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Simulation and optimization of mixed-model assembly lines using software agents

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Abstract: Intense pressure arising from global competition has brought significant challenges for manufacturers. To improve their productivity and profitability, manufacturers are striving to achieve desired throughputs in satisfying dynamic and diversified customer requests and to reduce work-in-process in ever changing environments. This paper presents a simulation system for mixed-model assembly lines that can dynamically respond to changes on assembly line layout configuration, mixed-model product demands, and resource availability, so that impacts of design and operation decisions can be simulated to verify their effectiveness before actual production. The proposed approach integrates discrete event simulation and distributed multi-agent paradigm. A key part of this dynamic simulation system is a runtime interactive interface allowing information transfer from shop floor operations to software agents, and propagation of decisions made by software agents (and/or human experts) to the simulation model. By preserving current operational conditions, the simulation results reflect real time operations. The simulation results can then support actual operation decisions. In addition, by changing strategies of software agents, alternative solutions can be simulated to assist decision making.

Keywords: mixed-model assembly lines, discrete event simulation, multi-objective optimization, software agents

1 Introduction

Intense pressure arising from global competition has brought significant challenges for manufacturers. While customers demand products with low cost, fast delivery,

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and high quality, they also want products customized to their unique needs. In order to respond to diversified customer needs, manufacturers have to shift production paradigm from mass production to mass customization. Mixed model assembly lines have been recognized as a major enabler to mass customization paradigm (Zhu, *et al.*, 2006). The variety of products offered in these lines has increased dramatically over the last decade. For example, in a typical automobile assembly plant, the number of different vehicles being assembled can reach tens of thousands in terms of the possible combinations of options. Due to the product variety, the fluctuation of assembly times at each station causes blockage and starvation and poses a significant negative impact on the performance of mixed-model assembly lines. Moreover, many such assembly lines mainly rely on manual labor. Operation times under manual labor are often subject to stochastic deviations, as the performance of workers depends on a variety of factors, such as motivation, work environment, or the mental and physical stress level of the persons involved (Tempelmeier, 2003).

In dealing with blockage and starvation caused by product variety, the design of mixed-model assembly lines has to address line balancing and sequencing issues. Line balance involves the assignment of tasks to stations to evenly distribute the total daily or shift workload between stations, while respecting precedence constraints. Sequencing involves the assignment of order of models entering assembly lines, to level the workload (total assembly times) at each station and keep a constant rate of usage of every part used (Miltenburg, 1989). In the research literature of mixed-model assembly lines, a common approach is to assume that the actual arrival sequence is randomly distributed according to the demand proportions of various models. Using this assumption, the design process is the balancing problem without a sequencing exercise (Bukchin, 1998; Bukchin *et al.*, 2002). In a situation where the model sequence can be arranged without compromising lead time, both line balancing and sequencing can be determined to achieve a better performance of the assembly line. Kim *et al.* (2000) developed a coevolutionary algorithm to consider line balancing and sequencing problems simultaneously, since the objectives for both problems are similar, and the two problems are very tightly interrelated with each other. Some other researchers argued that line balance and sequencing should be solved in different time frames (Bard *et al.*, 1992; Duplaga and Bragg, 1998; Ponnambalam *et al.*, 2003). The balancing decision is a long to mid-term planning problem with a typical planning horizon of several months. The sequencing problem arises per shift, day or week with particular demands of all models (Becker and Scholl, 2006). Typically, the balancing problem is first determined based on an average model-mix. The sequencing problem is then solved assuming that line balancing has been achieved.

In the above mentioned approaches, it is assumed that the assembly times of workers at each station are deterministic, not stochastic. However, in manual assembly lines, the assembly times are variable and are determined when the workers actually finish the operations. As the system size increases (*i.e.*, having more stations and larger buffer capacities), the use of the exact methods for stochastic processing times becomes infeasible due to the magnitude of the computational efforts (Altiok, 1996). Hence, the remaining viable approaches for the analysis of longer production lines appear to be the use of approximation techniques and computer simulation. Kotani *et al.* (2004) proposed an approximation method for a sequencing problem considering assembly times as discrete random variables. Computer simulation has been recognized as an effective way for performance evaluation and real time decision making in dealing with uncertainty and stochastic behavior presented in production operations (Hyun and Shen, 2006).

