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LEAN DESIGN AND ANALYSIS OF A MILK-RUN DELIVERY SYSTEM: CASE STUDY

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ABSTRACT

Multiple discrete event simulation models are developed to represent a milk-run delivery system in an automobile emissions system production facility as part of a logistics system overhaul. The aim of this study is to analyze resupply configurations and variability in key model inputs in order to make recommendations based on supply train utilization and workstation starvation. This study includes three experiments that compare optimized routing, recommended routing, and on-demand resupply systems. Sensitivity analyses are conducted to measure the effects of various factors such as number of supply trains, travel speeds, and load and unload times to find the best combination of input parameters. The results of the proposed simulation models demonstrated potential impacts of a milk-run delivery framework on pull systems with limited transport capabilities, but diminished improvements on systems with multiple supply trains.

1 INTRODUCTION

1.1 Background

As the global leader in the production of emissions systems for automobiles, an automotive company develops and manufactures complete exhaust systems from hot end manifold to cold end tailpipes. The facility located in Louisville, Kentucky was selected as the future model production site for the North American division. To achieve this feat, the plant manager established a number of improvement objectives including an internal centralized delivery system known as a *supermarket*.

The logistics team was tasked to develop an internal centralized supermarket delivery system for raw material storage in order to support lean manufacturing. The term lean refers to the implementation of a focused factory design that facilitates grouped technology, balanced production cells according to customer takt time, execution of a pull system for final and preceding lines, and emphasis on one-at-a-time production. In order to support lean manufacturing, the management designed a milk-run delivery system within the facility, stabilizing the on-hand inventory. The corporate business group provided resources for the site to develop and implement an internal storage location for raw material components. The raw materials were initially stored externally, on-site, under industrial sized canopies, on 48 inch by 45 inch pallets used for delivery via forklift. This method turned out to be difficult to manage and existed as an unnecessary security risk to profit loss, a decades old problem identified by Ireson (1952) in early factory planning literature. Furthermore, the production cells were forced to hold excess raw materials on line, which impacted the amount of floor space required and the length of lead time for customer products as a consequence to the large unit load. While large unit loads may expedite shipping and induction procedures, the delivery of large unit loads to the production cell required additional space to receive those materials and stage them within the production area.

To complement the management advantages to a supermarket, a small vehicle, known internally as a *train*, was used. A small train facilitates the delivery of highly dense and diversified unit loads to the production cells with materials delivered to multiple production cells along a single standardized route. The small train delivery method can result in stabilized lead-time of products to the customer, and potential savings in valuable floor space. The savings occurred from the increased frequency of small unit loads consisting of only products a production cell needs, at the time they are needed.

1.2 Literature Review

Previous work in material handling systems is extensive. For the purpose of this production facility redesign, we reviewed mixed model assembly lines, just-in-time (JIT) production cell design, material handling, warehousing operations, and shipping and receiving procedures.

An assembly line capable of producing several different models at the same time is known as a mixed model assembly line. These lines have the ability to quickly respond to variation in customer demand. Ding and Cheng (1993) stated that one of the biggest challenges is designing a line layout and balancing the work content amongst the operators. The line layout must be capable of allowing operators of performing the tasks to evenly distribute workloads involved in producing a part. Coleman and Vaghefi (1994) discussed this concept of production leveling, or its Japanese term *heijunka*, as essential to increasing flexibility and more constant part usage rates. Production leveling can lead to machine idle time, but given that customer demand is met, the machine idle time is secondary due to effects overproduction has on inventory levels.

The Nagara system discussed by Shingo and Dillon (1981) introduced the concept of freeing up operators from a single machine. In the Nagara system, a worker is assigned more than one process, or machine, at a time. For example, a worker may activate a machine with an automated process, then move to the next and repeat this for as many machines as possible within a worker's cycle time limit. The limit is on the basis of customer takt time, or minimum cycle time that a part may be produced in order to meet the given demand. A multi-train workforce was one of the most significant factors in the reduction of waste in the just-in-time functional model of Daugherty, Rogers, and Spencer (1994).

