# Decision Support for Smart Manufacturing

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## INTRODUCTION

A post-industrial revolution is encouraging the deployment of novel concepts both for designing smart factories and for creating a new generation of monitoring, control and man-machine collaboration systems. In general, companies are embracing an era of smart manufacturing built upon Cyber Physical Systems (CPS), the Internet of Things (IoT), and Cloud and Cognitive computing. Using digital technologies with advanced manufacturing tools can provide opportunities for building smart decision support systems (DSS) to improve manufacturing analysis, monitoring, output, and performance. Despite the potential of improved Decision Support Systems (DSS), the major challenge is successfully adapting smart manufacturing processes to use new digital technologies that can enable the implementation of Intelligent systems and improved DSS.

Additionally, to move towards smart manufacturing, better means are required for technology deployments. The speed of technology implementation should be significantly faster, and machines should have greater accuracy of calibration in comparison to traditional manufacturing. One approach to enhancing deployment is incorporating optimization models into manufacturing systems. This change should provide a design that provides ease of use for operators and decision makers in real-time during the manufacturing process.

This chapter defines requirements for various types of DSS (see Power, 2002 and 2004, for details on the typology of DSS) in a smart manufacturing environment based upon increased use of optimization. It focuses on identifying key barriers which prevent the development and use of enhanced or “smart” DSS in manufacturing and then provides the requirement and architecture for a system engineering design for using optimization and other techniques with advanced computing and manufacturing technologies.

This review aims to promote a standard design or framework that is useful for both the manufacturing and academic communities that can facilitate needed efforts and innovation while stimulating adoption and use of smart manufacturing technologies.

## BACKGROUND

Mathematical models and optimization techniques are the driver for model-driven DSS. With regards to the structure of data and a problem’s objective and constraints, many programming tools and mathematical algorithms are available to aid decision-makers in building a DSS with optimal recommendations. The critical step is to know the type of optimization algorithm needed to solve the problem. For more details on a taxonomy of optimization problems, one can refer to a comprehensive collection of optimization resources at https://neos-guide.org/.

Mathematical algorithms support convergence towards optimal solutions. This review classifies optimization problems in terms of traditional and intelligent approaches. The most commonly used intelligent optimization models are search-based (i.e., metaheuristic models), learning-based (i.e., machine learning models), uncertainty-based (i.e., robust optimization; stochastic optimization), simulation-based (i.e., Markov Chain Monte Carlo) and Markov Decision Process (MDP) (see Tao et al., 2016, for a comprehensive review on intelligent optimization).

Although using an intelligent optimization algorithm can gradually adapt a specific model-driven DSS for smart manufacturing, such a DSS requires several other criteria be met to be adequately intelligent. More intelligent DSS are created with a learning algorithm, a knowledge sharing system, and with cognitive computing capabilities. Nevertheless, in a smart manufacturing system, with connectivity among all manufacturing processes, an intelligent, integrated DSS is required to manage a manufacturing system. Features of an integrated, intelligent DSS include expert knowledge, risk management, production control, quality monitoring, marketing and sales management, project management, and supply chain (SC) support. Guo (2016) provides an extensive collection of DSS capabilities and features needed for managerial tasks of smart manufacturing integrated with intelligent optimization algorithms.

There is a gap in the literature on the applications of optimization techniques in DSS for smart manufacturing. Moreover, there is a lack of a comprehensive system design which can cover all types of DSS and managerial decision making (DM). This analysis identifies the requirements of parameter alignment, and conceptual design of an integrated, intelligent DSS for smart manufacturing by considering the core of an optimization procedure.

