Guest Editors’ Introduction: AI in Manufacturing

Stephen J. Buckley and Seshashayee S. Murthy,
IBM Thomas J. Watson Research Center
MANUFACTURING SPANS A VARIETY of activities. For example, the physical plant must be designed. For each product to be manufactured, the process plan—the recipe to assemble, test, and package the product—must be formulated. Resources such as machines, tools, and people must be identified to execute each process step. Numerical control data must be generated for certain types of machines. Parts must be purchased from suppliers, and stock must be maintained. The work must be scheduled— including high-level MRP (material requirements planning) schedules, order-release schedules, dispatching policies at work centers, and resource-availability schedules. And the work in process (WIP) must be tracked.

In our view, three characteristics have made manufacturing activities a prime area for the application of AI:

- **Manufacturing is a semantically rich domain.** Problems in manufacturing, such as scheduling, diagnosis, modeling, and design, are very difficult to solve. Therefore, it is possible for applications in this domain to display intelligence.

- **Large amounts of data are readily available.** Over the past three decades, manufacturing enterprises have grown increasingly computerized. Information about customer demands, bills of materials, and logistics is now available on most enterprise computers. The spread of the Internet has made it possible to quickly obtain information about all parts of the supply chain.

- **The increase in hardware speed and advances in algorithms have made it possible to solve problems in a fraction of the time it previously took.** Therefore, research on problems that could not be previously tackled, such as supply-chain optimization, is now becoming more common.

It makes good business sense for companies to use intelligent decision-support tools to solve such problems. By applying AI in manufacturing, companies obtain an information edge in the marketplace. The rewards can be large. With very small investments, production and distribution costs can decrease up to 5%. Because manufacturing costs are often approximately 50% of a company’s total costs, this is a big savings. Such investments in intelligent decision-support tools, therefore, compare well with investments in manufacturing equipment. The market for intelligent applications in supply-chain management already reached $300 million in 1996 and is growing rapidly.\(^1\)

We wanted to find out which areas of manufacturing were most appropriate for AI software. So, for this special track, we sought articles about the use of AI in actual manufacturing applications. In truth, the distinction between AI and non-AI software is blurred. We’ll take the rather simplistic view that AI software is software that is **surprisingly intelligent**.

To run an efficient manufacturing plant, there are some areas where software does not need to be surprisingly intelligent; it merely needs to be quick and reliable. A good example of this is WIP tracking. However, we expected that there were other areas where intelligent software would really pay off in manufacturing. The most obvious example was scheduling.

Not surprisingly, three of the four articles in this track are about scheduling, and illustrate three different approaches:

Jürgen Sauer and Ralf Bruns describe a generic knowledge-based scheduling framework that has been applied to continuous-flow scheduling in the chemical industry, job-shop scheduling in the metal industry, and patient scheduling in heart surgery.

Patrick Esquirol, Pierre Lopez, Luc Haudot, and Marc Sicard describe a cooperative scheduling system involving a human operator and a software system. This system is exemplified by a flanging application in an aircraft company.

Robert P. Goldman and Mark S. Boddy describe a constraint-based scheduling system for batch manufacturing—manufacturing of products that come in discrete lots, such as cosmetics, plastics, and beer.

Some other cooperative scheduling systems are similar to those built by Esquirol and his colleagues—for example, Scheiker.\(^3\) Such systems use human knowledge to guide decision making. The scheduling frameworks described by Sauer and Bruns and Goldman and Boddy also support such cooperative scheduling. The computer plays the role of an intelligence amplifier; it does not have to be able to solve the problem alone.

In the fourth article, Jürgen Frank, Birgit Rupprecht, and Veit Schmelmer write about *galenical formulation*, which transforms a drug substance into a dosage form that meets certain specified properties. In our terminology, this article is about process planning.

Currently, the industry uses a manual, experimental approach to develop these formulations, which can be very time-consuming. Automated software that can do this would indeed be surprisingly intelligent. Frank, Rupprecht, and Schmelmer’s approach is to build a knowledge base and to synthesize the plan using an inference engine that operates on the knowledge base.

We expect that, as competition forces enterprises to grow and to be more agile, manufacturing problems such as planning and scheduling will become increasingly more difficult to solve. Decision-makers will need the help of computers to reach decisions quickly and optimally. Applications in manufacturing should continue to be prime areas for research and development in AI.

We hope that you find these articles interesting. We are certain that many more examples of AI in manufacturing are out there, and encourage practitioners to publish more articles about their work.

**References**


**Stephen J. Buckley** is a manager at IBM’s T.J. Watson Research Center, with a research focus on simulation and optimization of supply chains. He has worked at IBM since 1978, and has been a research staff member at the T.J. Watson Research Center since 1987. He received his BS from Florida State University, his MS from Penn State University, and his PhD from MIT, all in computer science. For his PhD thesis, Steve developed a method for automatically planning and executing mechanical assemblies that require compliant robotic motions. Contact him at the Thomas J. Watson Research Center, PO Box 218, Yorktown Heights, NY 10598; buckley@watson.ibm.com.

**Seshashayee S. Murthy** has been a research staff member at IBM’s T.J. Watson Research Center since 1985. His main research interests are in the use of artificial intelligence to develop solutions for hard problems and in architectures for combining multiple problem-solving methods. He has developed and fielded leading-edge scheduling solutions for the paper and steel industries. He holds a PhD from Carnegie Mellon University. Contact him at the IBM Thomas J. Watson Research Center, Yorktown Heights, NY 10598; murthy@watson.ibm.com.