SIMULATION IMPROVES UNIVERSITY CAMPUSES BUS SERVICE

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ABSTRACT

Historically, discrete-event process simulation was first and most widely used in manufacturing contexts. As the technology has gradually matured and knowledge of its benefits has become more widely known, simulation usage has spread to warehouse design and operation, health-care delivery, retail customer service, and (as in this paper), the transport of people and/or goods.

This project simulated the Blue Bus system of the University of Michigan. We analyzed the waiting time of passengers at each stop and the utilization of buses under two strategies; one is based on the schedule, the other is adding eight buses of Bursley-Baits during peak time besides the scheduled shifts which is practical Blue Bus running strategy. Under the two strategies, we analyzed the different scenarios that number of passengers increases by some times. We compared these scenarios and found the practical strategy is more robust when there is a sharp increase of passengers.

1   INTRODUCTION

Early in the history of discrete-event process simulation, its use was almost entirely confined to the manufacturing sector of the economy. More recently, and now extensively, its use has expanded to the analysis of entire supply chains. Inevitably, its analytical power to identify and quantify improvements led to use in the design of both local and large-scale transportation networks. For example, locally, (Patlins 2008) greatly improved local delivery times in cities with unstable traffic patterns. The study by (Or, Özbaş, and Yilmaz 2007) greatly improved the efficiency and safety of maritime traffic in the İstanbul strait. Over much wider geographic compass, (Boesel and Bodoh 2004) studied redesign of airspace to use to best advantage the addition of a fourth runway at Detroit Metropolitan Airport.

This study examined and improved the operation of the campus bus system, scheduling, and routes on a large (more than 40,000 students, plus faculty, employees, and guests) metropolitan university campus. As can well be imagined, both the parking and the congestion problems, let alone environmental considerations, require the campus to provide a convenient, efficient bus service as a substitute for privately owned vehicles. The primary aim of the study was to plan for significantly increased capacity demands (expected if car registration fees or outright vehicle bans, both under consideration, are implemented), while identifying current and potential bottlenecks and, preventing current service metrics (waiting time, missed connections) from deteriorating.

Following this introductory section, we describe the current system and its contingencies. In the methods section, we introduce the data collection and sensitivity analysis method. The modeling section provides a basic model description of the Blue Bus system, establishing assumptions to build the model and identifying input based on the real system and data analysis. The results section reports the validation, verification and the direct output of the model, analyzing data from the running of the model. Finally, we provide conclusions drawn from the sensitivity analysis, evaluate measures to improve robustness, and indicate promising direction for follow-up studies.

2   SYSTEM DESCRIPTION

The "Blue Bus" system at the University of Michigan is the campus transportation system connecting three different campuses. The largest transportation demand occurs between north campus and center campus, connected by five bus routes during the day. The major stops are CCLittle at center campus and Pierpont at north campus. Routes connecting the two stops are shown in Figure 1 below
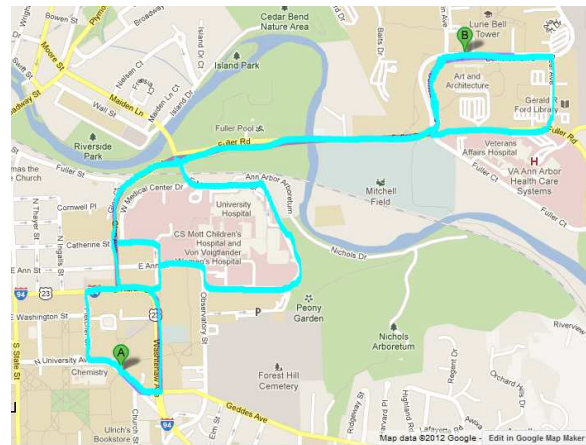

Figure 1: Route between C C Little and Pierpont

The routes and schedule are fixed for each bus line: Northwood; Northwood Express; Bursley-Baits; Commuter North & South; Diag[onal]-to-Diag[onal] Express; which meet needs of center campus, the medical center and north campus. The schedule of buses on the various routes is fixed and published. Yet in practice, several more buses are added, on an ad-hoc basis, at peak times. The frequency of the bus is every 10 minutes during the day on weekdays. Meanwhile, there is an interactive, real-time Magic Bus system tracing dynamic conditions throughout the system.