## DECISION SUPPORT CAN AID SMART MANUFACTURING INITIATIVES

Manufacturing in developed nations must incorporate more data capture and decision support to control costs and maintain product quality. Digital transformation of manufacturing means production must be transformed using technologies like robotics, IoT, Intelligent systems, and real-time analytics. Smart manufacturing means all aspects of production are transformed so they are data, computing, and decision support intensive. Smart manufacturing has been defined by i-SCOOP.eu as the "fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs." Various decision support and data-driven capabilities must be incorporated in smart manufacturing systems, including:

### Knowledge-Driven DSS

In a smart manufacturing environment, sharing expert domain knowledge at the manager-operator and operator-machine interface level is very important. Recommender systems and opinion mining can support real-time, data-based decision making. Machine/user relationship mining and clustering can increase the self-awareness, self-learning, and self-maintenance of production systems. Finally, Reciprocal Learning-Based DSS (RL-DSS) can make repetitive decisions and reduce the human decision making load. Routine decision tasks can be programmed and learning algorithms can enhance performance. Then decision makers can update their knowledge and the improved system helps create better decisions than previously possible for semi-structured decisions. Research challenges include:

- **Providing Man-Machine Knowledge-Sharing**
- **Knowledge-Mining**
- **Creating Reciprocal Learning-Based DSS**

### Data-Driven DSS / Document-Driven DSS

Big Data Management in the Cloud can improve data management and distribution for both "machine-generated data" and "human-generated data." Real-time automated fault detection, classification and root-cause detection should be optimized using data from sensors. Finally, data-driven DSS should integrate real-time and special study data analytics. New and expanded data sources can enhance predictive analytics and output can be quickly shared using visualization tools.

## Model-Driven DSS

Factories of the Future (http://www.effra.eu/factories-future) require integrated supply chain management, improved demand forecasting, and technology integration throughout the supply chain management process. Sensors combined with quantitative models can reduce costs and identify faults in the supply network itself, such as sensor failure and degradation. Ideally models will optimize the frequency and timing of sensor measurement and will eliminate or reduce supply chain network delays.

Creation of an Intelligent Feedback Control System can improve product quality and can provide feedback for system management, which can be used to improve production scheduling, to maintain machinery, and improve proactive maintenance.

## Communication-Driven DSS

More machine to machine and person to machine decision support can facilitate the sharing of machines across different tasks or under different conditions. Developing simulation tools can help train operators and decision makers, prevent impending problems, and help in taking corrective action in a timely manner. If Artificially Intelligent machines communicate, then security challenges will increase, but shared decision making will increase in the capabilities of the production network.

## Challenges to Improving DSS

Smart manufacturing requires intelligent systems and decision support for human participants. Improving DSS capabilities is necessitated by the development and deployment of smart manufacturing systems. The main sources of challenge are:

- **Innovation:** The fast growth of start-up firms has lead to accelerating change in manufacturing environments. The production function has become a source of innovation. On the other hand, innovation in an organization often leads to increased personalization. However, the sustainability in innovation due to rapid change in technology is often temporary. Invest in decision support may be delayed.
- **Changes in Social Behavior:** Customers are becoming more knowledgeable; and their demand for quality, customer service, and rapid product adaptation to new technologies is increasing. Therefore, manufacturing servitization, developing capabilities needed to provide services and solutions that supplement traditional product offerings, is required. New service capabilities often necessitate creating more integrated products, increased customer focus, more automated services, support, and more knowledge integration in an effort to produce value-added products. Additionally, rapid changes in leadership and culture must occur to respond to rapid market, business, and technological change.
- **Changes in Technology:** Changes in technology set new standards for evaluating the performance of manufacturing firms, such that from a quality management perspective, since 1987 (ISO 9000 series) society has moved to environmental management in 1992 (ISO 14000 series) and, recently, to an energy management perspective (ISO 50000 series). Other indices, such as the Key Performance Indicators (KPI), must radically change in both definition and metrics due to cross-factory integration.
- **Changes in Market Behavior:** Merging of small, medium, and large enterprises changes the nature of competition in many markets. Lowering the general cost of IT infrastructure like server and networks and market forces that are increasing the cost of innovative technologies are increasing the dynamism and volatility in many industries. Robots and machines participate in smart manufacturing systems by means of Artificial Intelligence (AI). Therefore, the concept of a supply chain is not limited to moving services and products from

the supplier to customers; rather, supply chains must describe all transactions among different parts of production systems and of the network both inside and outside of a manufacturing environment.

