Information Engineering Express
International Institute of Applied Informatics
2023, Vol. 9, No. 2, IEE765

Bottleneck Simulator for Wide Scope of Supply Chain Networks using Lead Time

Yoshiatsu Kawabata *, Yuta Hosokawa *, Katsuhide Fujita †

Abstract

With the introduction of the Digital Transformation era, It is now feasible to obtain digital data on the shop floor of the manufacturing facilities and across the whole supply chain (SC) network for improved management. Bottleneck (BN) detection is the first to achieve more effective SC management. We identified the SC bottleneck regardless of the production policy differences of factories between push and pull by simulating the accumulated lead time (LT) data on the SC network map. This study proposed the following features. First, a simulator is proposed that imitates the production of the entire SC network by assembling the materials into the finished goods. Second, this simulator is designed on the map only using the simple Key Performance Indicators (KPIs) that are the average LT per lot and the standard deviation of LT. It is simple enough so that the method would be viable in the real fields. Third, it can identify the BN from the remaining quantities of work in processes (WIP) between the nodes in a high-demand situation. Finally, it identifies the BN based on the use of nodes by creating the low-demand situation virtually. We ran this simulator on five different shapes of the SC maps, demonstrating that our simulator is deployable on each map.

Keywords: Bottleneck, Lead Time per a lot, Simulator, Supply Chain

1 Introduction

To avoid a loss of sales opportunity for the supply chain (SC) network, it must deliver the product in the Just In Time manner,[11]; however, the market demand and the capacity to produce the parts from each node fluctuate regularly in the real world. It is challenging to effectively change the production capacity for each factory or workstation (nodes) in response to demand fluctuations[13] because each node's flexibility varies. If a node cannot match the increased demand, it eventually becomes a bottleneck (BN), resulting in sales opportunity losses for all SC network members. This damages the balance sheet by creating unsold goods or overspending on capacity without generating enough revenue.

Normally SC network owner tries to deploy a special task force team of industrial engineers to resolve the BN, but it could be challenging to determine the appropriate BN within

* Graduate School of Engineering, Tokyo University of Agriculture and Technology
† Institute of Engineering, Tokyo University of Agriculture and Technology

the vast SC network that constrain the performance. Even if the owner increases the capacity of the non-BN, the result brings redundant work in processes (WIP) at non-BN in the push production system. Because the outcome from the actual BN is still insufficient, the increased WIP from Kaizen activities at the non-BN does not help the SC network improve the number of deliveries to clients. Thus, all non-BN activities represent a waste of time and money, and it would be critical for all stakeholders of the SC network to find the BN correctly. The emergence of the digital transformation enables us to detect information on the shop floor within the SC network[14]. It is feasible to increase the overall factory's efficiency by evaluating the obtained data through simulations[23]. Industries, like manufacturers, are attempting to visualize the status of the SC network at a glance using dashboards[21]; however, a feasible dashboard system to monitor the status of the whole supply chain network remains undiscovered.

We proposed a simulator that imitates the production of the entire SC network by assembling the materials at each node. We monitored the production performance under five different shapes of maps. Because it is flexible simulator, the magnitude of the demand from customer can be set freely. Unlike the real world, we can let each node order only the quantity of customer demand to upstream material suppliers. That enables us to eliminate both exaggerating redundant WIPs and redundant jobs. Then, the remained WIP quantity at high customer demand situation should be the first indicator to evaluate the balance of the node performances. If we set the customer demand lower than the supply side, the utilization rate of the nodes can be the other indicator. If the capacity of certain node is inferior to others, it runs longer. We lined up the data of nodes in the order of the utilization rate and named this magnitude the BN degree. This degree can be the priority of Kaizen activities[1]. Beyond the prior paper[8], we deployed the experiments on five varied maps.

The structure of this study is as follows. First, we presented the related existing works about SC networks and multi-agent simulation; second, we proposed two strategies for detecting the BN; third, we demonstrated that the proposed methods correctly detecting the BN; and finally, we provided the conclusion and the future projects.