3 PROBLEM DESCRIPTION

The current Blue Bus system works reasonably well in terms of meeting basic transportation needs. However, several problems exist when the system is inherently unstable. For example, the current system cannot meet the transportation demand when there is a sharp increase in passengers (e.g., near lunchtime and in between periods scheduled for large classes); also, the passengers' waiting time increases when weather and road conditions reduce bus speed. Hence, sensitivity analysis, undertaken in this study, is a valuable tool to assess system robustness – e.g., how much change in demand can the current system accommodate before the key performance indicators [KPIs] of passenger waiting times and bus utilizations deteriorate severely?

Additionally, disruptions to the system might cause more impact during peak time. For example, the first morning class ends at 10am on center campus, and the second morning class begins at 10:30am on north campus. During that half-hour, the system should fully meet the spike in transportation needs to reduce lateness for classes. Secondly, during peak time a bus might be so overcrowded that it must leave some passengers stranded at starting or intermediate stops waiting for the next bus. Therefore, additional adjustments are required to adapt to the disruptions, high demand variability, and uncertainty exogenous to the system. Therefore, the bus system transportation managers requested that this industrial engineering study develop, evaluate, and compare various alternatives, entailing various investments in capital, labor, and reorganization, to improve system service metrics and the robustness of system service. Predictions were requested for as much as a fivefold (500%) increase in passenger load over the next few years. Campus enrollments are projected to increase only moderately (5% 10% annually), but new regulations under consideration to "*force* people out of their cars" may greatly increase demand.

4 INPUT DATA COLLECTION AND ANALYSIS

4.1 Data Collection

Collection and analysis of model data is a fundamental step in simulation analysis: No model is any better than its data (Seila, Ceric, and Tadikamalla 2003). The data can be divided into two parts, Blue Bus's operational data and passengers' data. Blue Bus's data includes the running schedule (i.e. departure times of buses on different routes), traveling time, and arriving time. Since the schedule of Blue Bus is fixed and published, these data were accessed from the system's Internet web site. For the traveling times and arriving times, we needed to consider the different scenarios and collect the data under a variety of conditions. We collected data of total traveling times of all routes by riding a Blue Bus personally. Meanwhile, we also collected data of arriving time at each stop.

For passengers' data, the main task was to discover the demand at different times and on different routes. So at the bus stops, we collected the total number of passengers during a time period and the interarrival time of passengers. Onboard a bus, we collected the total number of passengers on different routes and the number of students' departures at each stop between Pierpont and C C Little. We also collected the arrival times data at Pierpont and at C C Little. We collected data specifically at these two stops because most passengers take the bus between these two stops and many routes stop at each. These data were collected by: (i) counting number of passengers at Pierpont and CC Little, and (ii) counting number of passengers taking different routes and recording the travelling time of routes between different stops by riding buses.

4.2 Surveys

Distributing surveys was important to improve the efficiency and service quality of Blue Bus. From the survey, we estimated how many students are satisfied with the Blue Bus and collected the feedback of students relative to the punctuality, crowdedness of bus, and suitability of setting each stop and routes. We also asked the passengers how they choose the different buses when different route buses can transport them to the same destination and their expectations when they ride a bus. The same survey was also conducted at different times during a day, to capture the influences of disruption to the satisfaction of passengers. Travel times are calculated from the arrival times and departure times, averaged, as provided by student survey responses.

