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WHY TRANSIENT ANALYSIS CAN BE DE-EMPHASIZED IN UNDERGRADUATE SIMULATION COURSES

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ABSTRACT

We present the results of coverage tests performed to validate our preliminary analysis indicating that determining 'appropriate' run length is more important for obtaining coverage than performing 'proper' transient analysis. Our preliminary experiment was designed with the intention of showing students the pitfalls of performing 'bad' transient analysis when estimating steady-state parameters. However, we found that for short run lengths any transient truncation diminishes coverage; and it is only beneficial to delete transient data when long runs of the output data are available. As with the preliminary analysis, two types of systems are analyzed (M/M/1/GD/∞/∞ systems and an M/M/s/GD/∞/∞); additionally, coverage tests are also conducted on 3-stage M/M/1/GD/∞/∞ queuing systems. The coverage analysis supports our preliminary conclusion: when first exposing students to the subject of output analysis on non-terminating systems, strong emphasis should be placed on choosing proper run length and the time devoted to transient analysis can be reduced.

1 INTRODUCTION

Estimating steady-state parameters for non-terminating systems often requires the identification and elimination of transient data from the output response. Most of the techniques available for identifying transient data (transient analysis) are too ad-hoc or mathematically too difficult to be understood by the typical undergraduate student. As documented by Court, Pittman and Pham (2005a) there are several issues a student must face when trying to learn how to identify the 'proper' transient deletion point. In addition to the basic issues of not generating 'enough' steady-state data in the output response and/or not deleting 'enough' transient data to avoid initialization bias; there are no scientific means for the student to validate their decisions unless the simulated system is simple enough to have closed-form solutions available for the system parameters. However, when the student becomes a simulation practitioner, simulation studies are usually not performed when closed-form solutions exist. Thus, there are no means for the practitioner to guarantee that the confidence intervals generated will cover the true mean, regardless of how much care was taken to determine the truncation point.

In (Court, Pittman and Pham 2005b), we conducted an experiment with the intention of showing undergraduate students that transient analysis should not be ignored. We explored two types of queuing systems (M/M/1/GD/∞/∞ systems and an M/M/s/GD/∞/∞) at various levels of ρ; where the parameter of interest is W_q – the average waiting time in queue. The cases were chosen since these systems are typically introduced in an undergraduate stochastic operations research course and well-known queuing theory results exist; so students are able to determine if a confidence interval contains the true mean. The method of independent replications was used to generate 95% confidence intervals on W_q, and a cumulative average approach was utilized for transient analysis.

The methodology followed in our paper required us to introduce two key concepts:

1. *Perfect transient analysis* can be achieved when in the output data, a '*perfect transient point*' (PTP) exists such that from that point to the end of the simulation run, the average of the remaining data equals the true mean of the unknown parameter of interest.
2. *Worst-case-transient analysis* occurs when the student/practitioner ignores (either intentionally or unintentionally) transient analysis altogether. In other words, no initial data is deleted from the simulation runs and hence, the method of independent replications will see its worst case of initialization bias.

We found that the worst-case transient analysis cases (those cases that left transient data in the output response) not only generated valid confidence intervals but were often more precise than the confidence intervals generated with 'perfect transient' data deleted, hence, the title, "Should transient analysis be taught?" (Court, Pittman and Pham 2005b). However, our preliminary results lack the coverage tests to validate our findings. This paper now answers the question of, "Should transient analysis be taught?", by providing the coverage tests to validate our preliminary findings. The next section outlines the methodology we followed for conducting the coverage tests, our analysis and our results.

2 METHODOLOGY, RESULTS AND ANALYSIS

As with the preliminary analysis (Court, Pittman and Pham 2005b), two types of queuing systems cases (Case 1 and Case 2) are analyzed and here, we add an additional set of queues-in-series (Case 3), defined as follows:

- **Case 1:** M/M/1/GD/∞/∞ systems at three levels of ρ (=0.50, 0.75, 0.90).
- **Case 2:** An M/M/s/GD/∞/∞ optimization problem with λ=2/minute, μ=0.5/minute, a per server cost of $9/hour and a delay cost to the customer of $0.05/minute, at s=5 and s=6.
- **Case 3:** Three M/M/1/GD/∞/∞ systems in series (tandem queues without blocking) at three levels of ρ (=0.50, 0.75, 0.90).

