UNDERGRADUATE REPORT

Simulating Manufacturing Cycle Time and Throughput in Flow Shops with Process Drift and Inspection

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Introduction

Manufacturing consists of many different processes and events. Process Drift is a common occurrence in many manufacturing processes where machines become contaminated or change causing degraded performance. There is also a process that has been formed to resolve this. Statistical process control (SPC) tracks process quality to determine when the process has drifted past its specification. SPC depends on inspecting the parts produced, measuring the features and attributes critical to their performance and quality. Parts that do not withstand inspection will be discarded. Some types of flaws are obvious and able to be caught immediately, while others need a more detailed examination of trained inspectors using special equipment and procedures. This will prevent these faulty parts from reaching the consumer and shows the importance of inspection stations using SPC.

When a process becomes out of control the rate at which it produces bad parts is increased. Preferably an out of control process would be detected, halted and fixed as soon as it goes out of control and then resumed. But, in practice there is a delay experienced between when the process loses control and when it is resolved. This creates time for the upstream process to produce more bad parts beyond the desired specifications. This kind of delay takes place due to the fact that once parts travel downstream to the inspection station only then can the system flaws be determined and corrected. While this occurs still more parts are upstream being created in the same contaminated manner. That builds a need for the upstream parts to be again inspected. This situation is very common in industries, especially semiconductor manufacturing and electronics assembly.

The time a batch or job spends at a workstation from its arrival at the workstation to its completion is known as its *manufacturing cycle time*. The time that the job spends in the manufacturing system between an order being request and completion is referred to as the *total manufacturing cycle time*. In a flow shop this is the sum of the workstation manufacturing cycle times. Reducing the total manufacturing cycle time has many positive benefits, reducing cost and inventory numbers while increasing system flexibility and creating a faster response time to customer orders. Throughput is another performance measure that is important. Throughput is the rate at which the system produces good parts. Increasing this measurement increases sales and revenue.

This paper will discuss several aspects of this topic. Section 2 clarifies the purpose of the research being conducted. Section 3 explains the design of the experiments and defines concepts and parameters within the model. Section 4 discusses the analysis, the method and the results found. Then the conclusion is in Section 5.

Purpose

Models of systems are useful tools for obtaining information about a system, which the model represents when it is not possible or desired to experiment with the actual system. In manufacturing this is very evident since the systems are usually large, complex and having special operations. These models are necessary over the model's lifetime in order to make good decisions on the design or operation.

There exist no models on how process drift relates to total manufacturing cycle time, yield and throughput. This paper describes the results of a discrete-event simulation model constructed for estimating the throughput and total manufacturing cycle time of a system with process drift and inspection. The results are compared to the results of a model that is based on queuing network approximations. To make the presentation more clear this study focused on a single-product case.

Experimental results show that the simulation model and analytical model provide similar results. The analytical model requires less data and less computational effort than that of the simulation model. It is therefore more appropriate for situations where a decision maker needs to compare numerous scenarios quickly.

Design of experiments

The simulation model was created using Arena. (Arena is a registered trademark of Rockwell Automation.) The simulation model represents process drift occurring at the first workstation as a independent and random process. When the first contaminated job arrives at the inspection downstream and travels through the process, the drift is detected. Within the model most of the parameters were fixed values while other were changed. There are six parameters that were varied to record their impact on the systems activity. Also it gives us a chance to compare the performance across a wide range of scenarios. *Normal yield* is the size of the fraction of the undetected flaws while the system operates within it specifications. *Reduced yield* is the size of the fraction of the undetected flaws while the system operates beyond it specifications. The rate at which the process goes out of control is the *drift rate*. The time the process remains out of control depends upon how long a job takes to move from that workstation to the downstream inspection station. This is called the *detection time*. The part processing times are independent random variables of the job processing time at each station. The job arrival rate is the part arrival rate divided by the initial batch size.

There were 64 scenarios created, as shown in Table 1.

Variable	Values
Arrival variability	1, 9
Drift Rate	0.01, 0.001
Reduced yield	0.5, 0.8
Part processing time	0.18, 0.24
Part processing time	0.18, 0.24
Part processing time	0.18, .024

Table 1: Scenarios for the model comparison

Data Analysis

For each individual scenario ten replications ran in the model. Each replication ran for 25,000 time units each with no warm up period. Running ten replication of the model took approximately one minute on a personal computer. Three categories of data was retrieved from the simulation final batch size, total manufacturing cycle time and throughput. Using the data created the sample mean and sample variance were found and used to calculate the 95% confidence interval. The confidence intervals were compared to the values calculated from the analytical model. In each column of Table 2 are tallies representing the number of scenarios (out of 64 total) where the value predicted by the analytical model was located compared the confidence interval. The complete results are presented in tables in the appendix.