4.3 Sensitivity Analysis

Sensitivity analysis is a powerful tool for enhancing the power and accuracy of simulation models (Biller and Nelson 2002). The purpose of the sensitivity analyses undertaken was to gain insight into the significance of the factors that influence the efficiency of our Blue Bus routes, especially on the specific routes between CC Little and Pierpont Commons. Although several factors affect the system, this report focuses on the passenger arrival numbers. Therefore, the sensitivity analysis was

conducted based on changing peak time passenger arrivals. Thus, data of average waiting time on major stops and bus utilizations of different lines were analyzed under vastly different arrival levels. Multiple systems, the current one and the proposed one, were compared under the scenarios of drastically increased load.
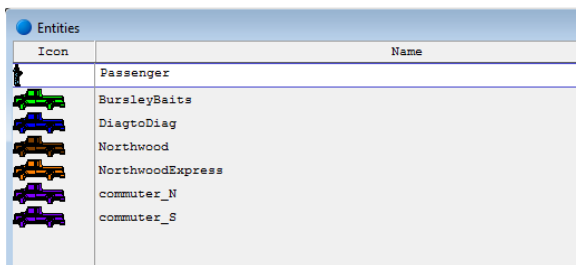
5 MODEL DEVELOPMENT AND CONSTRUCTION

5.1 Model Description

The Blue Bus model was built using the discrete-event process simulation software ProModel® (Harrell and Price 2003). In the model we established locations, entities, and process logic as follows:

As locations, this model contains most stops of five routes (Bursley-Baits, Northwood, Northwood Express, and Diag to Diag Express, Commuter Southbound, and Commuter Northbound), located mainly between North Campus and Central Campus. We omitted the final stops of Bursley-Baits, Northwood, Commuter Southbound, and Commuter Northbound routes, and focused mainly on the stops between Pierpont and CC Little. There are 54 total locations. Every stop has two locations in ProModel®, distinguished as location A and location B, to represent Blue Buses going through the stop in opposite directions.

Entities are passengers and buses. We have one type of passenger and six routes of buses, as shown in Figure 2. We conceptually attach passengers to a bus by using the logic "load" or "unload" when the passengers get on or off the buses. Since passengers and buses have different identities like arrival time and frequency, and the buses on different routes typically have different arrival points and travel schedules, so treating buses as distinct entities helped us control the identities of both passengers and buses much more efficiently.

Figure 2. Entities of Simulation Model

The arrivals of entities are subject to the different probability distributions according to the data we collected. For passengers, we used two distributions of frequency, i.e. regular arrival and peak time arrival to represent the fluctuation of number of passengers between regular time and peak time. To construct the

scenarios that different passengers may have different destinations, we analyze the data of passengers at different stops, and find the portion of passengers going to various destinations. Then we created user distribution of destination, and assigned the distribution to the passengers when the passengers arrived at various locations. Hence the passengers have a certain probability to get off the bus at any particular location (bus stop).

For the buses, we set frequency of 10 minutes for Bursley-Baits, Diag to Diag Express, Northwood, Northwood Express, and commuter from 8:00 am to 6:30pm, and 20 minutes and 15 minutes respectively for Northwood and Commuter after 6:30pm (18:30).

To implement processing logic in our simulation model, two locations with separation zero represent each bus stop. As illustrated in Figure 3, the basic processing for simulation model is: Once the passenger arrives at one location, the passenger will wait for a load request of a bus. When the bus arrives at a location, we chose to unload all the passengers from the Blue Bus at one location if it already loaded some passengers, and then check the destination of the passenger (in ProModel, we use "stop-re" to indicate, for example, CCLittle-re). We used conditional logic to check the passenger's destination to determine the route that the passenger should follow; if the destination is the current location, then the passenger, having reached his or her desired destination, exists the system. If the destination is not the current location, then the passenger will go to the adjacent location to get on the same bus with higher priority (connecting passenger) than the passenger who just arrived at (walked to) that location. This method successfully avoided the illogical situation that a passenger momentarily unloaded from a bus could not "load" again because of capacity of buses if the destination of the passenger is not the current location.
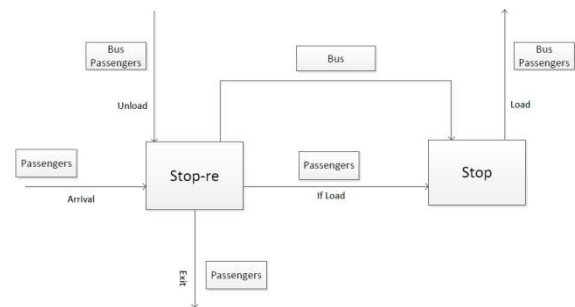