Assigning more than one machine requires the layout design to permit an operator to have capability to access all equipment and complete his/her process cycle within a time limit. Miltenburg (1989) discussed product scheduling and offered key performance indicators for a mixed model assembly line. Key performance indicators (KPI), e.g., inventory level and setup time, influence the process scheduling. A JIT system is most effective when there is a constant rate of usage for all parts. Boysen, Fliedner, and Scholl (2009) stated that it is best to plan small batch production schedules to reduce the variation in the usage of each part. Finished goods that have similar Bill of Materials (BOM), as in this case, help achieve a constant rate of production.

Another goal of the JIT production system is to achieve a zero inventory level with the focus on an "inventory is waste" philosophy (Bonney 1994). Ideally, material would arrive in the facility, and subsequently to the production line, one piece at a time and only when it is needed; without storing inventory between operations or processes. According to the Toyota Production System (TPS), stock and transportation are seen as two of the seven *muda* (or waste) and should be kept at a minimum (Shingo and Dillon 1981). The reason for targeting zero inventory is that inventory is expensive. In a 1999 study, it was found that US manufacturers purchased materials whose values were equal to 60% of total sales revenue (Gunasekaran 1999), alluding to that the cost of materials went over the purchase price. Akintoye (1995) stated that the costs associated with materials include: procurement, storage, insurance, guarding against theft, and risk of materials becoming obsolete.

While the goal of lean production systems is zero inventory, de Haan and Yamamoto (1999) concluded that zero-inventory management is not realistic to achieve in practice. A minimum level of inventory can have benefits. Heizer and Render (1991) stated that the three functions of inventories are to decouple production, to form a hedge against price changes, and to obtain order discounts. Slack, Chambers, and Johnson (2010) referred to the inventory that decouples production as buffer stock and concluded that such inventory is often necessary. In a lean manufacturing system, this buffer stock can be maintained on the production, or preferably in the supermarket.

Toyota divides waste into seven categories: overproduction, wait times, transportation, processing, unnecessary stock on hand, unnecessary motion, and production of defective goods (Ohno and Setsuo 1988). An effective tool in reducing stock on the production lines is the use of a milk-run delivery system. According to Bozer and Ciemnoczolowski (2013), milk-run systems represent route-based, cyclic material handling systems that are used widely to enable frequent and consistent deliveries of containerized parts on a need basis from a central storage area (e.g., supermarket) to multiple line-side deposit points on the factory floor. A supermarket delivery system aids in decreasing cycle time, which is also one of two process-driven performance measures of Feld (2001).

2 PROBLEM STATEMENT

Within the plant, the production lines uses a Kanban signal in the form of a card to notify operators when materials are needed. A Kanban card displays the material SKU identification number, where to deliver the material, the number of pieces per box, the material planner in charge of ordering the material, as well as other relevant information. A train driver picks up empty Kanban totes along a route and takes them back to the supermarket to be filled. The delivery of stocks and collection of Kanban cards at each location create variability with regard to future deliveries for the milk-run train. In addition, interruptions along the delivery route, weight of the train, and the configuration of the production facility create variability in the travel time of supply trains. Once back at the supermarket, the train driver collects only those materials for which a Kanban exists. These collected materials are then delivered back to the line according to the associated Kanban point of use.

The current facility estimate provided the square footage needed to house the raw materials, but not the means of delivering them to the production cells. In its beginning state, the facility layout was not capable of consistent deliveries, nor any efficient material flows. The limited capability was due to:

- production lines stacked next to each other with no traffic lanes between,
- aisles have obstructed views,
- aisles widths vary (not consistently 6 to 8 feet),
- aisles do not allow for two way traffic,
- traffic rules not applied throughout the building,
- delivery stations not located next to aisles,
- current delivery stations not able to hold small BOM (bulk containers only),
- designated location for materials not set (raw, WIP and finished),
- and materials received in non-standard containers (stored in large unit loads).

One of the main goals for our material handling system design was to be able to drop off materials to the production lines in small quantities at the point of use (Hanson and Finnsgard 2014). Initially, materials were not assigned entry points into the line, and rather dropped off in a central location. This means operators would have to walk to get their respective parts. This delivery method increased variation at the production line, causing delays in production. Also, when components were dropped off, the unit load on a 48”x45” pallet seized valuable floor space. This makes it difficult for logistics operators to determine the time of replenishments, leading to no signal to notify drivers.