2 Related Works

There are various main methods in Industrial Engineering for locating BN.

(1) The method for comparing the required production time based on the product mix, the cycle times and the average quantity, and other factors against the owner's capacity[20].

(2) The method for predicting the BN from the node's stacked WIPs[16].

(3) The method for predicting the BN from the rate of the node use, in other words, utilization rate[18].

(4) Value stream analysis: The process for drawing a diagram of the material flow and the information flow, which changes operations in the future by visualizing the current status, mainly in the manufacturing industry[19].

[1] Even after Kaizen's actions at the BN, the throughput development will come to a halt in the real world. This is because the initial BN is no longer a BN, and another node has taken place at the top BN. Thus, SC owners must continually look for the top BN to maintain their growth[13]

Still, the methods above are not always perfect for several reasons. (1) The methods may be inaccurate since they do not account for fluctuations of the product mix, even if the reality is dynamic, and they (2) may be inaccurate to the noises of non-market-driven works in the queue stacks. There are many WIP queues without orders from consumers in the real SC networks, aiming for preemptive manufacturing. Some of those works might become dead-stocks if unsold; however, obscuring the real BN after the stack-ups creates the impression that the node before the WIP stack-ups works better than the node after. Furthermore, the snapshot data of the WIP quantity might have been taken in an exceptional case of randomness from the statistical perspective. Works performed without the market's order increases the use of nodes by producing redundant WIPs, which is a waste that puts the balance sheet in jeopardy if unsold. The WIP inventories cannot be relied on for the judgment depending on the push or the pull production system. Therefore, the method (3) has the same noise as (2) in the utilization rate data. This method can depict only the limited area in the same picture that flow is simple and measured under the same production policy. The production policies of "push" or "pull" should be consistent within the scope of comparison. Make-to-order, or preemptive push production basically depends on the product's character; however, there may be factories with different production policies even among the same network producing the same product. In such cases, we cannot compare the utilization rates in the same manner between the factories that produce without orders and the factories that stay idle if there are no orders. (4) At a glance, this method is not good at showing the BN aside from the simple straight flow case, the widely branched river Amazon shape is not easy to draw in this diagram to find the BN and is challenging to draw without skills and time. Automation of drawing is also not easy.

Both (2) and (3) have the shadowing effect on the area after the BN. If the second-worst BN is located immediately after the worst BN, both the queue stack-ups and utilization rate of the second BN might be measured less seriously than the actuality. Additionally, the other nodes at the different branches of the streamline might be counted as second-worst, even if they are less severe. It is because the worst BN eases the workload of node just behind by delivering slower WIPs from the throughput's real pace. Therefore, the function of this simulator is important in lowering the pace of customer demand than the BN's pace without changing the production side specs to see the actual capability of nodes.

Smart manufacturing research has become popular recently. The introduction of the Internet of Things helps use information regarding production status, analysis, and different levels of stakeholders, such as machines, factories, and Enterprise Resource Planning; however, Industry 4.0 can bring networking, visualization, and automation to monitor resources, manage industrial lines, and assist with auto-set ups[23]. Inventory management is a perennial issue in the manufacturing industry, and a method to prevent the bull-whip effect has been researched[5]. As research on artificial intelligence progresses, the manufacturing industry uses machine learning and simulations to increase efficiency[2]. A recent study considered the batch size, due dates, production capacity, WIP quantity, machine utilization rate, and other factors [15].

It is crucial for business to focus on the competitive edge in supply chain management (SCM). It is important to select right suppliers, manage the lead time(LT), and cope with the changing market for building and running the SC, including global logistics. The SC network has spread worldwide; however, companies must strengthen the relationship for day-to-day operations between components manufacturing companies worldwide and the sales network to consumer. To supply the essential items that meet the market' s region-dependent features, alignment; quick reactions; and strong connectivity between procurement, production, and sales are necessary[4].

