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ALLOCATION PROBLEM AND MATHEMATICAL MODELING OF THE MANUFACTURING SYSTEMS

NAME - KRISHNA KUMAR CHOUDHARY
GUIDE NAME - Dr. SHOYEB ALI SAYYED
COLLEGE NAME - MALWANCHAL UNIVERSITY, INDORE, INDIA

ABSTRACT

Traffic control is expected to be an important task in urban areas for traffic management. Therefore, it is important to improve the traffic director for successful traffic management and better traffic, which indicates the conditions of greening. Road congestion on roads and paths is a fundamental problem that is disrupted by the expansion and over-urbanization of the number of vehicles. The average speed in improving open borders to widen new highways and roads and existing roads in some areas has forced municipal authorities to use the current foundations in a perfect world to move forward with the progression of traffic. Similarly, the loss of critical time during the period of traffic interruptions affects construction performance, performance, efficiency and fuel consumption.

These negative effects are extremely extraordinary in the creation of nations like India, where the improvement of the system is moderate given the costs and bureaucratic problems. Frustration about traffic barriers Traffic includes the increase in accidents caused by the movement of vehicles when the light arrives, indicating their prevention. The smart traffic card and better access to traffic data for workers can help reduce congestion issues at a certain point in time. Traffic lights ensure that each effect gives vehicles the ability to continue driving through intersection points. In general, we will change the traffic lights to free up time paths. Anyway, we see in the normal daily presence that traffic dominates on both sides, when such a situation is presented in the programming as opposed to the following, which are similar to the time for two types of traffic, congestion over long distances of heavy traffic, delays traffic.

INTRODUCTION

Companies have typically prioritized the cost-cutting benefits of mass production. Before the 1980s, managers and planners in a production system did not give much thought to the lead time of a product in the system. In the 1990s, as time became more of a strategic component in the competitiveness of businesses, the emphasis shifted to finding ways to shorten the production lead time. Naturally, there has been a rise in curiosity about the dynamics of queueing networks, which are used to simulate production processes through analysis of the time spent by parts in the system. Queue behavior at various production system resources has been studied using both analytical and simulation models.

The purpose of this article is to present a synopsis of the benefits gained by implementing analytical queueing models in the industrial sector. The modern field of queueing theory has been around for over a century. There is a vast literature due to the early pioneering work of networks. Before diving into specific recommendations, this paper provides a brief overview of several recent evaluations of queueing theory subfields pertinent to industrial flow line systems.

Performance Analysis

Products of all kinds can be processed by the many resources that make up a typical manufacturing system. When certain resources are in demand but temporarily unavailable, components arriving at those resources must form queues. As a result, the system features several queues for access to its various resources, with some of these queues interacting with one another. The system is dynamic because the rates of product arrival vary with the random fluctuations in consumer demand. Stochastic resource processing rates reflect the inherent variability of individual resources. There is also the risk of unexpected breakdowns in the system's resources. As a result of these features, manufacturing processes can be represented as queueing networks, where machines and parts are represented as servers and customers. Machine buffers serve as waiting areas for components awaiting processing. The stations make up the network's nodes, and the routing governs the direction of material movement between them. The components are received at one node, processed at numerous stations, and sent out of the network at another. When a station's servers are at capacity, incoming components wait in a line (called a buffer) until one becomes available.

Flexible Manufacturing Systems

The components of a flexible manufacturing system are controllers, automated machines, and an automated material handling system for transferring work between units. Pallets are a common component of the material handling system. The capacity of an FMS is typically limited by the number of pallets used to transport the components. Maximizing throughput necessitates immediately replacing processed components with new components as they exit the system. Since the number of components is supposed to be constant, we can call this a closed system. Because of this feature, it is possible to model these systems as closed queuing networks. The following are the aspects that influence the efficiency of a flexible manufacturing system.

