COVID-19 Pandemic Planning: Simulation models to predict biochemistry test capacity for patient surges

Martha E Lyon[1], Andrew Bajkov[2], Diane Haugrud[1], Barry D. Kyle[1], Fang Wu[1] and Andrew W Lyon[1]

[1]Department of Pathology & Laboratory Medicine, Division of Clinical Biochemistry, Saskatchewan Health Authority, Saskatoon, Saskatchewan, Canada

[2]Roche Diagnostics Canada, Laval, Quebec, Canada

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Corresponding Author:
Dr. Martha E. Lyon
Division of Clinical Biochemistry
Department of Pathology and Laboratory Medicine
Royal University Hospital
103 Hospital Dr
Saskatoon SK S7N0W8
Fax: 306-655-0235
Email: Martha.lyon@saskhealthauthority.ca

ABSTRACT

Background: Patient surges beyond hospital capacity during the initial phase of the COVID-19 pandemic emphasized a need for clinical laboratories to prepare test processes to support future patient care. The objective of this study was to determine if current instrumentation in local hospital laboratories can accommodate the anticipated workload from COVID-19 infected patients in hospitals and a proposed field hospital in addition to testing for non-infected patients.

Methods: Simulation models predicted instrument throughput and turn-around-time for chemistry, ion-selective-electrode and immunoassay tests using vendor-developed software with different workload scenarios. The expanded workload included tests from anticipated COVID patients in two local hospitals and a proposed field hospital with a COVID-specific test menu in addition to the pre-pandemic workload.

Results: Instrumentation throughput and turn-around time at each site was predicted. With additional COVID-patient beds in each hospital the maximum throughput was approached with no impact on turnaround time. Addition of the field hospital workload led to significantly increased test turnaround times at each site.

Conclusions: Simulation models depicted the analytic capacity and turn-around times for laboratory tests at each site and identified the laboratory best suited for field hospital laboratory support during the pandemic.

IMPACT STATEMENT

Healthcare professionals rely on the timely delivery of clinical laboratory test results to triage patients and make decisions that affect treatment. This vital role has been accentuated during the COVID-19 pandemic as critical care bed numbers are expanded and field hospitals are established to support patient care. In this study, simulation models were used to predict if current instrumentation in local hospital laboratories could accommodate the anticipated workload. Simulation models depicted the analytic capacity and turn-around times for laboratory tests at each site and identified the laboratory best suited for field hospital laboratory support during the pandemic.

INTRODUCTION

The rapid emergence of coronavirus disease 2019 (COVID-19) has had a profound effect on the delivery of clinical laboratory medicine. Many organizations have created surge capacity planning committees to organize and optimize local healthcare resources in response to the COVID pandemic. Bed number has traditionally been the metric of hospital capacity, although it does not directly capture the complexity of a healthcare system organization (1). Modern capacity planning has advanced to anticipate increased demand on hospital laboratories using the “Four-S” interdisciplinary approach which accounts for relationships and dependencies among staff, stuff, structures and systems (2). Computer simulation models have aided in projecting hospital wide surge capacity during extended periods of operational stress (3,4). Unfortunately, during a crisis there is seldom time to develop appropriate computer models to assist in surge planning.

The increasing demand for timely, accurate and precise methods to detect the presence of SARS-CoV-2 viral RNA has strained operations in many microbiology laboratories. Concurrent expectations for core clinical laboratories to support increasing numbers of COVID patients, in addition to non-COVID patients, have contributed to the stress on healthcare systems. For pandemic planning, laboratory test capacity (i.e. maximum number of tests per hour or day) is an important and dynamic metric to evaluate, complicated by varying parameters such as reaction time for each assay, analyzer processing (throughput) speed, automated track throughput, and laboratory staff dependent manual processes, etc. To this end, many clinical laboratory vendors have developed software to simulate and predict throughput, turn-around-time (TAT) and capacity throughout the workday with different analyzer configurations and volumes of

tests. The objective of this study was to use a pre-existing simulation model developed by a manufacturer to predict the throughput and TATs for chemistry and immunoassay instruments in two local hospital laboratories with scenarios of increasing workload derived during the COVID pandemic (up to 914 additional inpatients) in addition to the pre-pandemic workload.

