Applied Science and Engineering Journal for Advanced Research *Peer Reviewed and Refereed Journal*
ISSN (Online): 2583-2468
Volume-2 Issue-4 || July 2023 || PP. 32-40 DOI: 10.54741/asejar.2.4.6

Decision Support Model in Production and Customer Networks

Dr. Mukesh Mishra
HOD, Department of Mechanical Engineering, B.B.S. Institute of Engineering Technology, Allahabad, Uttar Pradesh, India

Corresponding Author: mishra_mukesh@gmail.com

Received: 29-06-2023	Revised: 18-07-2023	Accepted: 28-07-2023

ABSTRACT
We outline some of the issues that need to be taken into consideration in upcoming studies on model-based decision support in service networks and manufacturing. Integration problems that look at how independent the decision-making entities are when there is an imbalance of information, decision-maker preference modeling, finding robust solutions (solutions that don't change when the problem data changes), and shortening the time it takes to make and use models are all covered. The process of solving a problem involves analyzing the problem, designing suitable algorithms, and evaluating how well those algorithms work. We are interested in a field test using the expanded application systems after a prototype integration of the suggested ways within application systems. We contend that the proposed research agenda necessitates the interdisciplinary cooperation of researchers in business and information systems engineering with associates in computer science, management science, and operations research. We also provide a few representative examples of pertinent research findings.

Keywords: *industrial, service networks, model based, decision maker, challenges, product*

I. INTRODUCTION

Today's industrial and service networks face significant challenges in decision support due to the sheer size of their highly interdependent, worldwide supply chains, the speed at which change is occurring, and the variety of uncertainties that exist. It is still unclear how various components in manufacturing or service networks—like parts or transportation orders—interact with one another and use up capacity. Physical automation is becoming more and more important as a result of the need to improve manufacturing and service process quality, save costs, and boost productivity. Due to the growing complexity of decisions and the need to respond quickly in a setting that is becoming more and more dynamic, this kind of automation also lessens the capacity to utilize humans to make important decisions in specific situations. These drawbacks can be lessened, and planning and control decisions can be supported by decision models. There is proof that judgments made with the use of model-based decision support frequently result in increased asset utilization, lower inventory levels, and better customer service. Because of this, there is a strong business case for improving and expanding model-based decision support in new production and supply networks.

Instead of focusing on data-driven decision support and business intelligence, we address these issues in this work by utilizing model-based decision support or business analytics. The success story of Kiva Systems, a company specializing in the application of mobile robots to distribution facilities (cf. D'Andrea 2012), which was recently acquired by Amazon for $775 million, serves as an example of the significance of application systems that enable model-based decision support. Robots can now carry cargo in confined spaces without colliding, thanks to a mobility infrastructure developed and implemented by Kiva Systems. This architecture is built on a multi-agent architecture. Algorithms for learning and model-based adaptation are suggested, enabling the robots' performance to continuously improve.

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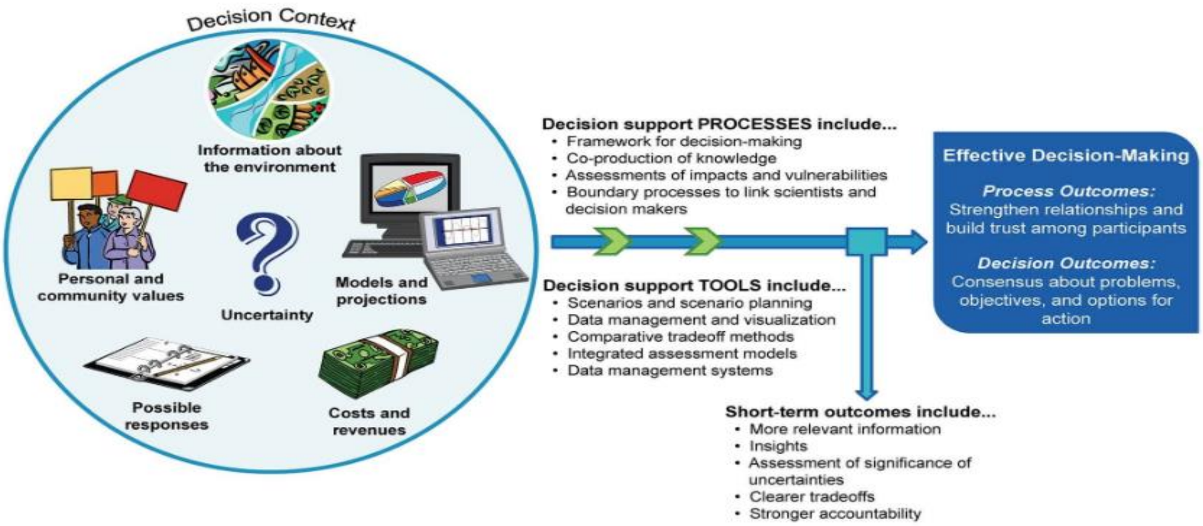