As before, these cases are chosen since well-known queuing theory results exist, and these systems are typically introduced in an undergraduate stochastic operations research course. The parameter of interest is the average waiting time in queue, W_q. Note, the Case 2 system types are characteristically used to introduce the formulation required to solve queuing optimization problems. Since the waiting cost to the customer and the per server costs are fixed, to solve the problem through simulation analysis is equivalent to determining a parameter estimate for the average waiting time in queue (W_q—the only unknown parameter). As with our preliminary analysis all cases were simulated via the Arena 7.01 software (Kelton, Sadowski and Sturrock 2004) and analyzed via Arena 7.01 and Microsoft Excel.

For our 95% coverage analysis, we use 25 sets of 95% confidence intervals on W_q obtained via the method of independent replications with 20 replications. Our methodology for all cases is illustrated through the Case 1 systems (as seen in Figure 1) and outlined below:

1. At a minimum, run lengths of 6,000; 20,000; 50,000; 100,000 and 1,000,000 time units are utilized for all cases to identify the perfect transient point at various run lengths and to allow the **worst-case transient analysis** (no deletion of transient) at various run lengths to be explored. For the worst-case transient analysis, all data generated by the simulated system are utilized in the confidence intervals. These cases will see the method of independent replications suffer its worst-case initialization bias and thus, should result in poor coverage. Tables 1-3 contain the estimated coverage for Cases 1-3, respectively, under the worst-case transient analysis condition.

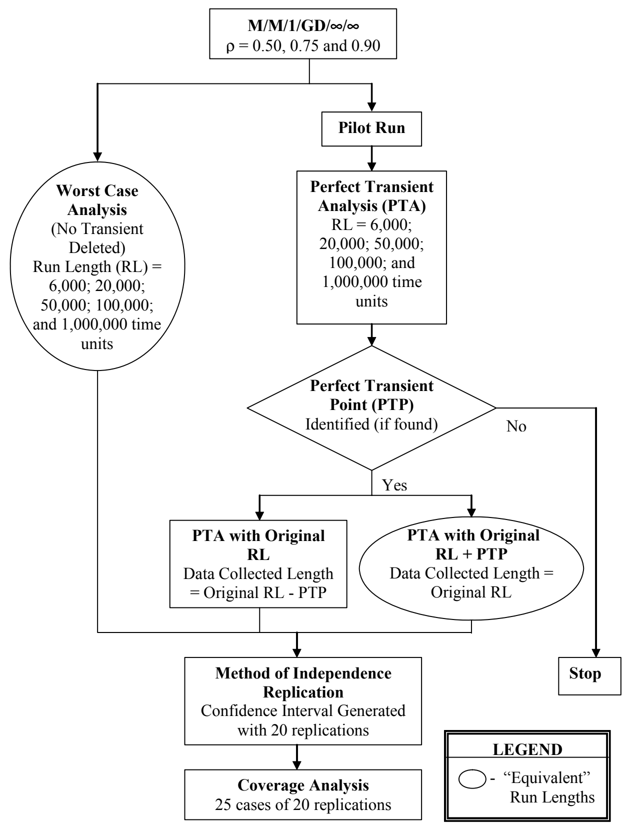

Figure 1: Methodology Diagram for Case 1 Systems

2. A pilot run for the cases is conducted at the run lengths of (1), to identify where in the output data the average of the output data first equals the theoretical value. This process can be called a "*reverse cumulative average*" approach, where the first observation is dropped from the cumulative average until the remaining data, when averaged, equals the theoretical value. The point after which the data's average equals the theoretical value is noted as the **perfect transient point** (PTP).
3. If a PTP can be found for a particular run length, two more sets of confidence intervals are gener-

ated via the method of independent replications. Tables 4-6 contain the 95% coverage tests of these two situations (a) and (b), described below, for Case 1-Case 3, respectively.

(a) First, the replications have the perfect transient deleted but the total run length is terminated at the original run length's time unit. For example, if the run length is 20,000 time units (Original RL) and the perfect transient point is found to occur at 12,000 time units (PTP), each replication will have a total of 8,000 time units (Original RL – PTP) worth of data available to calculate each replication's sample mean.