Figure 3: Flow Chart of Processing

5.2 Model Assumptions

In order to simulate the model, we made and documented several assumptions:

1. The passenger arrives at location where he/she is able to take some route to get to the destination. The destination choice of the passenger is modeled probabilistically.
2. If the bus is not full, the passenger boards the bus. If not, the passenger waits for the next available bus, but does not balk or renege.
3. The operation time is scheduled according to the online bus schedule.
4. All buses for different routes have the same capacity, 65 passengers.
5. The time which the bus spends at each stop depends linearly on the number of students who get off and on at that stop.

5.3 Input Modeling

After collecting data, the next step was to incorporate these data into the simulation model. As we verified by using the distribution-fitting software tool Stat::Fit® (Chung 2004), the interarrival times between two consecutive arrivals was exponentially distributed. Then, we needed to estimate the single parameter for exponential random variables based on the data we collected.

Based on our observations, arrivals of passengers at stops other than CC Little, Museum, Cooley and Pierpont are infrequent. Thus, we defined a macro to represent the mean of interarrival times at these stops. For the stops CC Little, Museum, Cooley and Pierpont, the arrivals of passengers are really numerous. Moreover, these arrivals of passengers comprise two types: One type, which we defined as "peak" type, which models the students just dismissed from class and/or just going to class. Arrivals of this passenger type of correspond to the starting and ending time of class in North Campus and Central Campus (for Central Campus, it's 8:30am, 10:00am, etc.; for North Campus, it's 9:00am, 10:30am, etc.). Other passengers are modeled as "regular." From the observations, there are eight peak times at Central Campus and six peak time at North Campus. For each peak time the number of passenger arrivals is modeled as a random number, selected from a uniform distribution with mean and variance again determined by a distribution fitter.

6 VERIFICATION, VALIDATION, AND RESULTS

6.1 Model Verification

Verification is a key step to check the model was correctly built, and that the desired output can be obtained from input parameters. We examined the model output under different input parameters.

To verify the output, we first changed the input parameters of passengers (directional verification). Under the current-situation parameters, the average waiting time was 3.25 minutes. Intuitively, the waiting times should increase when the interarrival time is decreased, because from the real system, the more passengers arrive at one location, the higher the probability that a passenger cannot board a full bus. This directional verification was successful. Second, we increased the frequency of bus arrivals, and waiting times, as expected, decreased. Other verification techniques, such as collaborative structured walkthroughs of the model, and close "stepwise" examination of the animation (for example, to ensure that a passenger is not forced off a bus prior to arrival at intended destination) also proved successful after routine identification and correction of errors.

6.2 Model Validation

This section describes the techniques used to validate that the simulation model represents the real situation. When modeling the arrival number of passengers during different times, we used two parameters of the fitted exponential distribution, i.e. regular rate and peak time rate to represent the fluctuation of arrival passengers through time. From the model, the data shows that the peak time arrival always occurs at the interval time between two classes; for example, 10:00am -- 10:15am, which coincides with a brief heavy demand for transport between north campus and central campus.

To re-validate the simulation inputs (it is perhaps rare to speak of "re-validating" input; in the context of this project, concerns inevitably arose that data values may have "drifted" during the semester as the project progressed), four team members rode various bus routes at different times, and recorded the passengers getting on and off at various stops, plus the travel times between consecutive stops. These observational data matched the inputs to the simulation model under default (current) conditions within 3.5%. Since this effort was concurrent with model development and verification, it did not extend total calendar completion time of the project.

