4.3. Decision-making issues for DELS

The decision-making cycle consists of building a decision model based on data available in the internal model. Subsequently, decision-making methods, algorithms, are used to determine actions from the decision field. A choice consists of analysing the alternatives and then choosing one. At the same time, human decision-makers can be involved in analysing and choosing actions when the decision-making process is not fully automated. This is often the case when the related decisions are ill-structured. The described situation is shown in Fig. 3.

In this subsection, we discuss the decision-making component shown in Fig. 3, while the development of decision models is already covered in Section 4.2. Note that the decision-making component and the decision model form the active component, while the internal model is passive with respect to decision-making.

4.3.1. Decision algorithms in DELS

We start by discussing challenges with respect to decision algorithms that are a major part of the planning and control and monitoring system. The first challenge is related to the emergence of sustainability as a major concern (cf., for example [65]). Therefore, the decision models need to consider criteria that may be quite different from those in the large body of legacy models, e.g., energy or water consumption, carbon emissions, or total environmental footprint. Some interesting examples for production planning algorithms that consider such new criteria that are related to carbon emission are provided by Benjaafar et al. [66] and Absi et al. [67].

A second challenge is given by approaches for automatically finding the appropriate type of (meta) heuristics and parameters, including auto-calibration, for a given DELS decision problem. Even questions that at a first glance look simple, like what are appropriate parameters in a composite dispatching rule, require tools from machine learning, statistics, or optimization. Neural networks and inductive decisions trees are used in Mönch et al. [68] to tackle this problem, while Dabbas and Fowler [69] use simulation and designed experiments to create a response surface model of the base system and process of the wafer fab. Optimization techniques are then used to select appropriate weights in the combined dispatching rule. Pickard et al. [95] uses a simulation model of a wafer fab to assess the performance of dispatching rules. Genetic programming is used to find new dispatching rules. However, it seems that the massive application of offline simulations required for assessing performance, creating a metamodel, or determining training data hinder a wide acceptance of these methods in real-world application.

There is still a need to design distributed hierarchical planning and control algorithms for DELS (cf. [16]). There is a lack of knowledge about how to implement such algorithms from a software technology point of view. It seems that software agents and the corresponding multi-agent-systems are appropriate. However, many more examples and case studies are needed to finally evaluate this proposal.

It is still hard to find approaches and specific methods for describing the capabilities of solution approaches in order to select appropriate decision support methods for a given situation. In the past, often knowledge-based systems were used to assist the decision-maker with an appropriate algorithm. It seems that such method bases developed using database technology (cf. [91]) tend not to be successful. However, it would be clearly desirable to have some guidance when an appropriate solution method is selected for a specific planning or control problem.

Despite the existing body of theory and applications (cf. [70] amongst others), there still is a need for useful techniques for multi-objective problems. It is well-known that considering multiple, often conflicting, objectives lead to better decision-making. A multi-criteria scheduling approach for complex job shops is discussed by Pfund et al. [71]. Often even solutions obtained by multi-criteria algorithms outperform solutions that are derived by algorithms that use only a single criterion (cf. [72] for an example in scheduling for complex job shops).

Another challenge is the design of decision-making algorithms covering a collaborative environment where independent actors have to align their local interests under common interests, i.e., if one of the partners fails – all together will fail. An interesting example is given by the airport collaborative decision-making initiative in Europe (cf. [73]). The main result is a more accurate Target Take Off Time which can be used to improve en route and sector planning of the European Air Traffic Management (ATM) Network. A multi agent system that supports collaborative decision-making in a supply chain is proposed by Ouzrout et al. [74]. Collaboration without sharing all the confidential data is supported by negotiations between the agents that represent the different decision-makers within the supply chain. Often software