The management proposed that new production line layouts, shown in Figure 1, needed to accommodate front feeding flow-through racks to disperse materials at the point of use. The front feeding racks extended from the train aisles to operators in the production line. These racks displayed labels that signified the materials to be located on each rack. The basic design of each rack enabled totes full of materials to flow from the aisle into the production line, as well as empty totes to flow from the production line back to the aisle. Thus, each rack served as a pick-up and drop-off station. These racks had the capability of holding multiple SKUs at each production line. Additionally, the flow-through racks were large enough to hold a limited amount of supply to account for production variation and prevent workstation starvation between train deliveries.

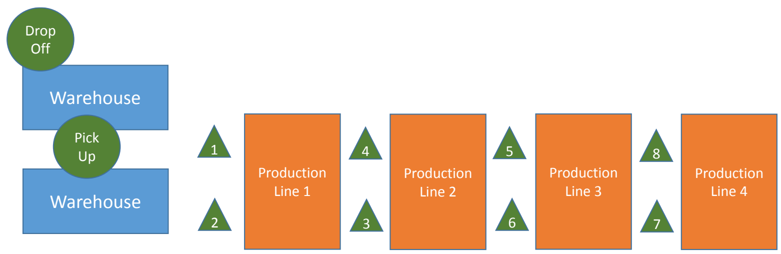

Figure 1: Production line layout with horizontally aligned warehouses.

The production lines operating in the plant are very similar to each other in configuration and processing. This is due to the fact that orders from the same customer vary only by one component of the final assemblies. The machines on these lines were designed by the same vendor, thus the processing speeds are nearly identical. This pre-processing of the assembly line allows for a more consistent rate of parts usage, thus facilitating a more predictable delivery of stocks. If the time between deliveries is greater than 45 minutes, the workstation risks starvation, resulting in work stoppage.

The contribution of this study is evaluation of effectiveness of the milk-run delivery system versus a dynamically-driven, on-demand delivery system within a pull (Kanban) planning framework. We built a discrete event simulation model to see how the effectiveness was affected by 1) one train continuously traveling the route versus two trains running on a predefined schedule, 2) multiple production facility configurations, 3) delivery times at each of the 10 stations, and 4) travel time between stations.

3 MODEL DEVELOPMENT

3.1 Data and Validation

The basic structure of the simulation model includes a series of workstations connected by a predetermined route for the supply train. The baseline model was validated by comparing the model output results to the observed data. One train (and a driver) was operated to simulate ten dry runs in the facility and had an average speed of 2.9 feet per second. It took approximately five minutes to receive part requests and load the supply train, but only three minutes to unload the empty containers at the end of the supply run. A series of tests demonstrated that the amount of time to unload supplies is a function of the number of SKUs for each workstation. Stations 1, 5, and 7 used fewer than four SKUs and had a lower average unload time than Stations 2, 3, 4, 6, and 8. We fitted the model input distributions in the column A to the collected original data in Table 1, and the distributions in the column B were used for the increased time scenarios for the experiments in Section 5.

3.2 Route Optimization

With limited floor space in the production facility, the management proposed two options under consideration for designing the facility layout in Figures 2 and 3, respectively. The two options (L1 and L2) changed the orientation of the supermarket within the production facility.

Table 1: Loading, unloading, and travel speed distributions.

	Distributions	
Input Parameters	A (Fast)	B (Slow)
Supermarket Pick-up Time (min)	Triangular(4,5,8)	Triangular(5,6,9)
Supermarket Drop-off Time (min)	Triangular(2,3,5)	Triangular(3,4,5)
Stations 1, 5, 7 Unload Time (min)	Lognormal(1.157,0.438)	Lognormal(0.985,0.478)
Stations 2, 3, 4, 6, 8 Unload Time (min)	Lognormal(1.303,0.408)	Lognormal(1.157,0.438)
Train Travel Speed (ft/s)	Triangular(1.5,2.9,4)	Triangular(1,2,3)