Figure 1: Decision making elements and outcomes
Source: https://www.pathwaysinternational.com/2017/05/12/business-intelligence-decision-support-systems/

These days, decision-making may make use of a lot of structured digital data, thanks to application systems. The performance of both hardware and software has gotten a lot better in the past few years. Modern middleware has also made it easier to build distributed systems, and cloud-based solutions have made it easier for many people to access IT services. Strong algorithms that cleverly blend accurate and heuristic methods are frequently created (see Maniezzo et al. 2009). Thus, big real-world models can be solved in a reasonable length of time, unlike the scenario two decades ago. The planning of IBM's corporate semiconductor supply chain using heuristics, linear programming, and decomposition approaches is one example (cf. Degbotse et al. 2013).A single production, shipping, and distribution strategy was created as a result, which increased on-time delivery performance by 15% and decreased inventory by 25%–30%. Another recent example that has made significant advancements in workplace planning and production scheduling possible is integrated production planning and scheduling in Ford facilities (cf. Barlatt et al. 2012). Significant savings have been achieved in overtime pay, inventory expenses, and premium freight costs as a consequence of the suggested strategy. The resolution of extensive vehicle routing issues at Coca-Cola, which involved 10,000 trucks daily (refer to Kant et al. 2008), is an additional instance that has led to a $45 million annual delivery cost savings. This is based on 1.5 billion cases in which dispatches were scheduled with the new software and significant enhancements in customer service.

Extended and modified application scenarios are anticipated as a result of recent technological advancements, such as in-memory data management (cf. Plattner and Zeier 2011). However, even though these conditions are good, modern methods and related application systems are still not widely used for making decisions in real life. Present application systems, particularly packaged software systems, do not capitalize on this new advantageous situation for decision-making in their functioning. Because of this, complex systems to help people make decisions must be developed. These systems will be made up of better algorithms that work with computers. We anticipate that addressing the following issues will make a major contribution to the widespread implementation of effective decision support tools fit for practical application:

1. Integration is critical because decisions in manufacturing and service networks are made by a variety of decision-makers, each with their own unique objectives, and they are dispersed across time and space. Therefore, we need to investigate how, for example, planning or negotiation processes can guarantee the integration of various subsystems and the decisions associated with them in production and service networks. Given this, it is especially critical to investigate the modeling of human decision-makers' preferences in application systems, as this represents a significant advancement towards automated decision-making.
2. It's critical to include uncertainty while considering robustness aspects. How to make decisions that can handle the stochastic and dynamic behavior of the underlying industrial and service networks is one of the key research questions.
3. Modeling is still a laborious and challenging process. For the desired model-based decision assistance to be more effective, the cycle of model creation and usage needs to be made simpler. Given that humans are the most adaptable resource, appropriate human-machine interfaces must be taken into account.

This is how the rest of the paper is structured. We go into greater depth about the issues that need to be resolved in Section 2. Section 3 covers scientific approaches pertinent to the issues. Section 4 lists pertinent academic fields and any potential interdisciplinary collaboration that may be needed. Section 5 presents examples of preliminary research findings.

II. PROBLEM OVERVIEW AND RESEARCH OBSTACLES

2.1 General Environment

A manufacturing and service network's information system may be made up of multiple subsystems. As an example, each machine and job in a single wafer fabrication facility that is part of an enterprise semiconductor supply chain has its own internal model that shows the data for that subsystem. This model is used for planning and controlling the network. There may be a number of decision models in each planning and control subsystem, like Manufacturing Execution Systems (MESs) or Enterprise Resource Planning (ERP) systems. These models are based on data from internal models and help other planning and control subsystems, physical network objects, or both. The foundation of every decision support system for intricate industrial and service networks is made up of these decision models.