(b) Secondly, perfect transient is deleted from the replications and the total run length is modified to equal that of the perfect transient's time units plus the original run length's time units. Following the same example in (a), the new run length is 32,000 time units (Original RL + PTP) for each of the replications, where the first 12,000 time units are specified as 'warm-up' and the remaining 20,000 time units of data are available for calculating each replication's sample mean.

Table 1: Estimated Coverage for Worst-Case Transient Analysis for Case 1 Systems

M/M/1 / W_q / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
	0.500	2.250	8.100
6,000	84.00%+/-14.37%	80.00%+/-15.68%	88.00%+/-12.74%
20,000	100.00%+/-0.00%	92.00%+/-10.63%	76.00%+/-16.74%
50,000	96.00%+/-7.68%	96.00%+/-7.68%	96.00%+/-7.68%
100,000	96.00%+/-7.68%	92.00%+/10.63%-	92.00%+/-10.63%
1,000,000	80.00%+/-15.68%	88.00%+/-12.74%	92.00%+/-10.63%

Table 2: Estimated Coverage for Worst-Case Transient Analysis for Case 2 Systems

M/M/s / W_q / Run Length	s=5	s=6
	1.108	0.285
6,000	84.00%+/-14.37%	96.00%+/-7.68%
20,000	92.00%+/-10.63%	96.00%+/-7.68%
50,000	96.00%+/- 7.68%	96.00%+/-7.68%
100,000	92.00%+/-10.63%	100.00%+/-0.00%
500,000		96.00%+/-7.68%

Table 3: Estimated Coverage for Worst-Case Transient Analysis for Case 3 Systems

3-M/M/1 / W_q / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
	1.500	6.750	24.300
6,000	96.00%+/-7.68%	100.00%+/-0.00%	100.00%+/-0.00%
20000	92.00%+/-10.63%	100.00%+/-0.00%	100.00%+/-0.00%
50,000	100.00%+/-0.00%	92.00%+/-10.63%	84.00%+/-14.37%
100,000	96.00%+/-7.68%	88.00%+/-12.74%	88.00%+/-12.74%
1,000,000	100.00%+/-0.00%	96.00%+/-7.68%	100.00%+/-0.00%

For Case 1 systems under worst-case transient analysis conditions, except for the estimated coverage at the 20,000 run length when ρ=0.90 (the upper bound on true coverage is 92.74%), the remaining 17 cases achieve 95% true coverage (see Table 1). Table 4 shows the remaining systems of Case 1; (a) is run at the original run length with a warm-up period set at the perfect transient point and (b) is run with the total simulated time equal to the original run length plus the perfect transient point; except for ρ=0.90 at a 6,000 run length, all other scenarios attain 95% coverage.

Table 4: Estimated Coverage for Two Run Lengths for Case 1 Systems

M/M/1 / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
6,000 (a)	94.44%+/-10.58%	100.00%+/-0.00%	
6,000 (b)	94.44%+/-10.58%	100.00%+/-0.00%	
20,000 (a)	95.24%+/-9.11%	100.00%+/-0.00%	100.00%+/-0.00%
20,000 (b)	95.24%+/-9.11%	100.00%+/-0.00%	100.00%+/-0.00%
50,000 (a)	100.00%+/-0.00%	94.44%+/-10.58%	92.31%+/-14.49%
50,000 (b)	100.00%+/-0.00%	94.44%+/-10.58%	100.00%+/-0.00%
100,000 (a)	100.00%+/-0.00%	95.24%+/-9.11%	95.24%+/-9.11%
100,000 (b)	96.00%+/-7.68%	100.00%+/-0.00%	95.24%+/-9.11%
1,000,000 (a)	84.00%+/-14.37%	92.00%+/-10.63%	91.67%+/-11.06%
1,000,000 (b)	96.00%+/-7.68%	96.00%+/-7.68%	95.83%+/-7.99%

Table 5: Estimated Coverage for Two Run Lengths for Case 2 Systems

M/M/s / Run Length	s=5	s=6
6,000 (a)	100.00%+/-0.00%	100.00%+/-0.00%
6,000 (b)	80.00%+/-24.79%	100.00%+/-0.00%
20,000 (a)	95.45%+/-8.70%	100.00%+/-0.00%
20,000 (b)	100.00%+/-0.00%	100.00%+/-0.00%
50,000 (a)	95.45%+/-8.70%	94.74%+/-10.04%
50,000 (b)	90.91%+/-12.01%	94.74%+/-10.04%
100,000 (a)	95.00%+/-9.55%	100.00%+/-0.00%
100,000 (b)	95.00%+/-9.55%	100.00%+/-0.00%
500,000 (a)		92.00%+/-10.63%
500,000 (b)		100.00%+/-0.00%