METHODS

Laboratory locations and Instrumentation: St. Paul's hospital (SPH) in Saskatoon, Saskatchewan is a 250-bed tertiary care facility consisting of emergency medicine, medical units, critical care, regional kidney health and provincial transplant programs. The SPH biochemistry service supports hospitalized patients however eighty percent of the test workload is derived from out-patients that attend clinics as well as analysis of outreach community-patient tests ordered by family medicine. Functionally, this translates into an approximate pre-COVID workload of 2,900 patient specimens and 21,000 automated chemistry, ion selective electrode (ISE) and immunoassay tests per day. The SPH laboratory instrumentation consists of a single automated track that links a Roche® c8100 pre-analytic module with two groups of ISEs, model c702 and c502 spectrophotometric chemistry analyzers, an e801 model immunoassay analyzer, and a single p701 model refrigeration unit. Royal University hospital (RUH) and the adjoining Jim Pattison Children's Hospital (JPCH) together represent a 606 bed trauma center for the province that provides acute care services, maternal and child services, neurosurgery and cardiovascular surgery. The biochemistry service for these hospitals is centralized at RUH where the pre-COVID workload is 1,200 patient specimens with 8,000 automated chemistry, ISE and immunoassay tests per day. The RUH instrumentation consists of a

single automated track that links a Roche® c8100 pre-analytic module with two pairs of ion selective electrodes, model c502 spectrophotometric chemistry analyzers and a model e801 immunoassay analyzer.

Dataset: De-identified patient data from 2016 was extracted from the laboratory information system (LIS) for a representative 24-hour period for the following parameters: site, specimen accession number, test code(s) ordered per specimen, specimen and container type, time of collection and arrival in the laboratory. Extracted data was increased by a 15% volume, proportionately distributed throughout the day, to reflect the pattern of the current workload.

Cobas Total Workflow Simulator: A simulation software application was developed by Roche® Diagnostics as a tool to predict the ability of instrumentation to meet customer workload and TAT requirements. The program was developed in a Simio® discrete event simulation environment (Simio LLP, Sewickly, PA, USA), which allows for a dynamic simulation of the system behavior, an alternative to WinCAEv previously reported (5,6,7).

The software relies on libraries of information about Roche® analytical methods and configuration of specific automated analytic devices required to mimic real time behavior with respect to throughput and TAT assessments. The simulation model incorporates logic to control and direct the flow of specimens based on the proposed instrumentation, time of receipt of patient specimens, specific patient orders, analytic time per method and instrumentation buffer zone capacity. To mimic real time behavior, the duration of instrument daily maintenance (3 hours/day) was also included in the model. Simulation output predicts the number of tests performed each hour and the TAT for each

specimen at specific times during the 24 hour period. The 90th centile of TATs were determined each hour and for each simulation condition for spectrophotometric chemistry, immunoassay (IA) and ISE tests. The 90th centile was selected to reduce the influence of low frequency high TAT predictions. Throughput testing capacity was calculated as (number of test requests/hour divided by the manufacturer identified maximal throughout/hour)*100.

Model Assumptions: During a pandemic, the workflow pattern of patient management and laboratory specimen collection would be subject to change. To simulate a worst-case scenario, we assumed the pre-pandemic volume and test pattern for each hospital at 100% occupancy and that community clinics continued prior to adding workload for additional pandemic hospital beds and a field hospital. In line with current processes, it was assumed that one fifth of specimens at the SPH derived from inpatients would require centrifugation (community derived specimens arrive pre-centrifuged), and all specimens would require centrifugation at RUH. To simulate workload capacity during the pandemic, incremental increases of planned additional COVID beds were evaluated for each hospital site (256 bed expansion for RUH, 364 bed expansion for SPH). Table 1 outlines the six simulation conditions in terms of bed number and predicted total tests performed per day.

The workload derived from patients admitted to COVID dedicated beds assumed a 100% physician adoption of tier 1 COVID tests once per day in addition to a 10% adoption of daily tier 2 test orders. Field hospital simulations assumed maximal occupancy of each hospital (SPH, RUH & JPCH) and all field hospital patients had tier 1 and one tenth had tier 2 COVID menu tests and that all specimens would require

centrifugation at the hospital. Weekly and monthly maintenance was not accounted for in the simulations.

Model Validation: The baseline workload was audited at each site in November 2019 and observed to be within 15% of the predicted baseline workload used in the model. Recent turn-around time was extracted from the Cobas® IT middleware to compare with the turn-around times predicted by the simulation software and validate the baseline conditions. On-analyzer 90th percentile turn-around time each hour was assessed separately for the RUH and SPH sites. The hourly pattern on 90th percentile turn-around times agreed well throughout the 24-hour interval for the RUH site. At the peak of community lab workload 12:00-14:00 the actual 90th percentile of hourly turnaround time pattern at the SPH site exceeded the simulation baseline by 20 minutes and the reason for this discrepancy was not investigated.