Building appropriate decision support capabilities that correspond to the related decision models is essential for the goals of our research program. In order to contextualize the ideal decision-making scenario from the preceding paragraph, the following insights must be considered while identifying specific research problems:

1. The data in internal models is often too broad, doesn't show the real world correctly, or doesn't have enough historical data to estimate the parameters of stochastic models. This means that the data isn't useful for making the decisions that need to be made. Clarifying how to estimate and preserve the necessary data in a constantly changing environment—typical of industrial and service networks—is crucial when creating a decision model.
2. Human decision-makers who have the ability to override application system decisions or make their own decisions are involved in the planning and control subsystems, which are not entirely automated. Because of this, it matters if a choice is made for a human or a machine. In the latter scenario, default measures must be considered when there is a violation of implicit presumptions, such as those about the availability of resources or jobs. As the level of automation in the physical networks rises, this enables a greater degree of automation in decision-making as well.

We make the assumption that the current hardware and software infrastructure is accessible, enabling a reliable connection between the real world and the realm of information technology. In theory, this enables sensor-driven, autonomous, self-organizing industrial and service networks. Nevertheless, there is little discussion in the literature about how to design the planning and control subsystems that make use of this infrastructure, such as how to take advantage of the autonomy and abundance of data that is available. We believe that these issues can be addressed in part by solving the research challenges outlined in the remaining portion of this section.

2.2 Integration in Large-scale Networks

The distributed decision-making process common to supply chain management (SCM) serves as the driving force behind this difficulty. SCM can be understood as the synchronization of a number of locally managed logistics processes by many independent decision-making units. Because the associated systems function on various time scales, asymmetry exists with regard to the moment in time when decisions are made, decision rights, and the information status of the decision-making units. This leads to coordination challenges. The many components of the network's general planning and control system frequently support regional goals, which can occasionally clash with the network's overarching goals. The idea of a single, central decision-making unit still forms the basis of many SCM systems and the majority of packaged SCM software, even if some recent work examines decentralized decision processes, such as negotiation procedures as outlined by Dudek (2009) (cf. Schneeweiss 2003).

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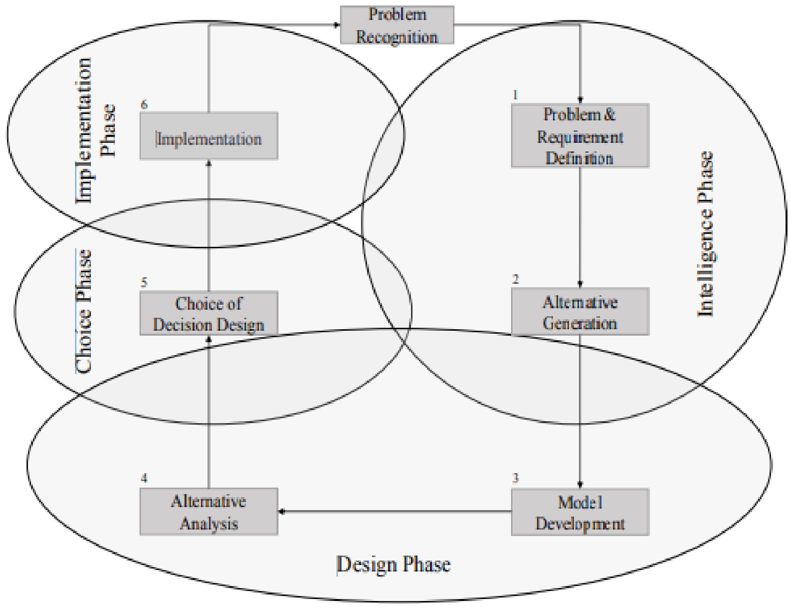

Figure 2: The decision-making process

Therefore, studies must be done on the planning and control system designs that guarantee the independence of local decision-making units. Simultaneously, these units must consider more comprehensive decisions made by units that rely on distinct, potentially superior information.

This raises the topic of how large-scale industrial and service networks' planning and control must be interconnected. It is necessary to study coordination techniques for autonomous actors in dispersed planning and control situations that take suitable incentives into account.