Exact Models

The concept of cyclic networks was developed before closed queueing networks were used to analyze FMS. A cyclic network has a predetermined number of components, a set number of machines, and a predetermined order in which the components are processed. Once the final resource has been processed, the components will cycle back to the initial resource. Cyclic queues were first developed to assess the quality of service provided in the aircraft maintenance industry. Analyzed underground mining operations using cyclic queues. These models presuppose an exponential growth rate for service times and no opportunity for user input.

RESULTS AND DISCUSSION

INVENTORY-QUEUE MODEL

Standard demand and special demand are assumed to arrive in this system at the Poisson processes' k1 and k2 rates, respectively. Times spent producing at a workstation in modes 1 and 2 are assumed to follow exponential distributions with rates l1 and l2 respectively. Assume that the initial quantity of finished standard products is S. In our system, special orders take precedence over regular orders, thus the workstation will stop making typical products temporarily in order to meet any pending special orders. Additionally, the system will set aside as many completed standard items as possible in order to meet the following requirements. To illustrate, suppose X is the total number of special orders waiting to be filled, and Y is the total number of regular products that have either been completed and are available for sale, or are now being processed in mode 2. When X is less than Y, the system will set aside Y finished standard products for the X needs; if X is greater than Y, it will set aside all of the Y finished standard products. After satisfying the first Y specific demands, the production will be changed to mode 1 for producing one standard product for the ðY þ 1Þst specific demand and then mode 2 on the same finished standard product to satisfy the ðY þ 1Þst specific demand and the same process will apply to the ðY þ 2Þnd specific demand and so on until all the specific demands outstanding in system are satisfied.

The system can be described by a Markov process with states ðn;mÞ, where n is the number of specific demands in the system(waiting or under processing); m is the number of finished standard products. Let l be the number of production orders for producing standard products, then we have l + m - S ¼ n. We denote our state space by X ¼ fn P 0; S P m P 0g. Since our system always reserves as many finished standard products available for the outstanding specific demands.

Table 1 Comparison results on various base-stock levels for case of q1 ¼ 0:2 and q2 ¼ 0:15.

S	P_f		L_F		L_{PO}		L_{SD}		W_{SD}		*OTDR*	
	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.
10	0.999	1	9.485	9.489	0.540	0.538	0.026	0.025	2.051	2.048	0.623	0.619
20	1	1	19.485	19.489	0.541	0.540	0.026	0.025	2.051	2.049	0.623	0.621
30	1	1	29.485	29.492	0.541	0.540	0.026	0.026	2.510	2.049	0.623	0.621

Table 2 Comparison results on various base-stock levels for case of q1 ¼ 0:2 and q2 ¼ 0:5.

S	P_f		L_F		L_{PO}		L_{SD}		W_{SD}		*OTDR*	
	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.
10	0.981	0.983	7.852	7.848	2.256	2.248	0.108	0.107	2.571	2.547	0.589	0.584
20	0.999	0.998	17.685	17.642	2.407	2.399	0.092	0.091	2.195	2.167	0.599	0.593
30	0.999	1	27.675	27.655	2.416	2.414	0.091	0.091	2.183	2.166	0.599	0.594

Table 3 Comparison results on various base-stock levels for case of q1 ¼ 0:2 and q2 ¼ 0:84.

S	P_f		L_F		L_{PO}		L_{SD}		W_{SD}		*OTDR*	
	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.
10	0.560	0.559	3.063	3.059	9.071	9.031	2.135	2.122	35.503	30.314	0.329	0.329
20	0.681	0.678	6.461	6.431	15.134	15.151	1.590	1.612	22.776	23.028	0.397	0.398

30	0.732	0.731	9.485	9.466	21.910	21.878	1.368	1.338	19.544	19.114	0.425	0.424

Table 4 Comparison results on various base-stock levels for case of q1 ¼ 0:8 and q2 ¼ 0:15.