SCM has characteristics that make the agent technology ideal for assisting decision-making based on the simulations. A multi-agents system can be used to model or perform tasks in SCM due to the similarities between the two systems[9]. The reasons for that are as follows:

- An SC consists of multiple parties working on multi-stage tasks, whereas a multi-agents system consists of different types of agents with varied roles and functions.
- There is no single authority. Knowledge is distributed among members, decision making in the SC is accomplished through multiparty negotiation and coordination, and agents are autonomous; they are responsive to changing environments, proactive in taking self-initiated action, and social in interacting with humans and other agents.
- The structure of the SC is flexible. It can be organized differently to implement different strategies, and the agent system is flexible; agents can be organized according to various control and connection structures.
- An SC is dynamic. Entities may join or leave the SC; agents can be created or discarded from a multi-agents system[7].

Kaihara et al. demonstrated a technique for determining the optimal SCM as a whole chain by letting the nodes negotiate in a virtual market to maximize each node's use. Three types of agent nodes were used in the virtual market: supplier agent, intermediary, and customer[6]. Supply agents employ capital to produce certain goods, and make and sell the goods to the consumers for a profit. The customer agent purchases the goods and delivers them to downstream markets. The intermediate agent is a player that provides a trading venue such as an e-marketplace. This process uses the 4-Heap algorithm[22].

Furthermore, previous works of simulation-based BN detection have been demonstrated. Lin et al. proposed a data-driven strategy for short- and long-term throughput BN identification. This method uses the production line blockage and starvation probabilities, and buffers content records to identify the production BN without building an analytical or simulation model. This method has been verified analytically and by simulation, and an industrial case study was used to demonstrate the implementation and validate the efficiency of the proposed BN detection method[10]. The Elba project was designed to achieve an automated iterative staging to mitigate the risk of violating Service-Level Objectives. As part of Elba, we conducted performance characterization of the system to detect BNs in various configuration scenarios, where the proposed BN detection approach showed resilience and accuracy; It uses Rice University Bidding System, a well-known benchmark application, to evaluate the classifier's performance in identifying various BNs[12]. Bodner et al. proposed high-fidelity models of manufacturing systems from a computer science perspective. Such high-fidelity modeling has important benefits in prototyping system performance; however, it requires support from a modeling discipline or structured approach to modeling factory operations. Results are implemented as generic code modules in Simulation Management and demonstrated with a case study in semiconductor manufacturing[1]. Roser et al. presented a method for detecting the BN in a discrete event system by examining the average duration of each machine's active time; the BN is the machine with the longest average uninterrupted active time. The method is widely applicable and capable of analyzing complex and sophisticated systems. The results are highly accurate, with a high degree of confidence in distinguishing between BN and non-BN devices[17]. Furthermore, they compared the two most used BN detection methods in terms of Automated Guided Vehicle usage and waiting time[3].

Although those technologies are available, it is still challenging to enhance the surveillance scope for the production status over the different SC tiers. Therefore we propose this method for the simple and viable surveillance system to enhance the monitoring area to more comprehensive entire SC network.

3 The SC Simulator to Detect the BN

This simulator runs on a map imitating the SC network for one kind of Finished Goods(FG). The node signifies companies, factories, and processes. Each node needs the data of the average LT per one lot (*mu*) and the standard deviation of LT (*std*) to run the simulation. The standard deviation can be calculated from the LT database obtained from the shop floors. Actions of each node are, ordering input materials upstream, processing items with received materials, and dispatching FG downstream. The order quantities for the materials are not above the customer's order quantity because the yield is not considered in this experiment. The processing of each node starts only after receiving the customer's order (Pull flow: No pre-emptive production starting) and the inventory of FG is shipped immediately (No FG inventory at dispatching side).