Despite the challenges mentioned above, Table 1 summarizes some specific suggestions for developing DSS and smart manufacturing solutions that can overcome them.

*Table 1. Optimization-based solutions for overcoming DSS challenges in smart manufacturing*

| **Quick Solutions** | **Detailed Solutions** |
|---|---|
| Digitalize knowledge-based DSS | • Incorporating the behavior of human decision makers with proposed solutions.<br>• Automating decisions previously made by humans.<br>• Improving the interface of Information Systems for humans. |
| Incorporate dynamics into the solutions | • Developing stochastic and dynamic versions of solutions and deterministic models.<br>• Anticipating stochasticity in the models based on dynamic programming, robust optimization, and stochastic programming. |
| Design software-based solutions with a user-friendly interface | • Considering the role of high-tech computing techniques, including cloud computing techniques in DM and parallel computing on Graphics Processing Units (GPU).<br>• Knowing the restrictions of management software for smart manufacturing management, process, and production.<br>• Proposing alternative software solutions, including service-oriented computing and software agents for planning and scheduling applications. |
| Create a hybrid configuration of optimization models | • Facilitating planning problems and a DM-based optimization and data analysis perspective.<br>• Implementing “Manufacturing Execution System” (MES), “Enterprise Resource Planning” (ERP), and “Advanced Planning and Scheduling” (APS) for developing integrated production planning and scheduling solutions.<br>• Decreasing measurement uncertainty by merging the hybrid metrology with state-of-the-art statistical analyses. |
| Enable Simulation and Data-driven solutions | • Simulating the physical environment to comprehend the connections amid real-world circumstances; and planning to find solution-based approaches in a risk-free environment before applying those solutions.<br>• Visualizing production planning processes by use of event-driven process.<br>• Modeling and analyzing manufacturing challenges by utilization of various simulation paradigms.<br>• Supporting the different aspects of DM in smart manufacturing by embedding the actual simulation methods in existing and forthcoming information systems. |
| Encourage Process integration | • Integrating decisions made by the different elements of the system to avoid *ad hoc* situations.<br>• Integrating high-tech computing procedures to derive computationally tractable models, and to engage in discourse regarding the diverse uncertainties encounterable in the industry.<br>• Incorporating sustainability aspects into proposed solutions and deterministic models.<br>• Taking the product’s lifetime into account and integrating with demand planning. |

## KEY COMPONENTS OF INTELLIGENT, INTEGRATED DSS

This section defines a framework and a reference architecture to support the requirements for more intelligent, “smarter” DSS. Three components are explored: 1) the environment, 2) the architecture, and 3) the requirements. The discussion is based upon common principles, assumptions, and terminology for better integration and interoperability.

## A. Environment

Cyber-Physical Systems (CPS) integrate computation, networking, and physical processes. A CPS links cyberspace with the physical world through a network of interrelated elements such as sensors and actuators, robotics, and computational engines. These systems are highly automated, intelligent, and collaborative. A CPS is sufficient when only standalone model-driven, data-driven, and document-driven DSS are implemented. However, when knowledge-driven and communication-driven DSS are integrated with other types of DSS, the CPS itself cannot adequately cover interactions among the system components. In this case, only a Cyber-Physical-Social System (CPSS) can support all aspects of decision support needed in the system. Semantic integration transfers information between the physical world and CPSS, and delivers knowledge between a CPSS and communities of practice. In smart manufacturing, communities include expert engineers/managers and/or machines/manufacturing tools. Communication can be defined in terms of its occurrence either on a vertical level (between members at different expertise and application levels) or on a horizontal level. Machines in the same group and similar application can form a community if they are carrying out knowledge activities and if they can either learn from or teach other members of the group. A schematic of the CPSS is illustrated in Figure 1.