COVID Test Menu: Tier 1 chemistry testing included daily monitoring of electrolytes and CO_2, creatinine, urea, calcium, magnesium, phosphate, AST, ALT, ALP, GGT, total bilirubin, lipase, creatine kinase and high sensitivity cardiac troponin T. Tier 2 chemistry testing comprised total LDH, high sensitivity CRP, procalcitonin, ferritin and NT-proBNP.

Statistical and Calculation Methods: For each simulation condition, the hourly predicted 90th centile TATs and the daily (24 hr) mean of the hourly predicted 90th percentile TATs were calculated. TAT was determined from when the specimen was introduced onto the pre-analytic module to when the analysis was complete and the result ready for reporting. The change in this index was determined by subtracting the simulation condition daily mean from the baseline condition daily mean. The mean changes (in minutes) were

compared by ANOVA (n=24). Confidence intervals for the mean changes in 90th percentile TATs for each simulation condition were also determined.

RESULTS

During the initial phase of the COVID-19 pandemic, laboratory leaders were asked to plan how to deliver services with expanded populations of patients in the local hospitals and in a field hospital. We approached the vendor of our automated laboratory systems to ask if the proprietary software used to simulate laboratory workflow for marketing could be adapted to predict workflow with expanded COVID patient populations during the pandemic. In a vendor–academic partnership, we simulated module capacities at both the RUH and SPH sites for chemistry, immunoassay and ISE for a 24-hour period for each of the six simulation conditions, Table 1.

Royal University Hospital: Figure 1 panel A shows the percentage of maximal test throughput anticipated per hour for chemistry assays at RUH for the series of simulation conditions. The baseline level occupancy condition consistently showed the lowest anticipated throughput during the 24-hour period. The extent of test throughput capacity consumed increased in a sequential manner with additional pandemic bed occupancy, with baseline being the lowest and 100% occupancy of both RUH and the field hospital being the highest. All simulations demonstrated the highest anticipated workload occurred between 7am and noon, reaching the highest point at 10am.

Immunoassay (IA) module capacity as a function of time is shown in Figure 1 panel B for baseline and each progressive simulation stress condition. Similar to the chemistry module capacity, the percentage IA capacity utilized increased with the simulation stress

condition in a sequential manner throughout the 24 -hour period. However, all simulation conditions were well within the 100% capacity of the IA module at RUH. Under baseline conditions, IA throughput capacity consumed slowly rose at 7am and maintained at approximately between 10% and 15% levels until 6pm. This general pattern of capacity consumption remained consistent with all simulated conditions. Predictably, the degree of module throughput capacity consumed increased with the increasing patient occupancy conditions.

RUH ISE capacities (figure 1 panel C) showed a similar pattern of increments to the chemistry and IA assays for each progressive simulated condition, with the important distinction that less than 13% of maximum throughput was consumed.

St Paul's Hospital

SPH showed a slightly different daily pattern of throughput consumption compared to RUH. Laboratory workload at the SPH site is largely derived from community-based patients collected throughout the daytime hours. Figure 2 panel A shows the incremental rise for chemistry module throughput consumed for each simulation condition throughout the 24hr time period, similar to that seen at the RUH. For the baseline condition, capacities peaked at 10am (~60%), and progressively declined until 2pm, where another small peak (~20%) was observed at 4pm, and then generally remained low for the remainder of the day. This pattern was consistent for the simulation conditions although the peaks increased approximately 2-3% respectively as bed occupancy increased up to 100%. Predictably, the condition simulating maximal COVID occupancy at SPH and the field hospital generated an 10am peak of ~75% followed by a 4pm peak of ~50%.

The simulation conditions for immunoassays (figure 2 panel B) depict a similar pattern to the chemistry module capacity (figure 2 panel A). Two peaks of IA capacity consumption were noted. The initial peak magnitude was observed at 10am and the second occurred between 4 to 6pm. The baseline condition had an initial 10am peak of ~65% throughput capacity consumed and a second peak of 50% at 6pm. IA throughput did not exceed the maximum module capacity. The final condition with field hospital workload generated an 11am peak of ~90% and a second peak of ~85% capacity consumption.

The anticipated ISE workload (figure 2 panel C) demonstrated a major peak between 9 to 10am and it generally decreased throughout the day for all stress conditions. For the baseline condition, the 9am peak consumed ~15% ISE module capacity. Each COVID stress condition increased the workload and required more throughput capacity, to a maximum of 20% with addition of the field hospital workload. Unlike RUH, the capacity consumed for the chemistry, IA and ISE modules at SPH resembled a more bimodal distribution, with the major increase in volumes occurring between 8am and noon and a subsequent smaller peak occurring between 4 to 6pm.