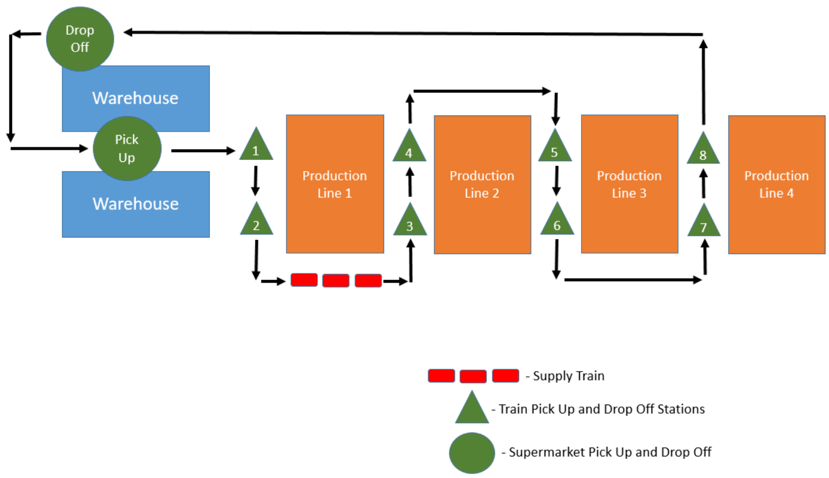

Figure 2: Suggested routing for horizontally aligned supermarket layout (L1).

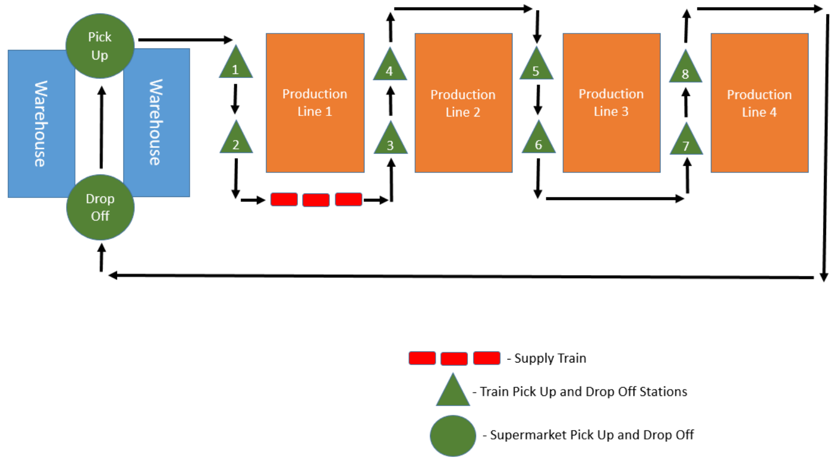

Figure 3: Suggested routing for vertically aligned supermarket layout (L2).

From each layout option, we constructed a distance matrix, D_{ij}, for the distances between each of the stations, the supermarket pick-up point, and the supermarket drop-off point. Based on the configuration and prescribed supply train route provided, we can determine whether the route is optimal; the shortest distance required to complete one loop visiting each of the ten stations. If the current route is sub-optimal, we can still obtain the optimal route and its distance. This is a more quantitative approach to the trial and error or similar approach used by Marchwinski (2003). Given the distance matrix, D_{ij}, we began by evaluating the route as the classic traveling salesman problem Dantzig (1963) structured as an integer programming (IP) problem:

$$Minimize \sum_{i=1}^{10}\sum_{j=1}^{10} D_{ij}\, X_{ij}$$

$$Subject\ to\text{:} \quad \sum_{i=1}^{10} X_{ij} = 1 \qquad j = 1,2,\dots,10 \tag{1}$$

$$\sum_{j=1}^{10} X_{ij} = 1 \qquad i = 1,2,\dots,10 \tag{2}$$

$$X_{ij} = \begin{cases} 1 \ if\ station\ i\ is\ visited\ immediately\ before\ station\ j \\ 0\ otherwise \end{cases} \qquad i,j = 1,2,\dots,10 \tag{3}$$