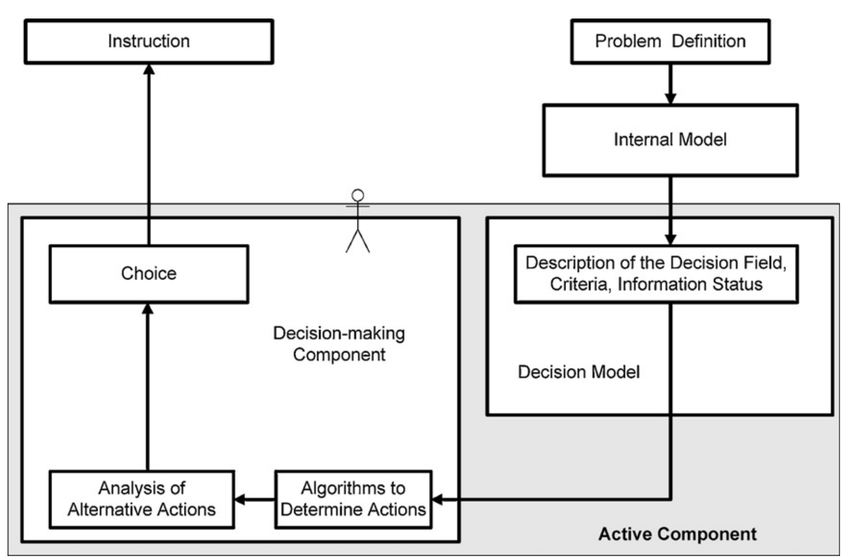

Fig. 3. Decision-making cycle.

agents are used to solve this kind of collaborative planning and control problems (cf. [75]).

There is also a great need for an integrated framework that enables the simultaneous use of both simulation and optimization. A closely related challenge is the development of approaches for the integration of different modelling techniques, for example, discrete-event simulation, mixed integer programming, queuing models, even hybrid approaches. We refer, for example, to Hung and Leachman [93], Kim and Kim [76], and Irdem et al. [77] where linear programming models are combined with discrete-event simulation for derive planning instructions for a single wafer fab. In this context, simulation is used to determine a load-dependent cycle time, whereas the production planning approach determines order release quantities assuming a given cycle time. A similar technique is used by Almeder et al. [78] in a supply chain context including also transportation between the nodes of the supply network. But an extension of these ideas to supply networks of real-world size is not straightforward.

Because of the huge progress made in information technology in the last decade, parallel computing capabilities have to be exploited in solving DELS related decision problems. This fits well with the recent increasing importance of grid or cloud computing. Based on high throughput computing software like Condor (cf. [79]) or software to build grids like the Globus toolkit (cf. [80]) it is not hard to use parallel technologies in enterprises. A parallel scheduling heuristic for complex job shops that is run on a cluster computer system and can be run in principle also on a grid is described in [81].

Planning and control and monitoring systems are often implemented as packaged software. It is hard to incorporate more sophisticated decision models and algorithms into these software systems. For example, an MES offers some dispatching and scheduling functionality. However, application systems different from the MES are used for dispatching and scheduling in most wafer fabs (cf. [82]). Therefore, it is often a challenge to find appropriate coupling architectures for the packaged systems and the various out-of-the-box software systems. In this setting, the packaged systems act as operative systems.

4.3.2. Quality of decisions

After decision-making, the quality of solutions has to be assessed. There is an unmet need for performance metrics and methods to assess the quality of solutions coming from decision support models. The corresponding performance measures should include risks, robustness, and stability.

Robustness and stability are two important attributes of predictive plans/schedules (cf. [83]). A predictive plan/schedule is called robust, when the quality of the eventually executed plan/schedule measured based on working objects in the base system is close to the quality of the predictive plan/schedule. A predictive plan/schedule is said to be stable if the decisions made in the eventually executed plan/schedule are close to the decisions made in the predictive schedule. In case of low quality plans/schedules usually there is no conflict between robustness and stability. The low quality can be maintained without changing any decision. On the other hand, if we have a high-quality plan/schedule, then there is a tradeoff between robustness and stability. A plan/schedule can be stable but not robust. In this case, we simply do not change decisions. Therefore, usually the performance of the executed plan/schedule will be less compared to its predicted performance. In contrast, a plan/schedule can be robust but not stable. Here, we change the plan/schedule as much as required to achieve the expected performance. Different stability measures for planning are discussed in [84].

As already discussed, stability and robustness refers to executed plans/schedules. Because of uncertainty in demand, resource availability, processing times etc., often rolling horizon approaches are applied to deal with the divergence of executed plans/schedules from predicted plans/schedules. The plans/schedules are executed within the base system. Therefore, simulation is necessary to represent the base system and process appropriately. It seems that simulation-based performance assessment of planning and control is not widely adopted, mainly because of the large effort to build the simulation models and because of the large amount of computing time to perform a simulation experiment. The latter is caused by the repeated determination of the plans/schedules during a single simulation run.

Some applications of the simulation-based performance assessment in manufacturing are discussed by Mönch [85]. A similar approach is used in the cooperative transportation domain (cf. [86]). While these approaches work well for a single enterprise or a small or medium-sized logistics network, only little is known about its feasibility in case of large-sized DELS. Note that the simulation-based performance assessment approach allows, in principle, studying the performance of entire planning systems and control and monitoring systems. A main advantage of such an approach consists in the possibility to assess the performance before the application system is deployed.