There is a natural trade-off between automation and autonomous decision-making, as was already covered in the second insight in Subsection 2.1, in that decision-makers' autonomy is somewhat restricted as automation increases. Modern computing paradigms like software agents attempt to ensure the autonomy of things that make decisions. But these methods necessitate understanding the decision-makers' stated or unstated goals. Therefore, it's crucial to provide suitable incentives for coordinating mechanisms that are linked to the network's overarching objectives. Since there are typically multiple decision-makers in industrial and service networks, the appropriate preferences of each individual decision-maker must be identified and ultimately combined for group-based decision-making. In the absence of an explicit representation, preferences would remain implicit personal beliefs that prevent automated decision-making. Preference elicitation is the process of converting implicit preferences into explicit ones. These techniques must account for the ambiguous desires that are common in dynamic, ever-evolving manufacturing and service networks. Imprecise, ambiguous, and subjective utility values are characteristics of human decision-makers' uncertain preferences (cf. Lang et al. 2012). Because sampling is frequently not feasible, techniques from stochastic modeling and statistics are not suitable to simulate this kind of uncertainty in automated negotiation contexts. With little regard for what to do in a transient situation, many of these technologies only offer steady-state answers. Consequently, it is necessary to take into account different, more quantitative modeling methodologies for uncertainty.

In recent times, various classes of problems in manufacturing and service networks have been proposed to be solved by an integrated planning activity-based approach. Integrated scheduling of production jobs, automated material handling decision-making, and integrated scheduling and process management are typical examples. New trends in hardware and software, such as in-memory data management, greatly support this development. This leads to centralized solutions that go against many efforts to make network decisions that are more localized (decentralized), which need to be coordinated properly (see Schütte 2012, p. 212). Considerable more research is necessary to determine the circumstances in which integrated planning approaches are appropriate or even advantageous.

2.3 Finding Sturdy Solutions: Taking Dynamics, Random System

These days, planning and control decisions can detect deviations from the original scenario due to the enhanced capabilities of information technology, such as state-of-the-art telematics systems in vehicle routing (cf. Crainic et al. 2009).

Typical examples include longer trip times due to traffic jams in real-time vehicle routing and unpredictable demand and supply from overloaded production systems, which can lead to Bullwhip effects, problems with reputation, and changes in quality. Frequently, the information at hand is only partially utilized to respond to changes in a dynamic manner. Improved data availability and algorithmic developments should result in new kinds of decision support systems, in our opinion. Robustness with regard to solution quality and the solution itself, i.e., stability, can be taken into consideration by anticipating uncertain system behavior and taking this foresight into account during planning, as opposed to a pure reaction to disturbances.

How to create systems and algorithms that can handle the underlying base system's stochastic and dynamic behavior is the subject of research. Interest also stems from a solution's robustness or stability characteristics. Since the intrinsic uncertainty seen in many real-world planning situations is currently addressed in rather simplistic ways (cf. Graves 2010), algorithms must be constructed with stochastic changes in mind from the outset. Determining when human decision-makers should intervene in automated planning and control systems is another difficult task.

2.4 Shortening the Cycle of Model Construction

Simulating and modeling is a well-established technique for decision support. However, even with increased data availability and significant efforts toward automated model generation, creating discrete-event simulation models still takes a lot of time (see Fischbein and Yellig 2011). Because highly detailed simulation models are needed in this scenario, the broad application of discrete-event simulation in industry is limited. Take the long-standing vision of supporting real-time control using simulation models based on current data from the network, for example. It is still far from straightforward to provide such precise models with elements from advanced automation such as automated material handling systems, assembly robots, or cluster tools, i.e., particular multi-resource minifabs in semiconductor manufacture.

If the models are simple to construct and the simulation runs quickly enough, they can be utilized in analytic solution approaches to simulate the expected stochastic behavior of large-scale networks. We are able to simulate individual nodes in these kinds of networks. But there isn't much research on how to use one or more simulation models to model the supply chain of a large company, like a multinational semiconductor manufacturer with dozens of wafer factories that each house hundreds of machines and lots. This is particularly true when it comes to the integration of optimization approaches. An intriguing example of an SCM modeling tool is the Supply Chain Optimization and Protocol Environment (SCOPE) (see Orcun et al. 2007).