$$1 \le U_i \le 10 \qquad i = 1,2,\dots,10 \tag{4}$$

$$U_j - U_i + 10X_{ij} \le 9 \qquad i,j = 1,2,\dots,10 \quad i \ne j \tag{5}$$

$$U_1 = 1 \tag{6}$$

$$U_{10} = 10 \tag{7}$$

$$U_i, U_j = \text{integer} \tag{8}$$

In the objective function, D_{ij} is a 10 x 10 symmetric distance matrix for each specified layout. The rows and columns represent the supermarket pick-up point, the eight workstations and the empty container drop-off location. Equations (1) and (2) ensure that each station in the system is connected to have only one previous station and only one subsequent station. Links between stations are identified by the binary variable X_{ij} in Equation (3). Equations (4)-(8) eliminate the possibility of sub-tours. The variable $U_i = t$ is used to denote when station i is visited on the t^{th} step of the tour, where $t = 1,2,\dots,10$. Given that the station drop-off point must immediately precede the supermarket pick-up point, we predefine $U_1 = 1$ and $U_{10} = 10$ in Equations (6) and (7), respectively. We solved this IP problem using Matlab, but it can be easily solved by a host of commercially available optimization software packages. Given the limited number of stations, it is also possible to write a program code using a brute force algorithm to check which of the 10! (3,628,800) routes is the shortest.

4 EXPERIMENTAL DESIGN

Completing this project required planning beyond simply finding the material amounts needed to meet demand. In order to properly implement a lean material handling system, the facility layout was designed to allow for the timely delivery of goods to the line, safe vehicle travel, and adequate shipping and receiving space for warehouse operations. The simulations gauged the timeliness of the milk-run delivery system under safe travel conditions, while the two alternative configurations of the production facility searched for adequate shipping and receiving space. The management assessed that workstations needed resupply every

30-45 minutes. If a supply train arrived within 30 minutes of the previous arrival, it would wait until the 30-minute mark in order to give the workstation operator adequate time to have a Kanban card. If a next arrival is greater than 45 minutes since the previous arrival, it is determined as workstation starvation. Figure 4 depicts the flowchart for the milk-run supply train.

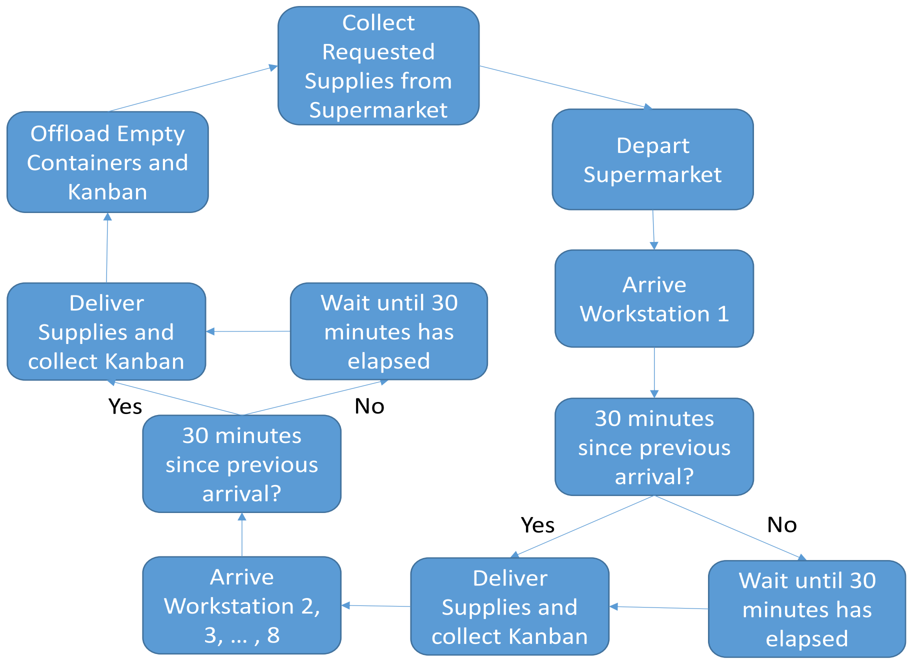

Figure 4: Flowchart for the milk-run delivery system.

Korytkowski and Karkoszka (2016) used workstation starvation and milk-run operator utilization as two primary measures of performance. Similarly, we defined starvation to include both idle time between processes and system delay. Workstation starvation occurs whenever it has been more than 45 minutes between deliveries at a workstation. Milk-run operator utilization represents the percentage of time the operator is actively participating in the resupply of workstations. This rate is affected differently between one-train versus two-train systems. In a one-train system, the amount of operator idle time equals the duration of waiting times in the input buffer. In a two-train system, the amount of operator idle time is the time spent in the workstation input buffers, plus the amount of time spent in the supermarket waiting for the next scheduled departure.