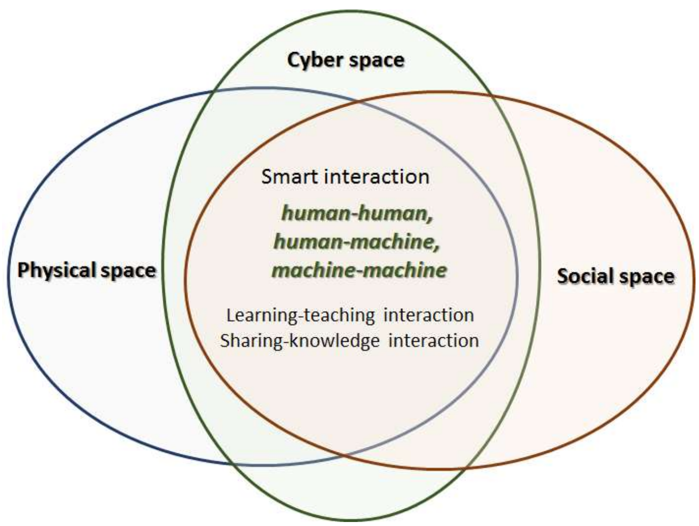


*Figure 1. Schematic of a Cyber-Physical-Social System*

Ideally, the CPSS environment will be an autonomous, sustainable, and intelligent system that can gather and organize resources into semantically rich forms that both machines and decision makers can efficiently use. Additionally, each space is required to be capable of self-evaluation.

The evolution of socialnomics, especially social network peer reviews, related to products/services in manufacturing organizations and more integrated operational structures defines a new concept of social manufacturing systems, see Jiang et al. (2016). Information technology and decision support must process these new data sources, especially for consumer facing goods.

## B. Architecture

DSS can create a sophisticated management system. In general, DSS can integrate multidisciplinary data sources and related tools to generate value-added information to support DM. This section outlines a functional description of components required for realizing a system based on CPSS. The architecture comprises inherent layers that are typically considered in requirements specifications for production systems and associated analytics, and decision processes. The ten proposed architecture layers are as follows:

1. **Data Layer:** Contains distributed spatial, constraint, and relational databases—and their meta-data information. This layer provides transparent access to data without concern for their original formats. Since the data layer is the most frequently accessed layer, a data warehouse system usually exists to help improve performance. The data layer also provides the base for building data-driven and document-driven DSS.
2. **Information Layer:** Contains a collection of domain-specific mathematic or analytic tools or simulation models that help aggregate data into information. The analytic tools can be distributed over a network of computers in each of the other layers in the architecture. The analytic tools include domain-specific statistics, optimization, and simulation models. These domain-specific tools can provide value-added information based on raw data from the data layer.
3. **Knowledge Layer:** Knowledge is created or discovered by combining information when it transfers from an expert/intelligent engineer/machine to other parties in the system. Tools or applications that provide or recognize domain-specific knowledge include data mining, knowledge discovery algorithms, or traditional statistical inference approaches. The tools in the knowledge layer do not make decisions. Instead, they contribute and organize knowledge that is used in the decision making process. This layer also provides the knowledge base needed to build a knowledge-driven DSS.
4. **Integration Layer:** In a smart manufacturing context, additional adapters for sensor and IoT object integration are required. Due to the extensive variety in the use of various sensors, an initial classification into an ontology-based enterprise data model is needed. The integration layer can provide access for all types of DSS. In the integration layer, data from multidisciplinary sources is combined into information that can be used as domain knowledge either by non-experts or by machines. Those multidisciplinary data sources and related tools can be organized under a hierarchical architecture structure to clarify their relationship. The system in this layer cannot express the information context inside a domain-specific application for decision making.
5. **Physical Configuration Layer:** This layer deals with the practical deployment of essential hardware for implementing CPSS such as sensors, actuators, machines, and personnel. Information about the task, process plans, quality requirements, and real-time data can be stored in the physical devices, which can repeatedly be read and written for production management usage. The physical devices flow via wireless communications in the manufacturing environment, and the information network and databases extracted from physical devices are configured and connected with each other for information sharing.
6. **Social Interaction Layer:** The social interaction layer plays the role of a mediator to assist the communication and collaboration among manufacturing components as described in the social space of the CPSS. This layer also provides the base to build more comprehensive communication-driven DSS.
7. **In-Memory Data Management and Connectivity Layer:** Due to the high volume of data and the velocity by which it is generated by physical devices, an in-memory data management platform is utilized, allowing for distributed in-memory data management with predictable latency and fast data access for real-time data handling. An in-memory data store will act as a central point of coordination, aggregation, and distribution. Besides data management, events such as alerts or system messages communicate with users in this layer.
8. **Predictive Learning Layer:** Real-time data access via the in-memory data management platform can be preprocessed, and the results are fed back to the in-memory data store. The aggregated data are used for in-situ analysis. Historical data can be analyzed for pattern detection and correlated with respective manufacturing process behaviors. Based on these patterns, manufacturing abnormalities can be detected, learned, optimized, and applied to monitor real-time data streams. Furthermore, modern Markov Decision Process (MDP) approaches could be combined with historical data to optimize the learning procedure.
9. **Presentation Layer:** To enable decision makers to make quality real-time decisions, all relevant data needs to be aggregated and visualized appropriately. Additionally, process engineers must be