However, only small-scale application scenarios are evaluated, and it is still difficult to characterize dynamics and stochastic behavior. Research is required on simplified reduction simulation models that are capable of capturing fundamental elements like dynamics and load-dependent cycle periods. Keep in mind that a lack of technique rather than improper simulation hardware is the main cause of this problem. There are currently very few reduction techniques that address the intricate process step modeling of bottlenecks. In these approaches, fixed time delays take the place of the remaining process stages rather than a full modeling of nonbottleneck machines. However, as Rose (2007) showed when simulating a wafer fab, this method needs more work because bottlenecks can change over time and delays depend on the load. It would be possible to use simulation-based optimization for large-scale networks with such simplified simulation models. Additionally, for large-scale networks, methods that alternate between simulation and analytical methods, like linear programming, would be feasible.

The problem of appropriately parameterizing planning and control heuristics based on situations is crucial for both software manufacturers and their users. Furthermore, a barrier that frequently prevents the adoption of quantitative methodologies is the preparation and analysis of the computational results. These issues can be dealt with at the same time if the right knowledge-based systems are created that tell the user which method to use based on a knowledge base of methods (access systems) and if output analyzers and interpreters are created to help with the analysis of the results. While these tools were made for certain methods, like discrete-event simulation (Belz and Mertens, 1994) or linear programming (cf. Greenberg, 1996), it is clear that more research is needed for decision support systems that use other methods. Furthermore, support mechanisms for a particular technique must be created, such as when parameters need to be set appropriately.

When using quantitative methods for interactive what-if scenarios, for instance, their lengthy computation times continue to be a barrier to application. Degbotse et al. (2013), for example, show that whereas many data sets can take up to a day to solve, single planning instances based on enterprise data can be resolved in a few hours. Consequently, research is needed to determine whether particular industrial and service network decision-making challenges can benefit from parallel computing. Large-scale stochastic production planning difficulties or scheduling issues are good candidates.

III. RELEVANT SCIENTIFIC METHODS

In the first three subsections, we address approaches that may be helpful in addressing examples of the three types of issues that are given in Sections 1 and 2. We address performance assessment difficulties in Subsection 3.4, as they are central to all the challenges.

3.1 Issues with Integration

The question of whether Schneeweiss's (2003) distributed decision-making paradigm or other fundamental organizational forms create a framework that can be improved by properly combining centralized and decentralized solution approaches has to be looked at. It is unclear how to predict the pertinent traits of other participating decision-making units. A software paradigm called multi-agent systems (MAS) is helpful for putting distributed decision-making techniques into practice. There aren't many effective implementations, though. It is essential to carefully compare the respective decentralized and integrated (centralized) approaches in terms of computing time and solution quality. Lastly, game theory processes can be used to determine incentives for autonomous actors. Furthermore, mechanism design can also dictate criteria for choosing the course of action that yields acceptable results, even in situations where agents may lie about their preferences.

If you want to model strategies for dealing with uncertainty in preference elicitation, you can use fuzzy set theory or other theories of uncertainty. Preference modeling can be assessed through the use of agent-based simulation.

3.2 Issues Concerning the Computing of Robust Solutions

Research in the robustness domain typically focuses on designing and evaluating online algorithms or on suitable rescheduling methods. We anticipate that techniques from Markov decision processes and approximation dynamic programming, or stochastic programming, can be applied to create reliable algorithms for a wide range of issues. A stochastic program's most basic form is predicated on the notion that a choice is made at the beginning. Then, a few arbitrary things happen that have an impact on how the first-stage decision turns out. In order to make up for any negative consequences that may have arisen from the first-stage decision, a recourse decision may be taken at a later stage. The recourse function, or the expected value of making this decision, is taken into consideration while making the first-stage decision in order to account for its potential future implications.

The primary challenge with Markov decision processes is formulating a policy that dictates what a decision-maker should do next when a particular condition is met. The determination of the policy maximizes the anticipated reward.

Simulation can be used in sampling techniques, meaning that it can be used to examine objectives. Simulation-based optimization techniques use the same method to figure out what the objective function should be when there is uncertainty.They do this by combining simulation and metaheuristics.

3.3 Issues Associated with the Model Building

The reduced simulation model technique for individual supply chain nodes needs to be expanded to complete supply chains in order to simplify the model construction process. It looks like discrete-event simulation models can't or don't need to include every node in a large-scale manufacturing or service network. This is why distributed simulation techniques must be used to compare the detailed models with the simplified ones.

We believe it's a good idea to mix general models from system dynamics, deterministic flow line models, or multivariate regression with more or less detailed discrete-event simulation models. As of now, only preliminary results have been found on how to use nonlinear fluid flow systems modeled with partial differential equations to explain how supply chains usually work Expert system design techniques appear to be promising options for developing output analyzers, interpreters, and access systems. Assistance systems must use machine learning techniques to enable the situation-dependent selection of heuristic parameter values.