This paper presents a dynamic simulation approach with the ability to reconfigure, optimize, and evaluate mixed-model assembly lines that can cope with manufacturing changes. The simulation model can benefit operations at three levels: long-term, short-term, and real-time. From the long-term perspective, the emphasis is on line layout configuration and line balancing optimization so as to respond to market demands and estimated product model mixture. The short-term perspective involves performance evaluation of alternative scenarios on production sequencing optimization to respond to actual product model mix on a daily basis. The real-time perspective provides support for operational decision making with uncertainty and disturbance arising from shop floor operations, such as materials missing and workers absence. With these three levels of support, the impacts of design and operation decision can be simulated to verify their effectiveness before actually committing actions.

The paper is organized as follows: the main characteristics of the mixed-model assembly lines including operation conditions and performance measures are described in Section 2. Section 3 presents an agent-based dynamic simulation system to support decision making in evaluating alternative design solutions. Section 4 presents a brief conclusion and discusses further research directions.

2 Characteristics of mixed-model assembly lines

A mixed-model assembly line is a production line where a variety of product models that have similar characteristics are assembled. To facilitate our modeling process, in this section, we identify the operational conditions and performance measures of the mixed-model assembly lines.

2.1 Operational conditions

An assembly line is usually organized as a serial line, where single stations are arranged along a conveyor belt. Specially, feeder lines can be considered, which provides a main line with subassemblies (Lapierre *et al.*, 2004). There is no buffer along the same serial line, but a buffer is often located on the merging point between a feeder line and the main assembly line to improve throughputs.

Mixed model assembly lines are often asynchronous to allow stations to make up time lost on a work-intensive workpiece on a subsequent low-work workpiece. Each station decides on transference individually. In terms of production control, either push or pull system can be applied to assembly lines. With a push system, workpieces are fed into the assembly line whenever required operations at the first station are completed. In a pull system, control is located at the last station of an assembly line. When operations at the last station are completed, the workpiece from the previous station is transferred.

The products assembled in mixed-model assembly lines usually have differences in product models, production quantity for each model, work contents for each model, and assembly time depending on the models (Kim *et al.*, 2000).

While work content and assembly time of each model are static information, the number of models and the quantity of production for each model are only available on a daily basis.

In a mixed-model production environment, assembly times are variable and assigned for each model at each station. On top of that, manual operations being relatively complex, assembly times have to be considered as stochastic. Hence, in the case of the mixed-model and stochastic assembly time, the cycle time is an average assembly time for a workpiece among all stations over all workpieces.

2.2 Operation performance evaluation

Operation performance is evaluated by efficiency, which is a measure of speed and cost. A general indicator of efficiency in speed aspect is the line throughput; higher throughput means higher efficiency in assembly lines. However, due to a variety of product models with different assembly time requirements at each station, the effects on the line throughputs are very difficult to evaluate. Therefore, alternative measures are used to evaluate system efficiency. Miltenburg (1989) suggested two measures for sequencing to achieve high throughputs:

1. Leveling the load (total assembly time) on each station on the line;
2. Keeping a constant rate of usage of every part used by the line.

When stochastic behavior is taken into account, bottleneck measure and station utilization measure can be used in simulation to verify line performance on sequencing.

The cost aspect of efficiency can be measured by the inventory accumulation in the work-in-process (WIP) buffers. Higher efficiency implies lower WIP levels of buffers. However, buffers can play two important roles in mixed-model assembly lines. First, a buffer is important to ensure that a bottleneck station will not be starved or blocked as a result of stochastic assembly times, e.g., unexpected machine break down, materials missing, or workers absence. Secondly, between a final assembly line and subassembly lines, it may be necessary to follow a different sequence for each individual line due to operational constraints. For example, prior to entering a final assembly line, workpieces may be required to go through a painting line, where workpieces with the same color are preferred to enter the line in batches. A buffer at the end of a subassembly line will allow these workpieces to enter a final assembly line with a rearranged sequence. Such a buffer will improve line throughput by reducing setup time. On the other hand, it will increase cost due to inventory accumulation. Alternate scenarios on sequencing and buffer size should be simulated and evaluated to find a trade-off.