notified proactively if a decision is required or when a deviation in the current state of a process is detected. Moreover, a recommendation should be generated based on historical process analysis, and drill-down functionality should allow for navigation to Bayesian information and enable decision makers to make high quality decisions. Also, the presentation layer creates a user interface platform for displaying decision rules to decision makers. It manages the multidisciplinary meta-information from the layers beyond it. Based on the meta-information, it can reflect and provide internal data and services to users by means of a user interface diagram. The user interface can take many forms, such as a Web portal.

10. **Intelligent Action Layer:** DM happens in this layer based upon presented information. Manufacturing processes can be adapted by adjusting the current decision. However, adaptations in one process can lead to necessary changes in other interlinked processes. A consistent transition of changes must be fed back into the process execution system(s) when adaptations have taken place.

Figure 2. illustrates the relationship among the different layers.

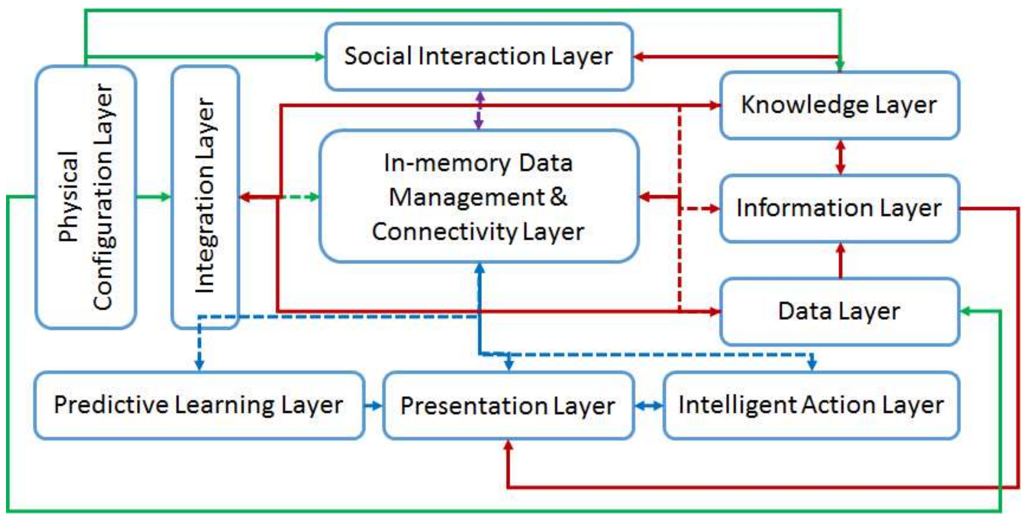


*Figure 2. The schematic of the relationship among different layers of architecture*