The set up of node relationship

The map is created with linking the nodes that represents both processes within the production line or factories. There are no limits on the number of nodes connected, provided the processing power is available; one simulation for 30 nodes up to 10,000 steps took around three seconds in the given environment in this experiment. The input and output parts numbers, and quantities are set; if all input parts have arrived, the nodes start assembling and producing predetermined quantities. For the simplicity, all quantities of each kind of input parts, and output parts are set as one piece. However there are no limitations on the number of input parts or their quantity and, shipping destinations can be multiple if the output product amount in one lot is multiple. Furthermore, all nodes are linked without isolation, and the last node produces the FG, which are then dispatched to the customer, with completing the order.

The flow of orders and the product

Different parts are handled on the steps between the various layers of the nodes in the simulator. In this simulator, the production system of all nodes is "pull" without preemptive production to eliminate the tasks that the customer did not order. The customer places the orders at specific intervals with random dispersion within the pre-set standard deviation. This research ignores the yield that means the good product rate among all production and all FG are considered a quality product. Therefore, nodes only sends orders to the upstream tiers in quantities needed to fulfill the current orders from downstream nodes. All nodes start production only if all required input parts have arrived; otherwise, the nodes stay idle waiting for the unreceived parts to arrive.

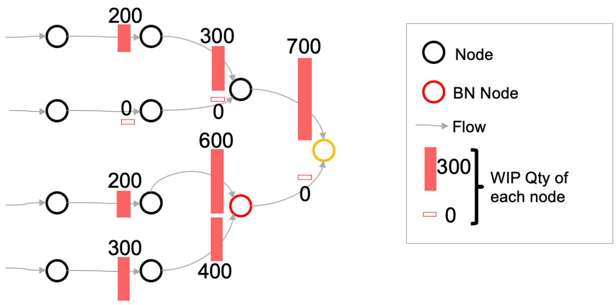

Figure 1: The quantity of WIP at the input side of the node (Method1)

Step procedures

Once ordered, the node calculates the needed lead time randomly with Gaussian distribution from the pre-set average LT (*mu*: the number of needed steps to finish the production processing at that node) and the standard deviation of the LT(*std*). After the calculated steps, that node's manufacturing is complete, and the product is delivered downstream instantly; the subsequent nodes follow after receiving all needed parts from upstream. After completing all the pre-set processes, the simulator outputs the records of all steps, such as the customer's received number of FG and all WIP traces. One step includes the sub-steps of renewing the latest order, processing the parts and dispatching the FG, and determining whether the next production should begin.

The simulator's parameters are as follows:

- the relationship connections between all nodes
- the quantity of both each input and output in a single lot on the node
- the average LT for production on each node (*mu*)
- the standard deviation of LT on each node (*std*)

4 BN Detection Method

This paper proposes two methods to detect the BN.

Method 1: Quantity of WIP Queue at the input side of the node

We proposed this method first to identify BN by finding out the node with the highest material quantity of stack-up WIP at the end of the whole iteration steps (Figure 1). This simulator runs with pure orders from the customer, and we can assume no noise of WIP that is not linked to the orders. The conditions are as follows:

- It is the BN node that has the largest material WIP quantity at the input side. In the Figure 1, orange color node has 700 WIP that is the biggest and seems to be the BN at a glance. However it's not, because of the next explanation.

- If one of the input WIP was zero, that node is excluded from the BN candidate. In other words, all materials at the input side of this node should not be zero. If this node's production is delayed due to shortages of input material, then the delay was not caused by this node's low capacity but rather the slow arrival of upstream materials. Therefore the red color node is the BN on the Figure 1 instead of orange one.

- The top upstream tiers should be excluded because the input side inventories of this tier were set extremely high to be able to run the simulation .

Method 2: Rate of the utilization of the nodes by creating the low-demand situation

Due to the flexibility of this simulator, it is feasible to change only the demand virtually without affecting the *mu* and *std* KPIs. The whole supply-side does not run for the unnecessary WIPs, and the supply side remains idle if there is no demand. We compared each node's usage by simulating a recession or poor sales situation where the pace of the customer orders is slower than that of the longest LT node. The usage means the ratio of the active steps of the node to the total iteration steps. We assumed that the low usage rate indicates the nodes' good capability, and the higher usage rate is deemed as the inferior node capability.