3 An agent-based dynamic simulation system

In order to coordinate complicated trade-offs among performance measures and respond to dynamic changes in manufacturing environments, we developed a dynamic simulation system that integrates a discrete event simulation system and an agent framework.

There are various definitions of software agents in the academic world. In the context of this paper, an agent can be considered as a software system that communicates and cooperates with other software systems to solve a complex problem that is beyond the capability of each individual software system (Shen *et al.*, 2006). In this context, a software agent should be able to act without the direct intervention of human beings or other agents, and should have control over its own actions and internal states.

The proposed agent framework enables the system to automatically make a design or operational decision in a distributed manner. The decision making process can be briefly described as follows: (1) software agents continuously observe changes occurred on market demands and shop floor operations; (2) an agent proposes alternative design and operational solutions; (3) a new solution triggers other agents to propose corresponding solutions; (4) discrete event simulation is invoked to evaluate the alternatives considering stochastic behaviors; (5) a solution is chosen based on predefined criteria.

The framework consists of two types of agents at the system level and component level (Figure 1). The agents at the system level include a layout configuration agent, line balancing agent, sequencing agents, market demand data agent, a process data agent, and a synchronization agent. These agents represent functions that are intended to achieve. At the component level, agents represent

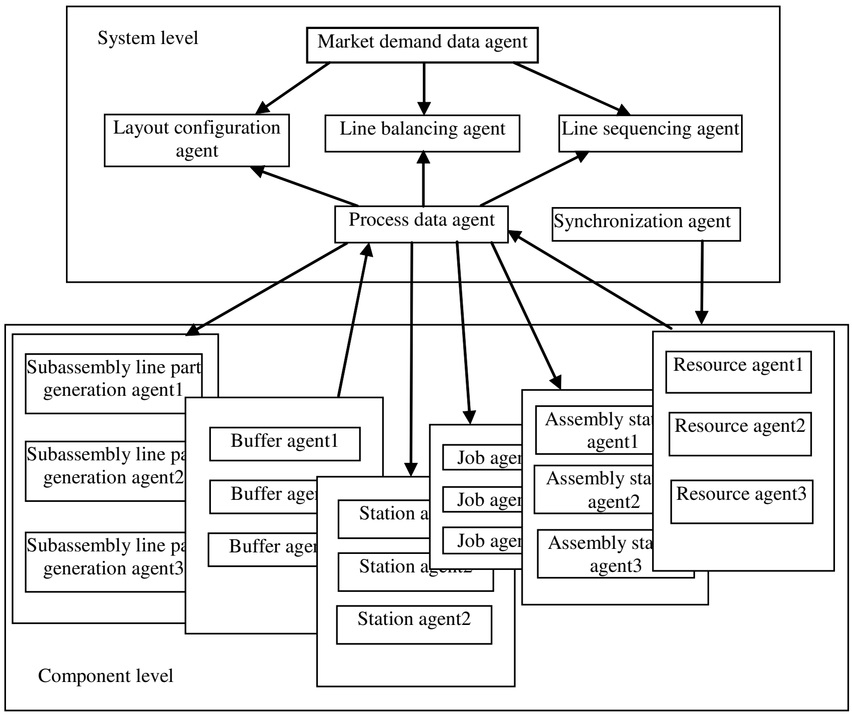

Fig. 1. An agent framework for dynamic performance simulation and evaluation

physical entities, including part generation agents, buffer agents, station agents, job agents, assembly station agents, and resource agents. These agents communicate their states and coordinate their actions.

3.1 System level agents

Decisions related to operation performance in a planning stage are made through the system level agents, including line layout configuration, line balancing, and line sequencing. Other system level agents are responsible for data processing and communication.