## C. Requirements

To create the architecture needed required reasoning about a CPSS. A generalized framework of methods, tools and concepts can describe the needed components required for all types of DSS in a smart enterprise manufacturing environment. We define the following requirements:

- **Engineering Methodologies:** The combining of different engineering tools to build different models of a smart plant; this may be expressed in the form of process models using different process modeling languages. Methodologies decide which model to produce and which modeling languages to use to describe the model.
- **Modeling Languages:** Used for shaping the different aspects of the system and its entities—aspects including human roles, operational processes, functions, information, the workplace, and production technologies.
- **Engineering Tools:** Used for implementing modeling languages, which are supported by engineering methodologies, and model concepts to create, use, manage, analyze, evaluate, and enact models for simulation and to provide a shared design repository or database.
- **Model Concepts:** Define and formalize the most generic concepts of models in the form of ontological models, meta-models, or reference models.
- **Modules:** Used to implement the operating systems supported by models.

- **Functional Components:** For connecting to DSS in the operation phase. The functional components of DSS are included in all defined phases of software development and support the rapid adaptability and reconfigurability of manufacturing within the smart environment.
- **Information Analysis:** Consists of the analytical process modeling, statistical data and information modeling and analysis, quality management, and optimization.
- **System Management:** Involves the definition of requirements and parametric constraints. The reference structure of system management is open, which permits the possibility of expansion and improvement of the system. It can also specify hardware, processes, personnel, and facilities.
- **Mathematical Models:** Adequate models of the processes for achieving the control tasks of the system modules and equipment are required. The mathematical models allow for the optimization of the process parameters, function, and behavior of the system, information maintenance, operations and data management, and organizational structure.
- **Database:** Methods, tools, and models are arranged in a database. The methods and tools have to be characterized by their attributes for a database. Attributes determine their applicability from the system requirements. The database contains a case library and a set of solutions related to these cases. The attributes represent the objects in the database.
- **Attributes:** Defined within the ontology model as relating to properties for each concept. The attributes which are only used by the corresponding methods in each group, form the basis for choice of a suitable method or tool for the given task. Attributes characterize the prepared cases in detail and are stored in the database to be utilized in case-based reasoning.
- **Ontology:** Describes the meaning and relationships among modeling concepts (definitions) available in modeling languages, to improve the analytic capability of engineering tools and the usefulness of the models. Different components have different ontologies that coincide only partially or even mismatch. However, ontologies can merge and create a single coherent ontology; or they can align and reuse information from one another.
- **Monitoring Agents:** These follow system behavior after applying the recommended method for design and control. The "data collection and acquisition" subsystem is available and connected with monitoring agents.
- **Control Agents (Actuators):** These execute control algorithms. During the real-time control, the actuators interfere with an equipment control block initiated by some industrial controller devices or which may occur following operator manipulation. State feedback regulators can be implemented after receiving signals from measuring devices.
- **Equipment Control:** Usually designed by equipment producers. It includes sources of the actual measurement of data for the state of the physical or cyberspace equipment by sensors or other measuring devices.
- **Object-Based Architectures:** The most promising approach in modeling interactive systems. These model the interface software as a composition of co-operating objects. These models are highly modular and support concurrency, distribution of applications, and multithread dialogues.
- **Interference Monitoring of a User's Requirements:** Defines outputs and inputs for the identification of control work for making connection of external applications via the internet or a local network for distributed computing. It is required to start as an independent component and to connect to a server for computing. The resources could be physically accessible in cyberspace.