S	P_f		L_F		L_{PO}		L_{SD}		W_{SD}		*OTDR*	
	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.	Num.	Sim.
10	0.919	0.910	5.467	5.460	4.570	4.574	0.038	0.038	3.007	3.040	0.574	0.574
20	0.968	0.969	11.807	11.776	8.223	8.202	0.030	0.033	2.429	2.640	0.604	0.603
30	0.991	0.991	26.666	26.664	13.361	13.342	0.027	0.027	2.152	2.153	0.623	0.621

the ordinary demands, for the case of$\rho_1 + \rho_2 > 1$, the remaining utilization of workstation that can be used for the ordinary demand is. "Therefore, when S is getting large, ordinary demands can only be served with the utilization at most (note that the specific demands will always be served). Based on this, we can make the following inference as the S increases to infinity: for ordinary demands, Pf will converge to the maximum fill rate, and ke will converge to Pf k1. On the other hand, when $\rho_1 + \rho_2 > 1$; ke will converge to k1 and Pf will converge to 1 as S tends to infinity. However, the response time of the specific demand will be the waiting time in system of a M/M/1 queue with arrival rate k2 and service rate l2. That is, the response time will be exponentially distributed with rate, while the fill rates will converge to 1. The OTDR obtained by the exponential waiting times for the cases corresponding to Table 5.4, 5.5 and 5.6 are 0.623, 0.599 and 0.623, respectively, and the numerical results also demonstrate these convergences".

Figs. 3 and 4 show the convergences of fill rate and OTDR on S as k1 and k2 increase, respectively. In either figure, when S is small, fill rates are always greater than OTDRs because of our reservation mechanism. However, for the case of q ¼ q1 þ q2 < 1, fill rate will be greater than OTDR as S gets large because fill rate will converge to 1 while OTDR will not. We also observe that, for small S, the increase rate (slope of the curves) of OTDR is greater than the corresponding fill rate. It means that the improvement on OTDR is more significant than that on fill rate when we increase the base-stock level starting from a small level.

For further consideration, we will use the following scenario taken from actual events. The printed circuit board (PCB) and the display, case, and peripherals (hard drive, DVD drive, etc.) are assembled in parallel during the first phase of laptop construction. The operator then moves on to the subsequent major assembly station, where the laptop's PCB and its many peripherals are assembled into a fully functional, industry-standard laptop. Additional RAM, a larger hard drive, and a better screen are common upgrades for laptops ordered to order to meet specific needs. By switching out the completed conventional laptops for the construction of custom computers, we can keep everything running smoothly. This location promises to have the bespoke computer ready in just 2 hours after the request is received. Main assembly takes about 40-45 minutes, while alternation is completed in about 30-35 minutes. On average, one request is made of this station's (operator's) services every hour, with a fraction of those requests being considered "special".

In the following examples, we presume custom products can be produced by alternating the production of already existing standard products with additional works, and that this procedure should be more expedited than that for a standard product, we assume that μ_1-μ_2.

Single job arrivals with parallel and serial batch processing (S-4)

Two examples support the S-4 model. Service times and job arrival intervals are normally distributed gammas in both circumstances. The average setup time for a product takes 80 minutes, while the average service time for a parallel batch is only 30 minutes. There are three different batch sizes k that can be considered simultaneously.

In the first scenario, employment arrivals are distributed according to a gamma with 10 possible rates. When calculating the SCV of job arrival intervals, the value obtained is 2. Each batch's wait time is distributed according to a gamma distribution with a standard deviation of 1.5 using the SCV method. Distribution of time to set up is exponential. The typical size of a serial batch, Np, is 20. The approximate mean cycle time (ACT) and the percentage difference between the ACT and SCT are shown in Table 5, along with the results of the simulated mean cycle time (SCT), the half width of 90% confidence intervals of the corresponding sample mean (90% CI), and the results of the computation.

Table 5. Cycle time comparison with Np = 20.