Table 6: Estimated Coverage for Two Run Lengths for Case 3 Systems

3-M/M/1 / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
6,000 (a)	100.00%+/-0.00%	77.78%+/-27.16%	100.00%+/-0.00%
6,000 (b)	100.00%+/-0.00%	88.89%+/-20.53%	100.00%+/-0.00%
20,000 (a)	100.00%+/-0.00%	100.00%+/-0.00%	
20,000 (b)	100.00%+/-0.00%	80.00%+/-35.06%	
50,000 (a)	100.00%+/-0.00%	100.00%+/-0.00%	81.82%+/-22.79%
50,000 (b)	95.65%+/-8.33%	91.67%+/-15.64%	81.82%+/-22.79%
100,000 (a)	100.00%+/-0.00%	92.86%+/-13.49%	91.67%+/-15.64%
100,000 (b)	100.00%+/-0.00%	92.86%+/-13.49%	91.67%+/-15.64%
1,000,000 (a)	100.00%+/-0.00%	89.47%+/-13.80%	92.86%+/-13.49%
1,000,000 (b)	95.83%+/-7.99%	89.47%+/-13.80%	85.71%+/-18.33%

Additionally, when precision for coverage is investigated for the Case 1 systems under the worst-case transient analysis conditions (see Table 7), we found that for all levels of ρ, the precision improves when the run length increases and the best precision is always attained at the longest run length. As with our preliminary analysis (Court, Pittman, and Pham 2005b), these results indicate that as the run length increases, the precision of the confidence interval improves even though transient data is contained within the output response.

We also found that for all levels of ρ, the precision of the (b) confidence intervals is the same or better than the precision of the (a) confidence intervals (see Table 8). And, in keeping with prior results on run length, precision improves as run length increases. So here one sees that there does seem to be an advantage to increasing run length for data collection once perfect transient is deleted.

Table 7: Precision for Coverage for Worst-Case Transient Analysis for Case 1 Systems

M/M/1 / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
6,000	0.0307	0.0518	0.1125
20,000	0.0169	0.0281	0.0646
50,000	0.0114	0.0193	0.0440
100,000	0.0081	0.0133	0.0268
1,000,000	0.0025	0.0043	0.0101

Table 8: Precision for Coverage at Two Run Lengths for Case 1 Systems

M/M/1 / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
6,000 (a)	0.0523	0.1241	0.0990
6,000 (b)	0.0312	0.0554	0.0954
20,000 (a)	0.0318	0.0482	0.1221
20,000 (b)	0.0166	0.0298	0.0613
50,000 (a)	0.0230	0.0262	0.0624
50,000 (b)	0.0117	0.0177	0.0396
100,000 (a)	0.0174	0.0323	0.0645
100,000 (b)	0.0076	0.0134	0.0310
1,000,000 (a)	0.0034	0.0058	0.0143
1,000,000 (b)	0.0025	0.0041	0.0103

Returning to the issue of coverage, one can compare ‘equivalent run lengths’. The worst-case transient analysis run lengths can be compared against ‘equivalent’ run lengths of the (b) systems of Table 4.

Table 9 reveals the number of 95% confidence intervals that contain the true means of both the worst-case transient analysis run lengths (w) and the corresponding ‘equivalent’ run lengths (b) of the Case 1 systems. In general, the worst-case transient analysis runs generated more ‘valid’ (W_q is within the confidence interval) confidence intervals at shorter run lengths than (b) (since some perfect transient points could not be found at the shorter run lengths). So, the runs with no transient deleted generated a total of 337 ‘valid’ confidence intervals, while the (b) runs only generated a total of 260 ‘valid’ confidence intervals.

Table 10 contains the precision of confidence intervals generated by the worst-case transient analysis run lengths (w) and the 'equivalent' run lengths (b) of the Case 1 systems. The runs with no transient deleted (worst-case transient analysis condition) generated confidence intervals with better precision 8 out of 15 times.