Decomposition techniques are important for dealing with the large amount of computing work that comes with solving decision problems in service and industrial networks. To get high-quality answers, meta heuristics and their conjunction with mat heuristics—mathematic programming approaches—where the math programming approaches handle the highly confined sub problems can be employed. Furthermore, it is possible to solve the sub problems simultaneously. It is now feasible for businesses to use powerful parallel computers, including classic multi-core and cluster systems as well as more specialized designs like the Compute Unified Device Architecture (CUDA), at relatively low costs. This covers using cloud resources or having such systems run on their own. For scheduling difficulties or car routing problems based on meta heuristics employing CUDA, only preliminary findings are available. Refer to Schulz et al. (2013) as an example.

3.4 Problems with Performance Evaluation

It is necessary to evaluate the suggested algorithms' performance using either newly created randomly generated problem instances or benchmark instances that are currently in existence. In the industrial setting of manufacturing and service networks, controlled experiments don't seem to be possible. Because of this, it is very helpful to test new planning and control methods in a dynamic and uncertain environment by simulating them before using them in the real world.

The innovative methods must be prototypically included in the current application systems. To evaluate the effectiveness of the suggested methods in environments other than research labs, field testing utilizing these prototypes is extremely desirable. Problems with develop include long development cycles at universities because of small research teams, prototypes that don't work well, organizational problems in companies because business processes and planning models don't match up, technical integration problems, pilot users who aren't committed in companies, and the fact that academic research labs often can't solve software problems quickly and effectively. Ypes and algorithms to be broadly applicable, meaning they should be able to handle a wide variety of scenarios.

IV. NECESSARY INTERDISCIPLINARY COLLABORATION

In order to effectively address the issues raised in Section 2, business and information systems engineering must work closely with other academic departments. The field of management science is in charge of recognizing and evaluating company issues. The significance of this field lies in its application to all three difficulties, as our research focuses on business concerns.

Techniques from operations research, statistics, theoretical computer science, algorithm engineering, artificial intelligence, and machine learning must be used to look at the problems and come up with good solutions for all three of them. To create software prototypes, data engineering and software engineering techniques must be used.

For Challenge 1, we need to look at economic issues and mechanisms from a more algorithmic point of view, or from a computer science point of view, within the multidisciplinary field of computational mechanism design (see Nisan et al. 2007). You can think about what psychology and the behavioral sciences have to say about possible incentives for semi-automated planning and control systems in Challenge 1 and the design of human-computer interaction in Challenge 3.

Let's look at the following illustration from the first challenge that highlights the need for conducting multidisciplinary research. It is taken into consideration to schedule production projects and preventative maintenance tasks simultaneously. A significant company's MES should integrate the algorithms that are to be supplied. We must examine the issue. Selecting suitable performance metrics that align with the company's worldwide business objectives is particularly crucial. Working on this task requires knowledge of management science. To obtain preliminary insights, a mixed-integer program is developed once the problem is thoroughly characterized. Operations research expertise is needed for this. To investigate the problem's computational complexity, we require techniques from theoretical computer science. In the event that the problem is NP-hard, we may need to create a powerful meta heuristic strategy in order to solve large-scale cases quickly. Algorithm design and artificial intelligence expertise are needed for this. Machine learning techniques could be helpful in determining the different parameters of the meta heuristic based on the circumstances. We have to wrap the offered scheduling capability within a web service that enables us to use data from the MES and to deploy the schedules in the MES because we are interested in using the suggested way in the company-wide MES. Methods heavily influenced by software development and data engineering are necessary to build this software prototype.

V. SAMPLES OF PRELIMINARY FINDINGS

For large-scale manufacturing systems, Mönch (2006) suggests a distributed, hierarchical production control system. The MAS is the system's implementation. It would nevertheless be intriguing to incorporate production planning techniques into the MAS. Steinzen et al. (2010) provide an integrated optimization strategy for the planning phases of personnel scheduling and vehicle scheduling. An automated project scheduling technique with consideration for conflicting objectives and information asymmetry was developed by Fink and Homberger (2013). Driessel and Mönch (2012) propose an integrated scheduling and automated material handling system that applies the shifting bottleneck heuristic to this scenario. But it is believed that there will be a simpler automated material handling system. Therefore, a great deal more research is required to include real-world problems.