Utilization	k-2				k-5				k-10			
	SQT	90%CI	AQT	Diff%	SQT	90%CI	AQT	Diff%	SQT	90%CI	AQT	Diff%

10%	124.1	0.1%	124.1	0.0%	171.4	0.1%	174.0	1.5%	187.4	0.1%	190.6	1.7%
20%	88.1	0.1%	88.0	-0.1%	106.9	0.1%	111.0	3.8%	113.4	0.2%	118.6	4.6%
30%	82.1	0.2%	82.1	-0.1%	89.7	0.1%	94.7	5.6%	92.5	0.2%	98.9	6.9%
40%	85.9	0.3%	85.9	0.0%	86.2	0.2%	91.9	6.6%	86.5	0.4%	93.9	8.5%
50%	97.2	0.4%	97.0	-0.1%	91.2	0.4%	97.0	6.4%	89.1	0.4%	97.0	8.9%
60%	117.0	0.5%	117.2	0.2%	103.7	0.5%	110.4	6.5%	99.5	0.7%	108.1	8.7%
70%	153.1	0.7%	153.5	0.3%	129.4	0.8%	137.0	5.9%	122.4	0.9%	131.5	7.5%
80%	228.7	1.0%	228.7	0.0%	187.8	1.6%	194.3	3.5%	175.6	1.9%	182.8	4.1%
90%	460.2	1.9%	457.7	-0.5%	374.7	3.1%	371.6	-0.8%	337.9	3.1%	342.9	1.5%
95%	918.1	2.0%	917.5	-0.1%	718.5	5.3%	729.1	1.5%	639.7	4.1%	666.3	4.2%

Table 6 Cycle time comparison with Np = 100.

Utilization	k-2				k-5				k-10			
	SQT	90%CI	AQT	Diff%	SQT	90%CI	AQT	Diff%	SQT	90%CI	AQT	Diff%
10%	112.2	0.1%	112.2	0.0%	155.2	0.1%	157.4	1.4%	169.9	0.1%	172.4	1.5%
20%	79.2	0.1%	79.1	0.0%	96.4	0.1%	99.9	3.7%	102.4	0.1%	106.9	4.4%
30%	73.3	0.1%	73.3	0.0%	80.4	0.2%	84.8	5.5%	82.9	0.2%	88.6	6.9%
40%	76.4	0.2%	76.3	-0.1%	76.7	0.2%	81.7	6.5%	77.0	0.3%	83.5	8.5%
50%	85.5	0.3%	85.6	0.1%	80.1	0.4%	85.6	6.8%	78.4	0.3%	85.6	9.2%
60%	102.6	0.3%	102.7	0.1%	90.6	0.4%	96.5	6.5%	87.0	0.7%	94.5	8.6%
70%	133.3	0.5%	133.7	0.3%	112.6	0.9%	118.7	5.4%	105.9	0.9%	113.8	7.4%
80%	197.4	0.8%	198.0	0.3%	160.5	1.2%	166.8	3.9%	148.5	1.5%	156.4	5.3%
90%	386.3	2.1%	393.8	2.0%	310.0	2.0%	315.8	1.9%	285.2	3.0%	289.8	1.6%
95%	762.7	3.3%	787.2	3.2%	596.0	3.7%	616.5	3.4%	545.7	4.3%	559.6	2.5%

Case 2 are shorter than that in Case 1 for each fixed k. As a result, the average cycle time decreases.
In both two cases, the approximations perform well at all utilizations if the parallel batch size is 2 (where c2a =k ¼ 1). The absolute Diff% is less than 0.5% when Np = 20 and less than 3.2% when Np = 100. This is consistent with the finding in S-2: the model gives reliable results when c2a =k is one.
When c2a =k is far away from one, the Diff% becomes larger. It can be as large as 9.2% at 50% utilization when Np is 100. However, the Diff% becomes smaller in both heavy and light traffic compared to that at the middle utilizations (40–70%).

CONCLUSION

At the start of a process plan, the least expensive combination of production facilities or machine tools, as well as operational manpower capacity, is selected from the Alternatives to determine the work flow. The break-even analysis must be used to select the best production facility in order to find the best solution. An efficient production facility must be selected based on production quantity, and in some cases, the nature of the processes is random, because output volume affects overall production cost and time. Work flow is a material of tasks that comprise the process of converting raw materials into a finished product. This is used to plan the layout and design of operations and is based on production and manufacturing technology. In general, depending on the amount of production, the technology already in place, the quality of the product, and the raw materials, there are various methods for converting raw materials and parts into a finished product. The best workflow, including raw material selection and process route selection, is determined by weighing each option against criteria that affect total production time or cost.