- **Readability of Knowledge:** Knowledge has to be represented in a form which can be read by a human or by a machine/computer.
- **Reusability of Data:** All data about the specific domains have to be stored, archived, and organized for future reuse.
- **Reproducibility:** New knowledge has to be reproducible (based on historical information), and it should be organized as a structured database.
- **Contestability:** Monitoring agents update the database with newly achieved results for subsequent usage and application if all of the requirements are satisfied – or else the monitoring and control agents have to repeat their operations.
- **Connectivity:** The data collection and acquisition, the information system, and system management have to connect to DSS to provide decision makers, operators, and managers with key information that enables them to make efficient and consistent decisions.
- **Knowledge Sharing:** Representation is the application of logic, computation, and ontology for the task of constructing models for an application domain. Knowledge can integrate with conjoint use of ontology and software patterns inside each component.
- **Rules:** Defined within an interference engine; serve to find solutions for the user according to the user's requirements.
- **Control Strategies:** Defined for searching solutions by predefined rules in both forward chaining and backward chaining.
- **Case-Based Reasoning:** Used within the system to find a solution that matches best with the user's requirements, using data stored in a database.

With regards to the environment and the architecture mentioned previously relative to intelligent, integrated DSS, Figure 3 is a block diagram of requirements for improved DSS to support the essential characteristics of smart manufacturing.

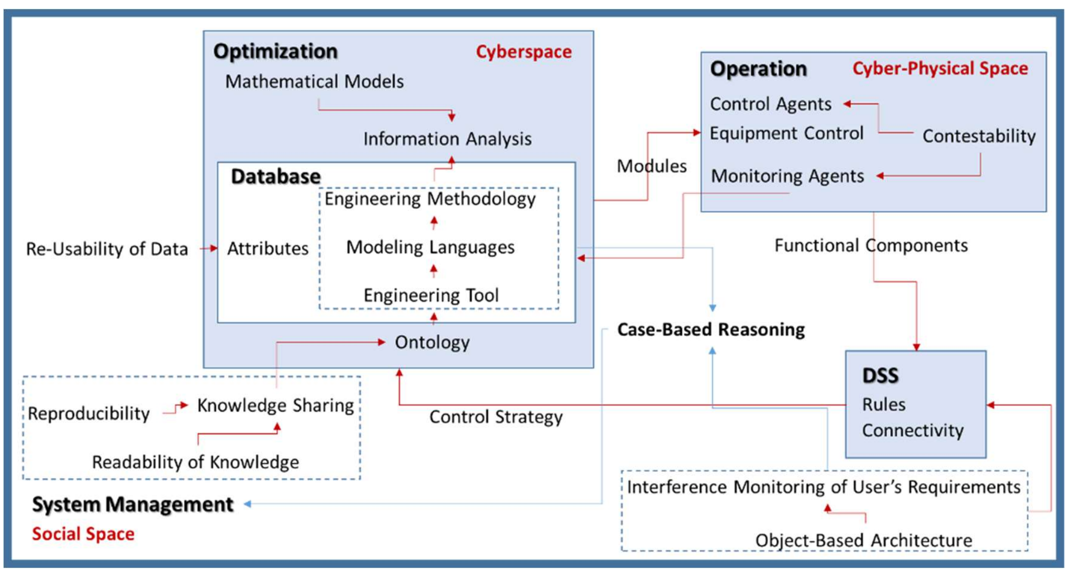


*Figure 3. Block diagram of requirements for intelligent, integrated DSS*

## FUTURE RESEARCH DIRECTIONS

In proposing future research directions, we attempt to provide a broad vision of a design for "smart" DSS for "smart" manufacturing. These design requirements are not discussed in the literature with regards to an analytic and decision support context and thus are new directions for the next step towards smart manufacturing. In the following bullet points, we discuss some of the highlighted topics in this technology chain.