Next, to validate the simulation *outputs* (the typical and indeed vital facet of model validation), we conducted observational and interpersonal surveys to confirm the waiting times of passengers as calculated by the simulation model. We surveyed the waiting time to take a bus among passengers getting off the buses at two main stops, Pierpont and CC Little. The survey found that the average waiting time for the Blue Bus at CCLittle stop is 2.42 minutes, which differs by 5% from our simulation waiting time of 2.31 minutes; the average waiting time for the Blue Bus at Pierpont is 1.44, which has 5% difference of our simulation waiting time of 1.37 (the client deemed agreement within 10% sufficient to support policy decisions). So this key performance metric output of our simulation can be validated. Similarly, bus utilizations and travel times

along entire routes in practice agreed well with predictions of the simulation model.

6.3 Model Outputs

Our outputs of the simulation model are the key performance metrics: Waiting time of passengers and utilizations of the buses. Five waiting time variables were tracked to trace the total waiting time of all stops and waiting time of passengers at Cooly, Pierpont, Museum, and CCLittle. We also tracked six usage variables to trace the usage of buses on each of six routes. For the convenience of model users and decision-makers, these model results were output to a Microsoft Excel® workbook, whence they could conveniently be plotted for easy visualization.

6.4 Output Analysis

In our simulation model, two different Blue Bus running strategies are considered; one based on the current schedule and policy ("Schedule"), the other consists of adding eight buses to the Bursley-Baits routes during peak times ("Practice").

After running the simulation for both scenarios (twenty replications per scenario, each terminating with zero warm-up time, and results compared by Student-t tests) we obtain average waiting times of 3.25 minutes for all stops under the current schedule and average waiting time of 3.10 minutes under the proposed addition of eight buses. So the difference of waiting times between two strategies is very small.

Likewise, comparing the utilizations of the buses, we find average utilization of 26.3% for all buses under the current schedule and average utilization of 28.5% under the proposed addition of buses. So the difference of utility between two strategies is also small, and both utilizations are well below 50% (an figure mentioned repeatedly in survey comments and of interesting origin – with this utilization, each student may have "one seat for myself and one seat for my bookbag," and bookbags do not clog the aisle), implying the buses can pick up more passengers and passengers can feel confident and unrushed when taking the buses to classes or appointments.

For individual bus routes, we observe that the utilizations of the Northwood Express and Diag to Diag routes are relatively lower than those of the other routes. Based on these results, those two routes never achieve 100% utilization even during peak times; however, other routes have been 100% used, briefly, at peak times. The average utilization for five routes is shown in Figure 4.
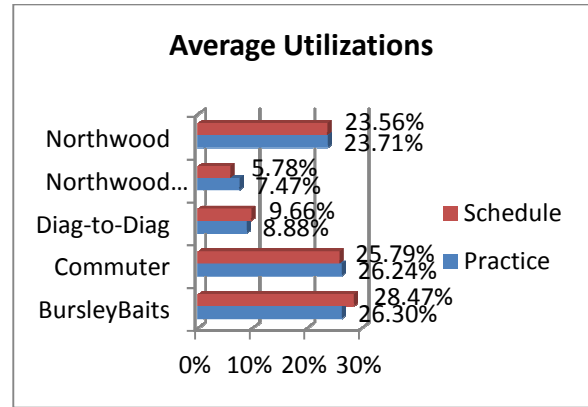