5 Experiments

5.1 Scenario of the experiments

In this experiment, the geographical end of production node sequence is named as manufacturer, and it produces only one kind of end product. All the production side nodes are finally connected to the manufacturer, and the all inputs are assembled into the end product, selling to the consumer without unconsumed leftovers. The FGs are promptly dispatched downstream; they are not kept in inventory of dispatching side. In the real world, production activities can occasionally fail. The rate of successful product among all production is called yield; however, we set the defect rates to zero, and the yield is 100% at all nodes in this simulation for the simplicity. Furthermore, all WIPs in this SC network are linked to orders. Because there are no stand-by FG in the dispatching warehouse, the consumer does not receive the goods immediately after placing the order and must wait for the components to flow downstream from the source. Thus, none of the nodes run without orders, which is the perfect the pull or the make-to-order production system. This is how to eliminate the noises of the dead stocks to focus only on the signals about capacity on this simulator.

The node relationships and the KPI figures are shown in Figure 2. For example on map 1, the Factory_00 is the manufacturer. Factory_01$\sim$04 are Tier1 suppliers. Factory_05$\sim$10 are Tier2. Factory_11$\sim$18 are Tier3. The most upstream Tier4 consists of Factory_19$\sim$29, and there are enough inventories on the input side of Tier4 at the starting point of the flow. We place the names of the nodes at the top center of the node boxes. *mu* and *std* are the KPIs for completing one lot's production. The finished product names can be found on the right side of the boxes. On one lot, the quantity of finished items is at the bottom right, and each input's needed amount is listed at the bottom left. We repeated the simulation 100 times, to reduce statistical fluctuations, with consisting of 10,000 steps per one simulation.

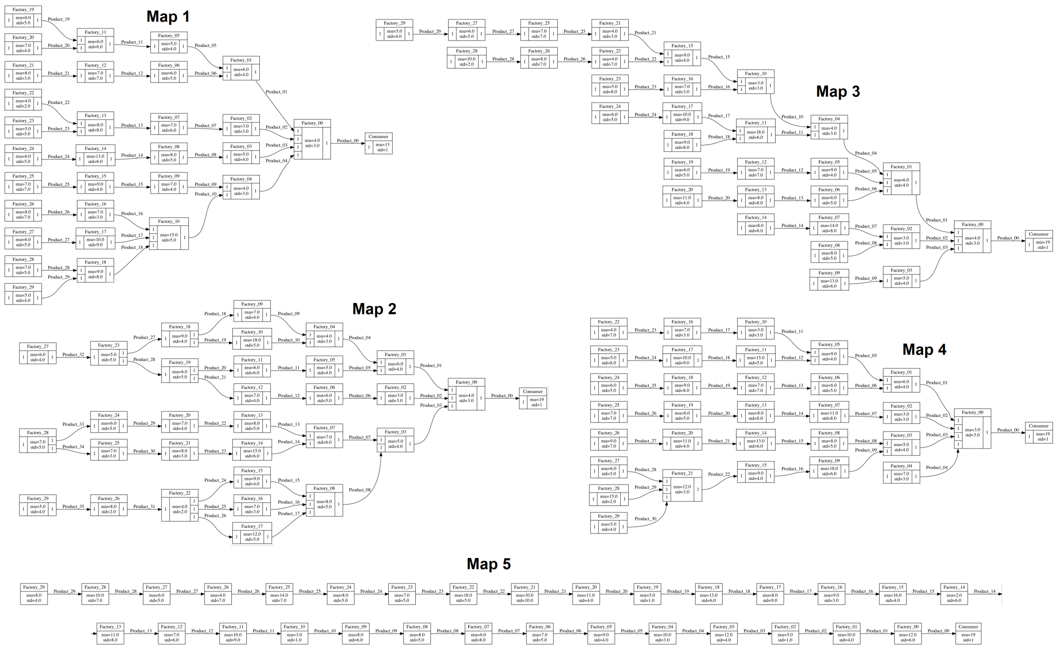

Figure 2: The structure of the SC networks for this experiment

Table 1: The detected BNs

Map name	map 1	map 2	map 3	map 4	map 5
BN names	Factory 10	Factory 10	Factory 11	Factory 09	Factory 22