- **Area 1:** ***Bi-level optimization*** is an approach where the outer optimization problem is embedded (nested) within an inner optimization problem (including lower-level variables). Many multi-level DMs exist—DMs such as strategic planning of marketing and sales channels; global SC simulation models based on a marketing-operations perspective; and positioning order penetration points (OPP) in global SCs in smart manufacturing, which can be modeled by Bi-level optimization approach. As an example, in a Bi-level DM, both the leader and the follower may have multiple objectives with uncertain values and constraints which can be modeled as a ***fuzzy multi-objective*** **Bi-level** ***programming*** DSS.
- **Area 2:** Developments in electronic communication, computing, and DM – coupled with new interest on the part of organizations to improve meeting effectiveness – are spurring research in the area of ***group DSS*** (GDSS). GDSS combines communication, computing, and DM to facilitate the formulation and solution of unstructured problems by a group of people. Another area of future research would be developing mathematical models of group DM in DSS of the smart manufacturing environment.
- **Area 3:** Optimizing the product design process in smart manufacturing has a significant impact on the global SC. The role of having a smart DSS for optimal product design in smart manufacturing is crucial. ***Multi-level DM programming*** can be applied for capturing different features in design stages and for evaluating design alternatives based on correlated criteria such as functionality, reliability, and manufacturability to perform automated DSS for product design criteria. Consequently, multi-level optimization – as a useful and practical tool – provides the what-if analysis for product design (i.e., "What would happen if a particular decision is taken?).
- **Area 4:** Smart manufacturing employs computer control and high levels of adaptability. There are an increasing number of computer systems in smart manufacturing which can be considered as autonomous agents. Another area of future research would be developing Game Theory models for making rational choices—***DSS in a negotiation and bargaining game***.
- **Area 5:** Applying ***cooperative and noncooperative multi-level programming*** is a generalized future research direction in control and optimization of cooperative systems in the smart manufacturing environment.
- **Area 6:** Other topics in SC and operation management in smart manufacturing: 1) Integrated DSS for operation and maintenance optimization; 2) Integrated and coordinated DSS for SC optimization; and 3) Integrated DSS for maintenance, spare parts, inventory, and logistics.

## CONCLUSION

More sophisticated decision support is critical for intelligent decision making in smart manufacturing environments. In this analysis, we have reviewed briefly the role of optimization and other mathematical and machine learning models in DSS to solve complex decision making tasks in smart manufacturing systems. We have proposed a systematic structure for engineering decision support applications. Integrating operations research modeling, optimization, big data analytics, and AI provide a means for making better decisions with complex objectives in a smart manufacturing setting. In smart manufacturing and in an Industry or Manufacturing 4.0 context, optimization techniques can play a critical role in automating strategic, operational, and tactical decision making and can provide more precise error analysis. Smarter decision support should lead managers to make better decisions to improve the efficiency and effectiveness of smart manufacturing systems.

We are early in the journey toward smarter manufacturing and personalization of goods. We are moving towards automation and using and integrating data capture is facilitating process improvements.

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## ADDITIONAL READING

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## KEY TERMS AND DEFINITIONS

**Advanced Planning and Scheduling:** Refers to a manufacturing management process by which raw materials and production capacity are optimally allocated to meet demand.

**Case-Based Reasoning:** The process of learning to solve new problems based on the solutions of similar past problems.

**Enterprise Resource Planning:** The real-time integrated management of core business processes, mediated by software and technology.

**Manufacturing Execution System:** Computerized systems used in manufacturing to track and document the transformation of raw materials to finished goods.

**Markov Decision Process:** Describes the environment for solving the optimization problem by reinforcement learning or dynamic programming. Provides a mathematical framework for modeling DM in situations where outcomes are fully or partially observable.

**Order Penetration Point (OPP):** Defines the stage in the manufacturing value chain, where a particular product is linked to a specific customer order.

**Semantic Integration:** The process of integrating information from diverse sources. In this regard, semantics focuses on the organization of, and action upon, information by acting as an intermediary between heterogeneous data sources which may conflict not only in structure but also in context or value.