	Below Confidence Interval	Inside Confidence Interval	Above Confidence Interval
Batch Size	20	10	34
Manufacturing cycle time	7	14	43
Throughput	21	18	25

Table 2: Analytical model data compared to the 95% confidence interval of the discrete event simulation, Arena.

There were at times some things that were similar in these comparisons. When the arrival SCV was equal to 9 (which occurs in half of the 64 scenarios), the manufacturing cycle times from the analytical model were very large and did not fall inside or near the 95% confidence interval provided by the simulation data. Also the batch times analytically repeated twice within a set of eight scenarios.

Conclusion

This paper presented the results of a simulation model for estimating the performance of a manufacturing system with process drift and inspection. The manufacturing system is a flow shop that produces a single product. The performance measures of throughput and manufacturing cycle time have a complex relationship in systems with process drift and inspection. Experimental results show that the analytical model results are similar to those of the discrete simulation model in many cases. It is therefore a good approximation of the data. Because it requires less effort, this makes it more appropriate for use.

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References

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Appendix

Scenario	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
B_0 Initial batch size (parts/job)	20	20	20	20	20	20	20	20
Part processing times								
t_1 (time units/part)	0.18	0.18	0.18	0.18	0.24	0.24	0.24	0.24
t_2 (time units/part)	0.18	0.18	0.24	0.24	0.18	0.18	0.24	0.24
t_3 (time units/part)	0.18	0.24	0.18	0.24	0.18	0.24	0.18	0.24
arrival variability c^r	1	1	1	1	1	1	1	1
process drift p	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
normal yield yn_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
reduce yield yr_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
ANALYTICAL MODEL RESULTS								
Final batch size	17.53434	17.53434	15.84312	15.84312	17.66228	17.66228	16.9656	16.9656
Total CT	18.68104	22.50994	48.50692	50.07478	73.26228	75.60862	83.45886	85.22683
Throughput (parts/time unit)	3.506868	3.506868	3.168624	3.168624	3.532456	3.532456	3.393121	3.393121
SIMULATION MODEL RESULTS (95% CONFIDENCE INTERVALS)								
Batch size: min	17.11051	17.1252	15.5384	17.19619	16.00237	17.1941	16.28432	15.14555
max	17.20841	17.21372	15.99174	17.28361	16.68411	17.2676	16.6218	15.85867
Total CT: min	16.34686	22.61647	48.62858	42.56165	61.92677	61.65736	61.84086	51.38309
max	17.15674	22.81135	64.44562	75.95445	98.95643	99.17576	119.9868	76.48845
Throughput: min	3.388819	3.380563	3.101261	3.364099	3.200526	3.404843	3.252611	3.046258
max	3.454981	3.455437	3.152739	3.471901	3.281534	3.504277	3.303669	3.136342

Scenario	9	10	11	12	13	14	15	16
B_0 Initial batch size (parts/job)	20	20	20	20	20	20	20	20
Part processing times								
t_1 (time units/part)	0.18	0.18	0.18	0.18	0.24	0.24	0.24	0.24
t_2 (time units/part)	0.18	0.18	0.24	0.24	0.18	0.18	0.24	0.24
t_3 (time units/part)	0.18	0.24	0.18	0.24	0.18	0.24	0.18	0.24
arrival variability c^r	1	1	1	1	1	1	1	1
process drift p	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
normal yield yn_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
reduce yield yr_1	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
ANALYTICAL MODEL RESULTS								
Final batch size	17.88358	17.88358	17.46078	17.46078	17.91557	17.91557	17.7414	17.7414
Total CT	18.80871	23.17748	48.89679	51.11653	73.32741	75.85768	83.6402	85.75867
Throughput (parts/time unit)	3.576717	3.576717	3.492156	3.492156	3.583114	3.583114	3.54828	3.54828
SIMULATION MODEL RESULTS (95% CONFIDENCE INTERVALS)								
Batch size: min	17.77611	17.77632	17.34113	17.76701	17.50374	17.78391	17.2881	17.484
Max	17.81163	17.81694	17.50763	17.79519	17.64496	17.81803	17.43162	17.663
Total CT: min	16.6475	33.81011	45.57818	25.93645	61.7477	55.23116	54.72483	64.611
Max	17.29166	108.0881	69.1807	28.20125	98.1172	79.79176	74.04743	152.779
Throughput: min	3.524985	3.496015	3.423733	3.565931	3.491666	3.51678	3.497308	3.489
Max	3.593755	3.564585	3.486267	3.626369	3.560414	3.57602	3.464292	3.548