5 SIMULATION RESULTS

We conducted three experiments in this study. The first experiment used results from the traveling salesman problem and compared the performance measures based on optimal routes for the horizontally aligned supermarket (L1) and the vertically aligned supermarket(L2). For each layout, we compared the effects of one vs. two trains, fast vs. slow offload/upload times, and fast vs. slow travel speeds. The second experiment compared the two performance measures based on recommended routes for both L1 and L2 configurations. The third experiment compared an on-demand system where the supply trains do not follow a prescribed route. Instead, whenever workstations need to be replenished, a demand signal was sent to the supermarket. After processing the request, the supply train loaded the parts in the order they were requested and delivered them to the stations in a first-in first-out order. Experiment three was designed on the recommended Layout L1 with the same performance measures as in two other experiments. Workstation starvation occurred when the time from resupply request to delivery was greater than 45 minutes.

5.1 Optimized Route Input Parameter Analysis

The travelling salesman algorithm for L1 yielded an optimal distance of 733 feet. The prescribed route was only one foot longer, but had the benefit of paths that do not cross. For this reason, and the fact that one additional foot of travel increased total travel time an average of 2.9 seconds, the prescribed route was considered as a preferable alternative to the optimal route. The corresponding optimal route for L2 via solving the travelling salesman problem is shown in Figure 5 and has a distance of 745 feet.

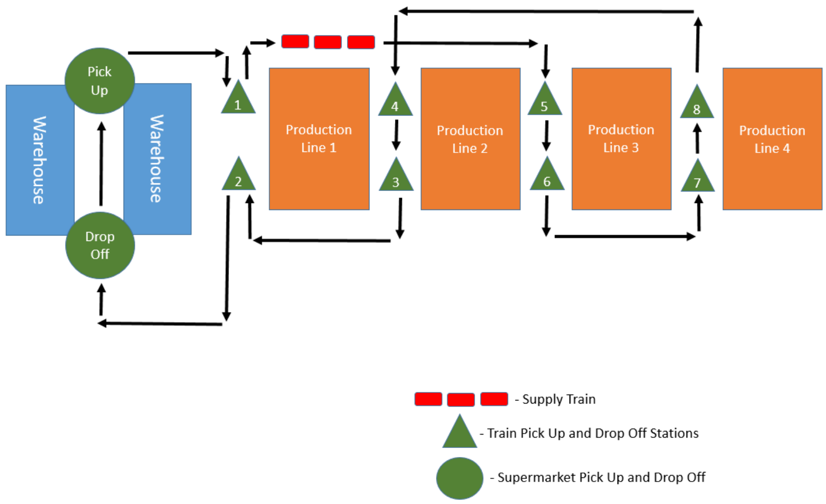

Figure 5: Optimal route for layout L2.

While the optimal route represented the shortest distance traveled, it posed potential problems in practice. First, the route had the supply train changing directions 180 degrees at Stations 1 and 2, which proved difficult to enforce based on the width of the aisles and length of the trains. Moreover, routes cross prior to Station 4 in Figure 5, and this could impede the progress of a train when another train is on the delivery route. Regardless of the implementation challenges, the optimized routes served as a theoretical minimum traveling distance for milk-run delivery systems. The simulation experiment was designed to require three 24-hour replications for each combination of the 16 input parameter settings, for a total of 48 simulation runs. After verifying the normality assumptions required for ANOVA based on the normal probability plot for the residuals, we ran an ANOVA to test statistical significance for each of the performance measures. Table 2 presents main effects and significant interactions at α of 0.05 for total workstation starvation time with optimized routes.