Figure 4. Average Utilization of Five Routes under Two Strategies

scenarios that number of passengers increases by some times. The waiting time under different scenarios are shown in the figure below. The horizontal axis represents the hypothesized percentage of increase in the number of passengers; the vertical axis represents minutes of waiting time on various routes. These comparisons are presented, superimposed in Figure 5.
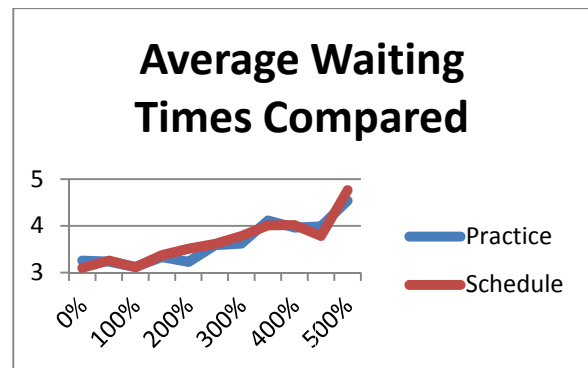

Figure 5. Superposition for Comparison

From Figure 5, we can deduce that the waiting time increases (note y-axis does not start at 0) as the number of passengers increases. The difference between the two strategies stays small when passenger numbers increase by 150% or less. However, when the passengers increase by more than 150%, the "Practice" strategy of adding eight buses becomes noticeably more capable of accommodating the increased numbers of passengers.

For each main destination, we have demonstrated that the waiting times at CCLittle stop increase sharply. Therefore, CCLittle is the bottleneck in the Blue Bus route map. Figure 6 shows the average waiting time at CCLittle under each scenario. We observe that the waiting time will be above five minutes, which is a relatively long time to wait for buses in the daytime for students (key "class breaks" are only thirty minutes), when the passengers increased fivefold. Since only two

routes go through the CCLittle stop, the number of passenger transfers there is higher than elsewhere.
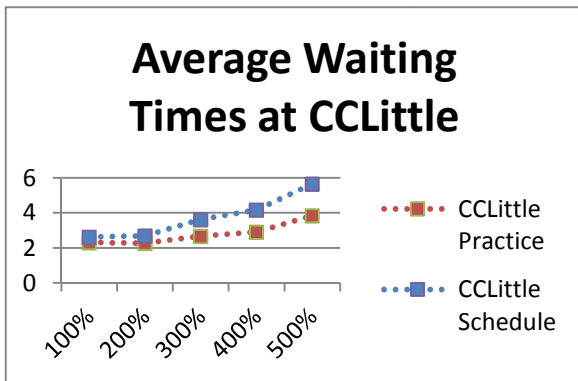

Figure 6. Average Waiting Time at CCLittle

The utilizations for buses on individual routes under different scenarios are shown in Figures 7 through 11. The utilization of buses will increase as arrivals do. For Northwood Express, a sharp increase happens when the passengers increases by 350%. For Bursley Baits, the utilization maintains a higher value compared with other routes. However, after the passengers increased by 350%, the utilization will be above 50%, which means spaces to accommodate more passengers become conspicuously limited.
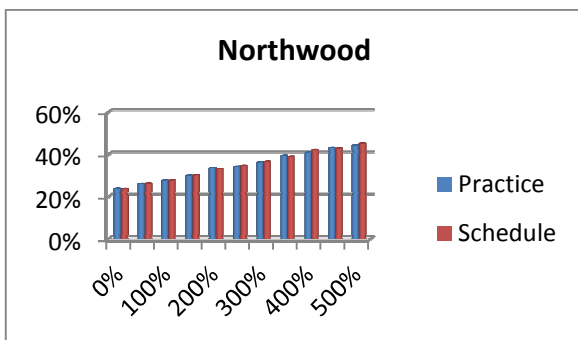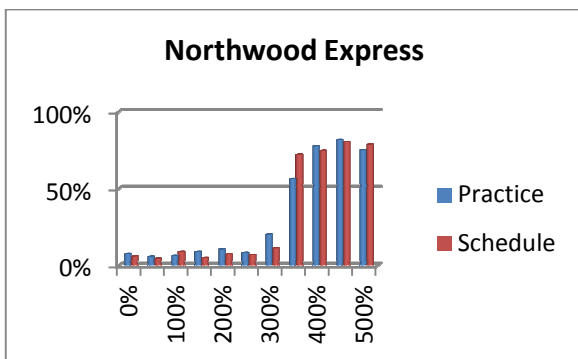