Scenario	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
B_0 Initial batch size (parts/job)	20	20	20	20	20	20	20	20
Part processing times								
t_1 (time units/part)	0.18	0.18	0.18	0.18	0.24	0.24	0.24	0.24
t_2 (time units/part)	0.18	0.18	0.24	0.24	0.18	0.18	0.24	0.24
t_3 (time units/part)	0.18	0.24	0.18	0.24	0.18	0.24	0.18	0.24
arrival variability c^r	1	1	1	1	1	1	1	1
process drift p	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
normal yield yn_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
reduce yield yr_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
ANALYTICAL MODEL RESULTS								
Final batch size	17.988	17.988	17.929	17.929	17.991	17.991	17.971	17.971
Total CT	18.848	23.405	49.016	51.557	73.347	75.939	83.695	85.952
Throughput (parts/time unit)	3.598	3.598	3.586	3.586	3.598	3.598	3.594	3.594
SIMULATION MODEL RESULTS (95% CONFIDENCE INTERVALS)								
Batch size: min	17.891	17.907	17.47	16.719	17.754	17.578	17.897	17.75
max	17.927	17.938	17.748	20.974	17.826	17.719	17.945	17.851
Total CT: min	16.557	54.278	49.05	24.618	68.046	50.789	61.862	59.687
max	17.463	93.219	80.509	28.842	92.552	73.924	97.229	129.83
Throughput: min	3.54	3.524	3.476	3.543	3.486	3.498	3.56	3.502
max	3.618	3.619	3.528	3.636	3.567	3.554	3.635	3.589

Scenario	25	26	27	28	29	30	31	32
B_0 Initial batch size (parts/job)	20	20	20	20	20	20	20	20
Part processing times								
t_1 (time units/part)	0.18	0.18	0.18	0.18	0.24	0.24	0.24	0.24
t_2 (time units/part)	0.18	0.18	0.24	0.24	0.18	0.18	0.24	0.24
t_3 (time units/part)	0.18	0.24	0.18	0.24	0.18	0.24	0.18	0.24
arrival variability c^r	1	1	1	1	1	1	1	1
process drift p	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
normal yield yn_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
reduce yield yr_1	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
ANALYTICAL MODEL RESULTS								
Final batch size	17.988	17.988	17.929	17.929	17.991	17.991	17.971	17.971
Total CT	18.848	23.405	49.016	51.557	73.347	75.939	83.695	85.952
Throughput (parts/time unit)	3.598	3.598	3.586	3.586	3.598	3.598	3.594	3.594
SIMULATION MODEL RESULTS (95% CONFIDENCE INTERVALS)								
Batch size: min	17.964	15.14	15.454	17.964	17.934	17.829	17.971	17.937
max	17.987	27.608	26.161	17.981	17.96	17.906	17.994	17.968
Total CT: min	16.331	41.632	50.241	25.882	65.773	55.379	54.835	78.692
max	17.487	57.3	79.647	28.371	108.938	107.608	74.766	111.382
Throughput: min	3.531	3.549	3.564	3.573	3.541	3.519	3.544	3.572
max	3.596	3.58	3.602	3.614	3.606	3.586	3.593	3.619

Scenario	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
B_0 Initial batch size (parts/job)	20	20	20	20	20	20	20	20
Part processing times								
t_1 (time units/part)	0.18	0.18	0.18	0.18	0.24	0.24	0.24	0.24
t_2 (time units/part)	0.18	0.18	0.24	0.24	0.18	0.18	0.24	0.24
t_3 (time units/part)	0.18	0.24	0.18	0.24	0.18	0.24	0.18	0.24
arrival variability c^r	9	9	9	9	9	9	9	9
process drift p	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
normal yield yn_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
reduce yield yr_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
ANALYTICAL MODEL RESULTS								
Final batch size	16.451	16.451	12.229	12.229	17.455	17.455	15.299	15.299
Total CT	77.165	89.654	306.931	308.238	537.715	542.398	580.098	581.593
Throughput (parts/time unit)	3.290	3.290	2.446	2.446	3.491	3.491	3.060	3.060
SIMULATION MODEL RESULTS (95% CONFIDENCE INTERVALS)								
Batch size: min	17.062	16.716	17.092	17.194	16.837	16.821	17.204	16.745
max	17.145	16.911	17.171	17.233	16.976	16.946	17.269	16.856
Total CT: min	28.043	34.574	31.171	34.428	39.498	41.013	37.209	36.166
max	28.165	35.013	31.268	34.82	40.292	41.905	36.518	36.626
Throughput: min	3.412	3.342	3.418	3.437	3.365	3.362	3.439	3.347
max	3.429	3.381	3.434	3.445	3.393	3.387	3.451	3.37