Table 2: ANOVA results for total starvation time with optimized routes.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Layout	1	0.251	0.251	0.28	0.601
Trains	1	269.934	269.934	300.56	0.000
Unload	1	130.076	130.076	144.83	0.000
Travel	1	16.099	16.099	17.93	0.000
Trains*Unload	1	130.076	130.076	144.83	0.000
Trains*Travel	1	16.099	16.099	17.93	0.000
Unload*Travel	1	4.851	4.851	5.4	0.027
Trains*Unload*Travel	1	4.851	4.851	5.4	0.027
Error	32	28.739	0.898		
Total	47	601.675			

Given the significant interaction of number of trains, unload times, and travel speed, the Tukey test in Table 3 shows that any scenario with two trains minimized total workstation starvation time in addition to the combination of one train, fast unload times, and fast travel times. One train with slow unload times and slow travel times was the least desirable configuration, maximizing the total workstation starvation at 9.82 hours, or an average of 1.23 hours per workstation during a 24-hour period.

Table 3: Tukey test (95% confidence interval) of the significant three-way interactions comparing starvation times for the optimized routes.

(Trains, Unload, Travel)	Mean	Grouping
(1, B, B)	9.82926	A
(1, B, A)	6.24113	B
(1, A, B)	1.97291	C
(1, A, A)	0.92803	CD
(2, A, B)	0	D
(2, A, A)	0	D
(2, B, A)	0	D
(2, B, B)	0	D

Similarly, Table 4 shows the main effects and significance from ANOVA results for the train utilization performance measure. The interaction of number of trains and unload times as well as that of number of trains and travel speed were both significant at α of 0.05.

Table 4: ANOVA results for train utilization with optimized routes.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Layout	1	1.02	1.02	4.06	0.052
Trains	1	9480.11	9480.11	37888.07	0
Unload	1	192.26	192.26	768.36	0
Travel	1	22.14	22.14	88.5	0
Trains*Unload	1	191.64	191.64	765.9	0
Trains*Travel	1	21.94	21.94	87.67	0
Error	32	8.01	0.25		
Total	47	9919.1			

From the Tukey test results in Table 5, configurations with two trains and fast unload times minimized the utilization rate with a mean utilization of 67.890%. Any configuration with one train maximized the utilization at nearly 100%. Additionally, two trains with a fast travel speed minimized the utilization rate at 70.534%.

Table 5: Tukey tests (95% confidence interval) of interactions comparing train utilization rates for the optimized routes.

(Trains, Unload)	Mean	Grouping	(Trains, Travel)	Mean	Grouping
(1, B)	100	A	(1, B)	100	A
(1, A)	99.994	A	(1, A)	99.994	A
(2, B)	75.889	B	(2, B)	73.245	B
(2, A)	67.890	C	(2, A)	70.534	C

5.2 Suggested Route Input Parameter Analysis

Next, we used the suggested routes for both the horizontally aligned supermarket (L1) and the vertically aligned supermarket (L2). The route length for L1 was 734 feet and the route length for L2 was 924 feet. According to the ANOVA results, the layout itself was statistically significant as a main effect (α=0.05) with a p-value of 0.024. In addition, with the three-way interaction of number of trains, unload times, and travel time was statistically significant with a p-value of 0.023.

As in the experiment of Subsection 5.1, we conducted a Tukey test comparing the starvation times when number of trains, unload times, and travel times were varied. Any configuration with two trains leads to no starvation time, whereas the configuration with one train, slow unload time, and slow travel speed resulted in the highest amount of starvation time. Furthermore, unload times had a greater effect on starvation time than travel speed.

Regarding train utilization, all four main effects were most significant followed by the two-way interactions of pairs: layout and number of trains; number of trains and unload times; and number of trains and travel speed. The resulting Tukey test indicated that L2 with two trains achieved the minimum utilization rate whereas both layouts with one train required a utilization rate near 100%. In configurations with two trains, fast unload times yielded statistically lower train utilization rates. Additionally, fast travel speeds in two-train configurations produced significantly lower train utilization rates. Figure 6 illustrates the starvation times and utilization rates for each configuration. In terms of high utilization coupled with low starvation as a point of interest to management, Table 6 ranks the top four scenarios based on the respective performance measure.