As with the Case 1 systems, the same trends exist for the Case 2 systems' coverage analysis:

- For the worst-case scenario (see Table 2), as the run length increases, the precision of the confidence interval improves (see Table 11).
- For the perfect transient runs, there seems to be an advantage to increasing the run length for 'steady-state' data collection once perfect transient is deleted; and, as with all previous results, precision improves as run length increases (see Tables 5 and 12).

Under 'equivalent' run lengths, the worst-case transient analysis runs generated more valid and precise confidence intervals at shorter run lengths than (b) (see Tables 13 and 14).

Likewise, as with the Case 1 and Case 2 systems, the same results are observed for the Case 3 systems:

- For the worst-case scenario (see Table 3), as the run length increases, the precision of the confidence interval improves (see Table 15).
- For the perfect transient runs, there seems to be an advantage to increasing the run length for 'steady-state' data collection once perfect transient is deleted; and, as with all previous results, precision improves as run length increases (see Tables 6 and 16).
- Under 'equivalent' run length conditions, the worst-case transient analysis runs generated more valid and precise confidence intervals at shorter run lengths than (b) (see Tables 17 and 18).

Table 9: Number of 95% Confidence Intervals Containing the True Means for Case 1 Systems

Run Length \ M/M/1	ρ=0.50	ρ=0.75	ρ=0.90
6,000 (w)	21	20	22
6,000 (b)	17	9	1
20,000 (w)	25	23	19
20,000 (b)	20	19	6
50,000 (w)	24	24	24
50,000 (b)	22	17	13
100,000 (w)	24	23	23
100,000 (b)	24	21	20
1,000,000 (w)	20	22	23
1,000,000 (b)	24	24	23

Table 10: Precision of 95% Confidence Intervals for Case 1 Systems

Run Length \ M/M/1	ρ=0.50	ρ=0.75	ρ=0.90
6,000 (w)	0.0307	0.0523	0.1184
6,000 (b)	0.0312	0.0554	0.0954
20,000 (w)	0.0169	0.0281	0.0642
20,000 (b)	0.0166	0.0298	0.0613
50,000 (w)	0.0114	0.0193	0.0424
50,000 (b)	0.0117	0.0177	0.0396
100,000 (w)	0.0081	0.0133	0.0267
100,000 (b)	0.0076	0.0134	0.0310
1,000,000 (w)	0.0025	0.0043	0.0101
1,000,000 (b)	0.0025	0.0041	0.0103

Table 11: Precision for Coverage for Worst-Case Transient Analysis for Case 2 Systems

Run Length \ M/M/s	s=5	s=6
6,000	0.0636	0.0571
20,000	0.0330	0.0294
50,000	0.0213	0.0197
100,000	0.0152	0.0140
500,000		0.0065

Table 12: Precision for Coverage at Two Run Lengths for Case 2 Systems

Run Length \ M/M/s	s=5	s=6
6,000 (a)	0.1265	0.1065
6,000 (b)	0.0593	0.0542
20,000 (a)	0.0490	0.0399
20,000 (b)	0.0340	0.0291
50,000 (a)	0.0358	0.0426
50,000 (b)	0.0213	0.0195
100,000 (a)	0.0532	0.0547
100,000 (b)	0.0162	0.0140
500,000 (a)		0.0109
500,000 (b)		0.0062

Table 13: Number of 95% Confidence Intervals Containing the True Means for Case 2 Systems

Run Length \ M/M/s	s=5	s=6
6,000 (w)	21	24
6,000 (b)	8	16
20,000 (w)	23	24
20,000 (b)	22	23
50,000 (w)	24	24

50,000 (b)	20	18
100,000 (w)	23	25
100,000 (b)	19	24
500,000 (w)		24
500,000 (b)		25

Table 14: Precision of 95% Confidence Intervals for Case 2 Systems

M/M/s / Run Length	S=5	s=6
6,000 (w)	0.0636	0.0571
6,000 (b)	0.0593	0.0542
20,000 (w)	0.0328	0.0297
20,000 (b)	0.0340	0.0291
50,000 (w)	0.0210	0.0194
50,000 (b)	0.0213	0.0195
100,000 (w)	0.0151	0.0140
100,000 (b)	0.0162	0.0140
500,000 (w)		0.0065
500,000 (b)		0.0062