The line layout configuration agent first determines line cycle time and the number and sequence of stations on the line based on market demand projection and technical constraints. It can then establish the line layout and connections between component level agents for a simulation model. Alternatively, it supports the use of existing line layout data for the simulation model.

The line balancing agent allocates tasks into each station based on precedence constraints and average model mix from market demand to level the total workload among stations. Since several tasks can be performed on a single station, assembly times can be obtained by adding task times for the station and be used by the line sequencing agent in a subsequent step.

The line sequencing agent determines job sequence based on actual daily orders. In the first phase, a final assembly line sequence is to be determined with multi-objective optimization. One objective is to level the workload for each station. The other objective is to minimize the setup time on a painting line by grouping the same color workpieces together. Since these two objectives are in conflict with each other, the best sequence for one objective may not be the best solution for the other objective. Hence, a set of trade-off solutions (Pareto optimal set) which are good compromises among the objectives can be determined. Note that a solution is called Pareto optimal if there is no other feasible solution which would decrease some criterion without causing a simultaneous increase in at least one other criterion (Coello, 2006). Multi-objective genetic algorithm can be used for implementation. In the second phase, the painting line sequence is optimized to minimize the cost of setup time and inventory of a buffer, while respecting the constraint of the sequence of the final assembly line. The third phase is a simulation process, where alternative solutions obtained from the two phases are simulated to determine the best solution based on station utilization and bottleneck criteria. Note that the assembly times used in the first two phases are mean times. Probability distribution should be applied in the simulation model to consider variable times in manual operations, missing materials, and machine break down and repairs.

Interactions among agents occur bi-directionally across the system and component levels, as well as at the same level. The changes of a model mix pattern on the market demand agent will trigger the line balancing agent to modify the task allocation for stations. The daily changes of a model mix on the market demand agent will cause the line sequencing agent to propose alternative sequence solutions. These alternative solutions are sent to the component level agents for simulation. The line sequencing agent determines the best sequence based on simulation results.

3.2 Component level agents

Component level agents support decision-making on both the planning stage and a run time stage. At the planning stage, these agents interact with the system level agents in the simulation process. The part generation agents send the parts into assembly lines according to the sequence and start time. The station agents process jobs according to assembly times for a particular job at the station. The assembly agents wait until two merging jobs arrive and process them. The buffer agents can rearrange the job sequence for a next line. Based on simulation results, the line sequencing agent determines the best solution by evaluating station utilization and bottleneck criteria.

At the runtime stage, the component level agents support decision-making responding to dynamic disturbances in shop floor operations, respecting the configuration and sequence set out by the system level agents. For each component level agent, a runtime interactive interface is provided to a user for entering any changes on production line operations, such as delay in a station, current buffer inventories or worker absence. The status of assembly lines can be updated through the synchronization agent, which in turn updates the status for every agent at the component level. With the runtime interface and the synchronization agent, current operating conditions can be mapped to a simulation model. Hence, decisions made based on simulation results can be applied to actual operations.

In an event of delay or worker absence, a resource agent is triggered for resource allocation. Various control strategies can be applied for resource allocation. For example, when two stations compete for one resource, one strategy would be that the resource goes to the station with the longest delay, and another strategy would be that the resource goes to the station close to the end of the line. By using different strategies in simulation runs, the resource agent can evaluate and make a right decision. The criteria in such a decision making process is minimizing the impacts of disturbances in production. That is to bring the current operation conditions to the planned one as close as possible.

4 Conclusion

In this paper, we present a dynamic approach for simulating mixed-model assembly lines with an agent framework. The uniqueness of this approach includes:

- Considering stochastic behaviors in mixed-model assembly lines optimization by simulating alternative solutions generated in multi-objective optimization, and finds the best solution.
- Automatically detecting dynamic changing environment in assembly line operations to propose design and operational solutions with the support of an agent framework.

This paper presents some preliminary results of our ongoing work towards a agent framework with a dynamic simulation environment. Further research and development is required in building a real-time decision support system that integrates the simulation system with physical environments for real time monitoring, planning, scheduling, and execution of shop floor operations.

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