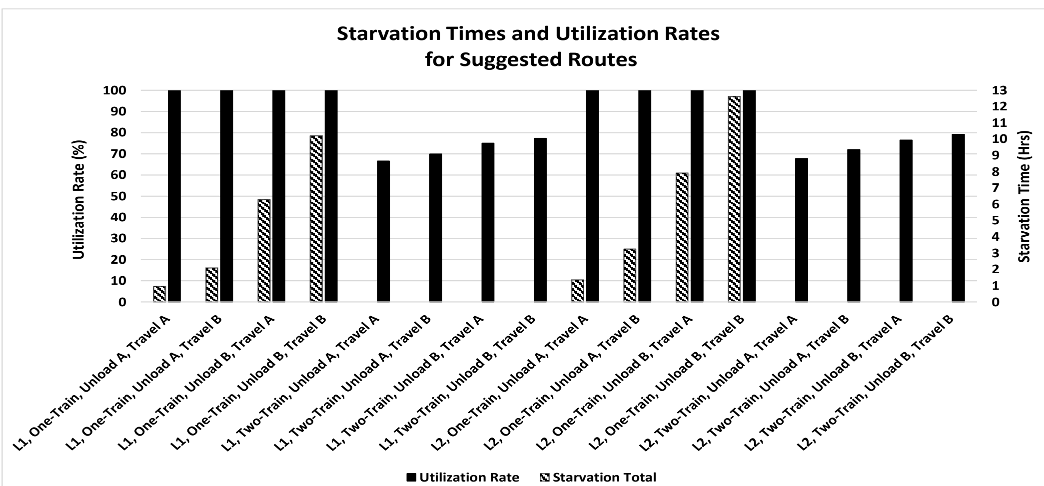

Figure 6: Comparison of starvation times and utilization rates for suggested routes.

Table 6: Scenario ranking based on utilization rate and starvation time.

Scenario	Utilization Rate (%)		Scenario	Starvation (Hrs)	
(Layout, Trains, Unload, Travel)	Value	% Gap	(Layout, Trains, Unload, Travel)	Value	% Gap
(Any, 1, Any, Any)	100.000	0.000	(Any, 2, Any, Any)	0.000	0.000
(2, 2, B, B)	79.165	18.593	(1, 1, A, A)	0.965	92.356
(1, 2, B, B)	77.288	16.133	(2, 1, A, A)	1.359	89.240
(2, 2, B, A)	76.468	14.893	(1, 1, A, B)	2.088	83.463

5.3 On-Demand Delivery Analysis

Finally, we considered an on-demand, dynamically-driven system where workstations sent a demand signal for parts at the supermarket. Trains loaded the requested parts and delivered them in the order requested by the workstations, traveling only to the stations requiring parts, taking the shortest route between stations. The results from ten replications of each level of trains are summarized in Table 7. The symbol δ represents the relative error, which is the half width divided by the mean of the performance measure. The utilization rate for on-demand delivery systems with one train was close to 100% while the total starvation time was 3.520 hours. The utilization rates for an on-demand delivery system with two trains was similar to the utilization rates for milk-run delivery systems with two trains. The on-demand system and the milk-run delivery system both demonstrated the same trends in variability of performance measures. There was much more variability in total starvation time than there was in utilization rate.

Table 7: Summary of utilization rates and starvation time for on-demand delivery systems with one, two, and three trains.

	Utilization			Starvation		
Trains	Percent	Half-Width	δ	Hours	Half-Width	δ
1	99.525	0.133	0.00133	3.520	0.648	0.184
2	70.763	0.594	0.00839	0.00423	0.00760	1.797
3	46.662	0.741	0.0158	0.000	0.000	N/A

6 CONCLUSIONS

L1 had a nearly 100% utilization rate and a total starvation time of less than one hour per 24-hour period, or equivalently seven minutes per workstation. If the cost of a second train is less than the cost of starvation time (approximately 1 hour per 24-hour period), then the investment in a second train would be justified. If the management decides to choose a vertically aligned supermarket, the optimized route would provide significantly less total starvation time for one-train systems over the suggested route.

When one train was used, an on-demand system increased nearly four times the total starvation time in comparison with a milk-run delivery system. The utilization rate for a two-train on-demand system was 70.76% compared to that of 66.56% for a milk-run delivery system with two trains. Using two trains in either the on-demand system or the milk-run delivery system resulted in virtually no starvation time. Therefore, we conclude that the benefits of a milk-run delivery system are increased in systems that utilize only one train. Also, we note that additional trains made little difference between on-demand and milk-run delivery systems with respect to the performance measures of workstation starvation and train utilization.

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