REFERENCES

1. Rajesh, R. (2019). A fuzzy approach to analyzing the level of resilience in manufacturing supply chains. *Sustainable Production and Consumption*, *18*, 224-236.

2. Fazlollahtabar, H. and Gholizadeh, H. (2019). Economic Analysis of the M/M/1/N Queuing System Cost Model in a Vague Environment, International Journal of Fuzzy Logic and Intelligent Systems, 19, 3, 192-203
3. Itoh, E. and Mitici, M. (2019). Queue-Based Modeling of the Aircraft Arrival Process at a Single Airport, aerospace, 6, 103.
4. Keith, A.J., Ahner, D.K. (2019). A survey of decision making and optimization under uncertainty, Annals of Operations Research, https://doi.org/10.1007/s10479-019-03431-8
5. Prameela, K.U. and Kumar, P. (2019). FM / FEk /1 Queuing Model with Erlang Service Under Various Types of Fuzzy Numbers, International Journal of Recent Technology and Engineering, 8, 1, 2277- 3878.
6. Priya, R.S. and Sudhesh, R. (2018). Transient analysis of a discrete-time infinite server queue with system disaster, International Journal of Mathematics in Operational Research, 12, 1, 91-101
7. Kannadasan, G. and Sathiyamoorth, N. (2018). The analysis of M/M/1 queue with working vacation in fuzzy environment, International Journal Applications and Applied Mathematics, 13, 2, 566-577.
8. Thangaraj M &Rajendran P 2017, 'Analysis of bulk queueing system with single service and single vacation', IOP Conf. Series: Materials Science and Engineering, vol 4, no. 11, pp. 01-08.
9. Gou, X., Xu, Z. and Liao, H. (2017). Hesitant fuzzy linguistic entropy and cross-entropy measures and alternative queuing method for multiple criteria decision making, Information Sciences, 388, 225-246.
10. Walker, A.J. and Bright, G. (2017). Modeling arrival-to-departure sequence disorder in flow-controlled manufacturing systems, International Journal of Production Research, 55, 6, 1780-1790.
11. Vijayalakshmi, T &Thangaraj, V 2016, 'Transient analysis of a fluid queue driven by a chain sequenced birth and death process with catastrophes', International Journal of Mathematics in Operational Research, vol. 8, no. 2, pp. 164-184.
12. Fathi-Vajargah, B. and Ghasemalipour, S. (2016). Simulation of a random fuzzy queuing system with multiple servers, Journal of Contemporary Mathematical Analysis, 51, 2, 103-110.
13. Sharma, P. (2016). Optimal Flow Control of Multi-server Time Sharing Queuing network with priority, International Journal of Mathematics in Operational Research, 9, 3, 363-374.
14. Singh, C.J., Jain, M. and Kumar, B. (2016). Analysis of Single Server Finite Queuing Model with reneging, International Journal of Mathematics in Operational Research, 9, 1, 15-38.
15. Sundari, M.S. and Palaniammal, S. (2015). Simulation of M/M/1 Queuing System Using ANN, Malaya Journal of Mathematik, S, 1, 279-294
16. Picart, Delphine&Ozier-Lafontaine, Harry &Omrane, Abdennebi&Louison, Loic. (2015). Modeling plant nutrient uptake: Mathematical analysis and optimal control. Evolution Equations and Control Theory. 4. 193-203. 10.3934/eect.2015.4.193.
17. Vadivu, AS &Arumuganathan, R 2015, 'Cost Analysis of MAP/G(a,b)/1/N Queue with Multiple Vacations and Closedown Times', Quality Technology & Quantitative Management, vol. 12, no. 4, pp. 605-626.