Figure 7 Northwood Route Buses Utilization

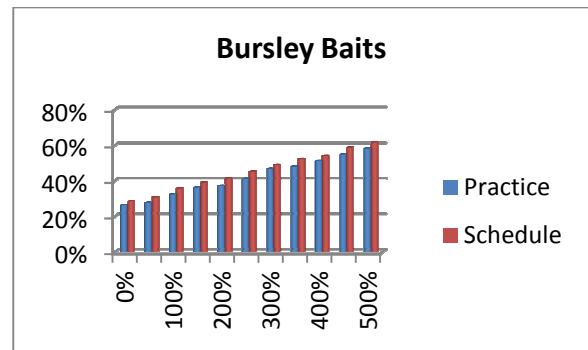Figure 8 Northwood Express Route Buses Utilization

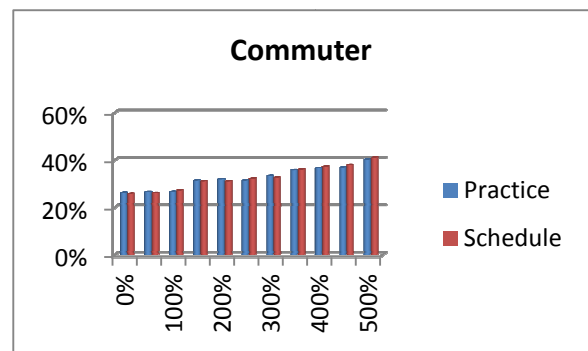Figure 9 Bursley Baits Route Buses Utilization
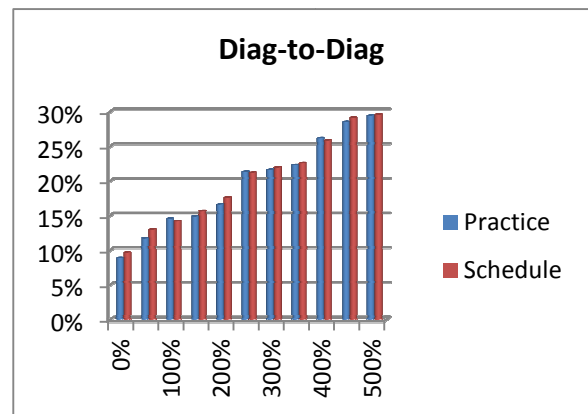

Figure 10 Commuter Route Buses Utilization

Figure 11 Diag to Diag Route Buses Utilization

7 CONCLUSIONS AND FURTHER WORK

This simulation study has confirmed that the CCLittle station is the bottleneck of the entire Blue Bus system; hence, should the arrivals of passengers increase markedly, the waiting times of the passengers at this station will also increase sharply. Therefore, adding more routes at this station by reconfiguring the route map is an effective short-term expedient to reduce waiting times and improve service. Over a longer planning horizon, the university is considering stringent traffic control measures, already described, to reduce severe congestion on campus. These measures will not only increase demand, but also may affect optimality of bus schedules – more surveys will be required, and

these future surveys must reach people *not* currently using the Blue Bus system. In these scenarios, specified in advance by the client, the sensitivity analyses undertaken to assess service quality under greatly increased passenger load are valuable to enhance capital-expenditure predictions for the additional buses which would be required. Additional aspirations of further analysis include a more stringent examination of correlated delays (e.g., if a snowstorm causes longer travel time on one route, it will surely cause longer travel time on others) and explicit inclusion of the KPI "bus connections missed." From a passenger's perspective, an 11-minute delay and consequent missed connection is far worse than a 9-minute delay (connection successful).

ACKNOWLEDGMENTS

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