Scenario	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
B_0 Initial batch size (parts/job)	20	20	20	20	20	20	20	20
Part processing times								
t_1 (time units/part)	0.18	0.18	0.18	0.18	0.24	0.24	0.24	0.24
t_2 (time units/part)	0.18	0.18	0.24	0.24	0.18	0.18	0.24	0.24
t_3 (time units/part)	0.18	0.24	0.18	0.24	0.18	0.24	0.18	0.24
arrival variability c^r	9	9	9	9	9	9	9	9
process drift p	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
normal yield yn_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
reduce yield yr_1	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
ANALYTICAL MODEL RESULTS								
Final batch size	17.613	17.613	16.557	16.557	17.864	17.864	17.325	17.325
Total CT	78.667	98.957	308.289	311.746	537.892	543.402	580.596	582.885
Throughput (parts/time unit)	3.523	3.523	3.311	3.311	3.573	3.573	3.465	3.465
SIMULATION MODEL RESULTS (95% CONFIDENCE INTERVALS)								
Batch size: min	17.76	17.684	17.796	17.783	17.702	17.793	17.694	17.756
max	17.795	17.723	17.821	17.819	17.739	17.813	17.722	17.717
Total CT: min	28.2	34.774	34.702	31.579	39.379	36.695	36.661	41.244
max	28.325	35.152	35.198	31.702	40.079	37.109	37.065	42.097
Throughput: min	3.552	3.535	3.558	3.556	3.539	3.557	3.537	3.54
max	3.559	3.543	3.563	3.563	3.546	3.56	3.542	3.549

Scenario	49	50	51	52	53	54	55	56
B_0 Initial batch size (parts/job)	20	20	20	20	20	20	20	20
Part processing times								
t_1 (time units/part)	0.18	0.18	0.18	0.18	0.24	0.24	0.24	0.24
t_2 (time units/part)	0.18	0.18	0.24	0.24	0.18	0.18	0.24	0.24
t_3 (time units/part)	0.18	0.24	0.18	0.24	0.18	0.24	0.18	0.24
arrival variability c^r	9	9	9	9	9	9	9	9
process drift p	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
normal yield yn_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
reduce yield yr_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
ANALYTICAL MODEL RESULTS								
Final batch size	17.953	17.953	17.589	17.589	17.985	17.985	17.903	17.903
Total CT	79.175	103.106	308.704	313.633	537.947	543.753	580.749	583.465
Throughput (parts/time unit)	3.591	3.591	3.518	3.518	3.597	3.597	3.581	3.581
SIMULATION MODEL RESULTS (95% CONFIDENCE INTERVALS)								
Batch size: min	17.882	17.902	17.867	17.885	17.869	17.829	17.908	17.865
max	17.916	17.931	17.9	17.927	17.914	17.879	17.948	17.92
Total CT: min	28.194	34.47	34.707	31.794	39.613	36.751	36.871	41.231
max	28.323	34.929	35.603	31.863	40.274	37.126	37.588	42.177
Throughput: min	3.576	3.579	3.572	3.576	3.572	3.545	3.58	3.571
max	3.583	3.585	3.579	3.585	3.581	3.629	3.588	3.582

Scenario	57	58	59	60	61	62	63	64
B_0 Initial batch size (parts/job)	20	20	20	20	20	20	20	20
Part processing times								
t_1 (time units/part)	0.18	0.18	0.18	0.18	0.24	0.24	0.24	0.24
t_2 (time units/part)	0.18	0.18	0.24	0.24	0.18	0.18	0.24	0.24
t_3 (time units/part)	0.18	0.24	0.18	0.24	0.18	0.24	0.18	0.24
arrival variability c^r	9	9	9	9	9	9	9	9
process drift p	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
normal yield yn_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
reduce yield yr_1	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
ANALYTICAL MODEL RESULTS								
Final batch size	17.953	17.953	17.589	17.589	17.985	17.985	17.903	17.903
Total CT	79.175	103.106	308.704	313.633	537.947	543.753	580.749	583.465
Throughput (parts/time unit)	3.591	3.591	3.518	3.518	3.597	3.597	3.581	3.581
SIMULATION MODEL RESULTS (95% CONFIDENCE INTERVALS)								
Batch size: min	17.96	17.966	17.957	17.964	17.963	17.964	17.976	17.961
max	17.992	17.996	17.986	17.989	17.989	17.99	17.995	17.994
Total CT: min	28.268	34.592	34.7	31.772	39.29	36.839	36.804	41.55
max	28.354	35.146	35.235	31.902	40.158	37.186	37.542	42.521
Throughput: min	3.586	3.592	3.59	3.592	3.59	3.591	3.593	3.59
max	3.616	3.598	3.596	3.597	3.596	3.596	3.597	3.596