5.2 The pre-experiment to find the BN in this scenario

Using the method below, we detected the correct bottleneck before running the experiments of Methods 1 and 2. We improved the KPIs of *mu* and *std* by 20% at only one node to run one experiment and repeated this experiment 30 times, improving different nodes each time. If the improvement was on the non-BN, the total throughput delivered to the customer should not be changed; however, it improves the total throughput if the BN was correctly selected.

The total quantity that the customer received showed the improvement at only one factory as Figure 3 among 30 trials, on all five map shapes. All results are shown on the table 1. With this as the proper BN names, we deployed evaluations on two proposed methods of the experiments. To find the correct BN, these simulations require massive, time-consuming calculations and are impossible to perform manually.

5.3 The result of detection method 1 by evaluating the WIP

Table 2 shows the rate of the correct answers from each map detected by Method 1. This method detected the BN correctly almost every time. Scrutinizing those few failure cases indicates that some nodes received the WIP at the last step due to randomness, even through input material were almost always 0 at the node. If one of the input side's WIP was 0, that

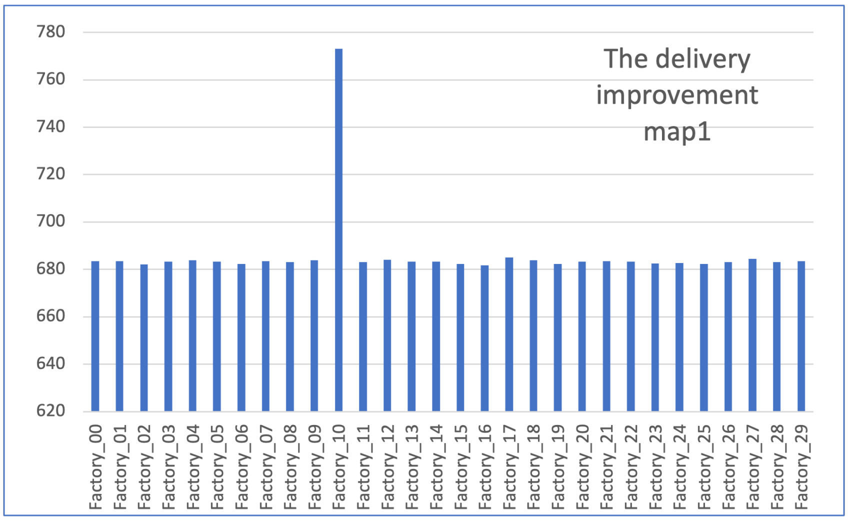

Figure 3: The number of the total delivery when the nodes are improved 20% on map 1

Table 2: The rate of the right answers on method 1 by WIP

Map name	map 1	map 2	map 3	map 4	map 5
The rate of the correct detection by method 1	99%	100%	98%	99%	100%

node should not be considered the BN. Therefore, Method 1 must be improved for more accurate detection, however, this method worked for most cases. In a certain experiment, We made only one node extremely long as 55 for trial, even other LTs are 18 or less. We did not find any stacked WIPs in this case because all other nodes completely finished productions during the BN node taking extremely long LT, and failed to detect the BN. Therefore, Method 1 can not detect BN correctly in the case that one node has extremely longer LT than others. The balance of LT among all nodes is important for this method.