Besides engineering performance measures like cycle time, throughput, or on-time delivery, it is becoming even more crucial to be able to quantify the monetary value generated by decision-making algorithms and by decision support systems. Furthermore, robust decision-making tools with real-time capabilities are needed that explicitly consider performance measure trade-offs, rather than simply optimizing some criterion. It is well-known from production planning applications that optimal solutions with respect to a certain performance measure often have a low performance in an uncertain environment. Therefore, new theories and approaches that enable highly sustainable and robust performance by exploiting dynamic networks in open supply webs are highly desirable.

As DELS and their decision support systems become even more complex, it is important for decision support systems to explain what they suggest when the suggestion is not intuitive (cf. [87] for the discussion of self-scheduling capabilities in nurse scheduling). A component that explains its solutions to the users might reduce the lack of acceptance.

As DELS and the corresponding planning and control and monitoring systems become more complex, they need capabilities for self-diagnosis and automated error checking. They should be capable of automated analysis of results, and for providing explanations of the results to their users. Such self-healing planning and control and monitoring systems are highly desirable. However, it seems that the design and application of such software systems is in a very early stage (cf. [88]).

4.3.3. Crossing boundaries

Increasingly, DELS grow organically, often with distinct DELS joining at least temporarily to accomplish some goal. In this setting, there are many boundaries crossed on a routine basis – not only between organizations within a single enterprise but across enterprise boundaries. This leads to different types of challenges.

Coordinating decision-making when crossing the boundaries of several enterprises, requires embedding quantitative decision support into collaborative decision-making within the DELS domain. Collaboration across DELS boundaries requires an ability to smoothly integrate information/decisions in multiple DELS. Here, it seems necessary to define appropriate standards for the information exchange. Electronic Data Interchange For Administration, Commerce and Transport (EDI/EDIFACT) and several XML-based data formats seem to be not flexible enough for large-scaled DELS.

Effective collaboration requires consistent re-usable key performance indicator (KPI) classes with (dis-)aggregation functionality. It seems that aggregation and disaggregation is the subject for research for a long time (cf., for example, [89]), but it is still challenging and there is still a lack of widely accepted methods to do it.

5. Some future research needs

In this section, we translate the challenges identified in Section 4, into more concrete research needs for the near future. Of course, this selection might be biased by our own preferences and it might be possible that some subjects are omitted.

It seems that a major problem that is touched by many challenges is the inability to model large-scaled, real-world supply chains in a timely, cost-effective way. Therefore, it is highly desirable to find methods for reasonable model reduction that allow for simulating such supply chains. Applications for simulation-based performance assessment and also for network design are a consequence of this capability. Closely related is the question of reference models for large-scaled DELS. While for single enterprises in specific domains such reference models are available, this is not true for large-scaled DELS. However, their existence would drastically increase the comparability of planning and control algorithms for DELS.

Future research effort should be devoted to the design and development of a universal DELS language. It seems interesting to extend research on graph transformation (cf. [90]) and UML to this universal DELS language. This would reduce the effort for generating simulation models from data in the operative system to a large extent. Furthermore, the universal language could be used to transform simulation models for a given simulation engine into the format of a different simulation engine. In addition, the simulation-based performance assessment of planning and control systems for DELS would be made easy.

More research is also needed for distributed hierarchical algorithms. Here, we can differentiate between vertical and horizontal integration. It is highly desirable to study the interaction of the planning system and the control and monitoring system for concrete application scenarios. Here, we also have to look for appropriate domain-specific aggregation and disaggregation techniques. It seems important to take the uncertainty into account, at least on the upper levels. Appropriate software representations are necessary that serve as a platform for the different algorithms. This is especially useful in a distributed setting. Parallel computing techniques can be used to tackle subproblems that are a result of horizontal decomposition.

More effort is needed on considering multi-criteria decision-making approaches for DELS. Such approaches are heavily based on the assumption that the preferences of the users can be modelled. We expect that the acceptance of the DELS algorithms can be significantly increased through this work.

In order to design truly adaptive application systems, new methods to offer capabilities of the planning system and the control and monitoring system to adapt to certain situations in the base system and in the environment have to be researched. It seems that techniques beyond traditional machine learning are required to tackle this type of problems.

As explained within Section 4.2, missing data and low data quality is a major barrier in transferring results from academic into real-world applications for DELS. Therefore, more research is needed to overcome this weakness. Because more and more data are available in the today's operative systems, we strongly believe that data mining techniques have to be used to deal with missing or erroneous data.

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