Table 15: Precision for Coverage for Worst-Case Transient Analysis for Case 3 Systems

3-M/M/1 / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
6,000	0.0251	0.0455	0.0974
20,000	0.0129	0.0235	0.0500
50,000	0.0081	0.0140	0.0302
100,000	0.0061	0.0103	0.0237
1,000,000	0.0016	0.0028	0.0064

Table 16: Precision for Coverage at Two Run Lengths for Case 3 Systems

3-M/M/1 / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
6,000 (a)	0.0270	0.0653	0.0961
6,000 (b)	0.0253	0.0418	0.1017
20,000 (a)	0.0248	0.0286	
20,000 (b)	0.0123	0.0200	
50,000 (a)	0.0189	0.0243	0.0480
50,000 (b)	0.0076	0.0161	0.0304
100,000 (a)	0.0160	0.0190	0.0435
100,000 (b)	0.0052	0.0088	0.0223
1,000,000 (a)	0.0065	0.0212	0.0243
1,000,000 (b)	0.0018	0.0029	0.0070

Table 17: Number of 95% Confidence Intervals Containing the True Means for Case 3 Systems

3-M/M/1 / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
6,000 (w)	24	25	25
6,000 (b)	11	8	2
20,000 (w)	23	25	25
20,000 (b)	23	4	0
50,000 (w)	25	23	21
50,000 (b)	22	11	9
100,000 (w)	24	22	22
100,000 (b)	23	13	11
1,000,000 (w)	25	24	25
1,000,000 (b)	23	17	12

Table 18: Precision of 95% Confidence Intervals for Case 3 Systems

3-M/M/1 / Run Length	ρ=0.50	ρ=0.75	ρ=0.90
6,000 (w)	0.0251	0.0453	0.1000
6,000 (b)	0.0253	0.0418	0.1017
20,000 (w)	0.0129	0.0235	0.0495
20,000 (b)	0.0123	0.0200	
50,000 (w)	0.0081	0.0140	0.0303
50,000 (b)	0.0076	0.0161	0.0304
100,000 (w)	0.0061	0.0103	0.0236
100,000 (b)	0.0052	0.0088	0.0223
1,000,000 (w)	0.0016	0.0028	0.0064
1,000,000 (b)	0.0018	0.0029	0.0070

3 CONCLUSIONS AND FUTURE RESEARCH

Three types of queuing systems were analyzed to investigate the impact coverage analysis has on transient analysis decisions: single server queues, a multiple server queue and several tandem queues with three servers in series. The coverage tests support the preliminary results in that performing transient analysis does not guarantee that the analyst/student will obtain ‘better’ confidence intervals.

In particular, the coverage tests reveal:

- As congestion in a system increases, the ability to find a perfect transient point decreases.
- There is no advantage to eliminating perfect transient for data collection if a perfect transient point can be found. That is, under ‘equivalent’ run lengths, confidence intervals generated with the perfect transient point deleted have less ‘valid’ confidence intervals compared to confidence intervals with no transient deleted (worst-case tran-

sient analysis). Additionally, the confidence intervals from the worst-case transient analysis have greater precision more than 50% of the time.

However, while in the preliminary research the run length is concluded to be the most important factor to obtain the 'valid' confidence intervals (confidence intervals that contain the true mean), the coverage tests show that the run length is only important when trying to achieve the perfect transient point. In fact, the run length has to be increased so that a perfect transient point can exist. So, in general, it still can be concluded that strong emphasis should be placed on determining run length. Additionally for long run lengths, the precision analysis shows that it is worth the effort to do transient analysis so as to improve the accuracy of the confidence intervals' coverage.

Thus, this work supports the conclusion that in simulation education for undergraduate students, when introducing parameter estimation for non-terminating systems via the method of independent replications, strong emphasis should be placed on deciding the proper run length and transient analysis can be de-emphasized or even eliminated. The topic of transient analysis may be more suitable for graduate-level simulation analysis courses.

In addition, only simple queuing systems were analyzed since they represent the set of systems typically simulated in an undergraduate operations research course, and our conclusion to emphasize run length over transient analysis is only for those types of queuing systems. Future research can be aimed at examining other systems, such as networks to evaluate the generalization of our conclusion.

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