5.4 The result of detection method 2 by utilization

Table 3 shows the rates of the successful detection by Method 2. The simulator worked perfectly, and Method 2 produced the bottleneck degree as the side effect. We also deployed the extreme case where only one node has LT of 55 like what we did on Method 1. Method 2 did work even on the unbalanced map because the bottleneck with LT = 55 is just running at a higher rate than others and it's possible to detect it.

5.5 Discussions to LT to each node

Method 1 was affected by the unbalanced LT within the map. The unbalance will be caused in the real world by the difference of the scope whether the node represents the process in the production line or represents the whole factory. Some factories in the SC network may refuse to disclose the production capability data at each process in real use cases. Such suppliers only show grudgingly low resolution LT data from when the material arrived to

Table 3: The rate of the right answers on method 2 by utilization

Map name	map 1	map 2	map 3	map 4	map 5
The rate of the correct detection by method 2	100%	100%	100%	100%	100%

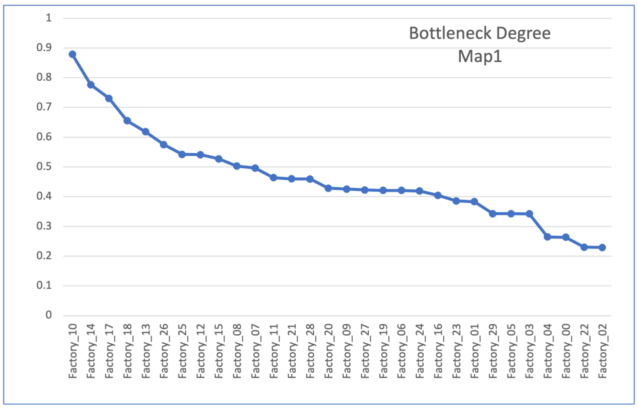

Figure 4: The BN degree of map 1

this factory till when the FG dispatched. It is because the internal data is sensitive. That means the Method 1 is not viable with unopen suppliers. Contrary, Method 2 could detect the BN correctly even with exclusive suppliers that causes the unbalance on the map with extremely long LT. However, it would be expected that such data with rough granularity without detail, contains the waiting time of the inventories between the processes. Therefore most provably such bad granularity node would be wrongly named as the BN among high granularity nodes. It will be required for the accuracy to prepare the homogeneous LT data within similar range. Therefore, the next step of this research requires to resolve this granularity issue for precise BN detection.

6 Conclusion

Industrial engineers frequently find the BN from the stacked WIP quantities between nodes; however, those can be inaccurate in many cases. Those WIPs may include dead stocks that are not linked to market orders. The node could be misunderstood as the BN based on the long queue of WIP of dead stocks, even if this node promptly produced the needed parts. The utilization rate is the other famous parameter in the industry to find the BN; however, push or pull policies and ordering conditions should be the same to compare the sampled utilization rate in the same picture. It had been challenging to enhance the visualizing scope to entire SC network.

This study developed the simulator from the SC map and the simple KPIs of each node obtainable from the accumulated LT records, enabling BN detection using two different methods. The ratio of product mix, the yield, and the variation of the production lot size were not considered this time for simplicity. The two methods to identify the bottleneck are focusing on the remaining stacked quantities of WIP between the nodes in the high-demand situation and the usage rate of nodes in the low-demand situation. We evaluated the ability of this simulator on five different maps, and the proposed methods showed promising results coherent to the pre-determined result of correct BN names. The simulator could detect the utilization rate even for nodes located immediately after the BN without the shadowing effect. The second method that use the utilization rate also showed how each node's magnitude is close to the BN. This simulator would be practical and adaptable to a broad scope of SC because the database of LT per one lot is one of the most popular data obtainable from actual SC networks. Additionally, this simulator can neglect the policy differences of the production system of the real SC network, regardless of push or pull, which had not been negligible previously.

This research will require future consideration concerning the yield, the product mix, and the mixture of different granularity of LT. Furthermore, the proposed simulator does not consider the interactions between nodes, such as negotiations. An improved simulator will be able to analyze more wider aspects in actual cases in the following research.

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