Challenge	Content	Reference
Integration in networks	MAS for wafer fab scheduling	Mönch (2006)
	integration of crew and vehicle scheduling	Steinzen et al. (2010)
	automated negotiation mechanism	Fink and Homberger (2013)
	integrated scheduling and automated transport	Driessel and Mönch (2012)
	reference point-based modeling of preferences	Pfeiffer et al. (2008)
	Fuzzy sets to model uncertainty in preferences	Lang et al. (2012)
Determination of robust	usage of real-time data in city logistics	Ehmke et al. (2012)
solutions	robust crew and airline scheduling	Dück et al. (2012)
Reduction of the model	fast design/implementation of metaheuristics	Fink and Voß (2003)
building and usage cycle	design of metaheuristics	Rothlauf (2011)
	supply chain simulation using reduced models	Ehm et al. (2011)
	parallel computing in scheduling	Bilyk and Mönch (2012)

Pfeiffer et al. (2008) offer multi-objective evolutionary algorithms that take decision-makers' preferences into account as reference points. However, a large number of additional application situations must be used to evaluate the suggested approach. Linguistic ambiguity frequently coexists with decision-makers' preferences. In their work, Lang et al. (2012) address the use of fuzzy sets in electronic negotiations to elicit, simulate, and process human decision-makers' unclear preferences. It is necessary to evaluate uncertainty theories that differ from fuzzy sets, though. Applications related to supply chain coordination must be taken into account.

According to Ehmke et al. (2012), real-time data can improve decision-making in the field of transportation logistics. Dück et al. (2012) propose methods for resilient crew and aircraft scheduling that take into account the delays and disruptions typical of air travel.

Fink and Voß (2003) describe the construction of meta heuristics using an object-oriented framework for industrial planning challenges. Classifying meta heuristics, Rothlauf (2011) shows how problem- and instance-specific knowledge can be used to develop such heuristics. Ehm et al. (2011) examine the simulation of supply chains in semiconductor manufacturing. Techniques for reduced simulation are used for a small-scale supply chain. The approach must be expanded to include large-scale supply chains, though. The shifting bottleneck heuristic was proposed by Bilyk and Monch (2012) as a way to help large semiconductor wafer production facilities with their scheduling problems. This makes it possible to solve the next subproblem using contemporary meta heuristics. However, it is necessary to conduct planned simulation experiments in order to use meta heuristics.

In this paper, we summarize the key takeaways from the conversation and suggest the following research agenda for the upcoming years.

1. Using particular examples from production scheduling and planning, we will investigate the subject of how planning and control have to be coupled in large-scale manufacturing and service networks. By taking into account various uncertainty theories and looking at application cases, we will increase our understanding of preference modeling for decision-makers. We will explore coordination strategies for self-governing actors that take incentives into account. In contrast to decentralized, coordinated approaches, we are interested in learning more about the benefits and drawbacks of integrated planning techniques.
2. Taking into account the dynamic and stochastic behavior of the underlying base system, we will design, implement, and evaluate algorithms and the accompanying application systems. First, we will look at the dynamic and stochastic analogues of well-known static problems in scheduling, production planning, and transportation with deterministic data. We want to know what limits the oversimplified approaches that are currently employed to solve these kinds of issues. We will build on increasingly sophisticated methods based on this newfound understanding
3. We'll create, put into practice, and evaluate methods that let us simulate extensive supply networks. We will concentrate on methods for large-scale manufacturing and service networks that combine simulation and analytical techniques based on these simulation models. We'll look into the potential applications of these simulation-based techniques in systems for commercial use. We will concentrate on parameterizing heuristics used for decision support in manufacturing and service networks based on specific situations. We will examine examples from various domains to investigate the potential applications of parallel computing techniques.

VI. CONCLUSION

We covered a number of issues with model-based decision support in manufacturing and service networks in this study. The primary obstacles include distributed decision-making throughout extensive manufacturing and service networks, considering the dynamic and stochastic nature of the system during decision-making processes, and enhancing the model construction and utilization cycle. We outlined the reasons behind our belief that addressing these issues is critical to achieving widespread adoption of effective decision support tools fit for practical implementation. Additionally, the necessity of the necessary efforts being interdisciplinary by nature is shown. A projected research program is presented for the upcoming years.

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