Turn-Around Times

The effect of various simulation conditions on the hourly 90th centile TAT is shown in Figure 3 for RUH and SPH. Simulations indicated that only the addition of the field hospital workload influenced the anticipated 90th percentile for TAT at each site. Tables 2 and 3 illustrate the statistically significant mean changes in the 90th centile TAT over a 24 hour period at each site. Maximal occupancy of field hospital COVID beds started to

lengthen hourly TATs by 7am which remained lengthened until midnight at RUH (Figure 3 panel A). A similar lengthened TAT pattern was observed at SPH that resolved by 6pm (Figure 3 panel B). As test volumes increased with the scenario of maximum patient numbers, TATs were predicted to significantly lengthen causing tubes to remain in the instrument buffer and be analyzed in the subsequent hour. The simulations predicted that both hospital sites could not accommodate the workload from the field hospital in addition to their expanded COVID beds and the pre-pandemic workload without extending TATs. It is anticipated that the 90% percentile TATs will remain constant until the maximum throughput of the analytic system is exceeded. When this occurs, we speculate that the 90% TAT will likely begin to increase in a non-linear manner. However, an investigation of the relationship between the specific saturation point and the 90% TAT was not conducted.

DISCUSSION

The World Health Organization (WHO) classified the COVID-19 outbreak as a pandemic in March, 2020 and, as of October 26th , more than 43.1 million COVID-19 cases and over 1,155,438 deaths have been reported globally. Our local pandemic planning interdisciplinary team has been preparing new wards for an additional 250 patients at RUH, 364 patients at SPH and a nearby field hospital, a renovated hockey facility, for up to 550 patients. The impact of adding this patient workload to the existing tertiary care hospitals was unknown. For effective planning, it was necessary to assure that hospital laboratory services could accommodate this increased workload and existing pre-COVID clinical monitoring requirements would not be compromised. In this study, we used the simulation software application developed by Roche Diagnostics to determine

the ability of current chemistry instrumentation to meet the heightened COVID workload expectations.

Six workload conditions were simulated to assess chemistry, IA and ISE module capacities and anticipated TATs during a 24 hour time period at our two hospital clinical biochemistry laboratories. In general, all RUH chemistry, IA and ISE module capacities were able to accommodate the simulated COVID workloads. TAT data were determined by the length of time it took for test analysis to be complete and results ready for reporting from when the specimen was first introduced onto the pre-analytic module. We expressed TAT data for each hour as 90th centiles which are more representative values than the infrequent maximum values. When both RUH and the field hospitals were completely filled with COVID patients, the anticipated workload for the chemistry module at RUH reached 88% of the maximum throughput by 10am and the overall TAT exceeded 120 minutes and progressively worsened to over 360 minutes at 3pm. Both the IA and ISE module capacities were also able to accommodate all simulation conditions but the chemistry module capacity (maximal throughput of 1200 tests/ hour) appeared to be the rate limiting step that lengthened TATs. The baseline pre-COVID workload at SPH was about 2.5 times larger than for RUH. Recognizing this, larger capacity chemistry, IA and ISE instrumentation had been implemented at SPH. SPH instrumentation was more suited to accommodate the simulated COVID conditions than instrumentation at RUH. Interestingly, the IA modules and not the chemistry modules were the rate limiting step that affected TAT at SPH. Under the condition of complete SPH and field COVID hospital occupancy, the IA module anticipated capacity peaked at 88% maximum throughput by 11am that was associated with TATs of 75 minutes at 8am that progressively increased

to 180 minutes by 2pm. The simulation analysis revealed an unexpected outcome that the RUH site had limited capacity of additional chemistry tests and the SPH had limited capacity for additional IA tests as pandemic workload increased. At this time between the first pandemic infection wave and forecast of a second wave, based on this simulation we will direct future field hospital chemistry and IA tests to the SPH site and will plan to move a portion of the immunoassay test volume from SPH to the RUH site if a long term strategy is required.

Simulation studies also prompted a re-assessment of our scheduled instrument daily maintenance times. Our current practice, at both hospitals, is to perform maintenance of one analyzer line during the middle of the day (noon to 3pm) which translates into peak workload time and the second line maintenance is scheduled for midnight to 3am. Workload efficiencies can be gained if instrument maintenance were instead conducted during “off peak” times. Such changes in maintenance times however will impact technologist/operator shift scheduling.

Simulation modeling and its forecasts are not without limitations. The usefulness of simulations will be dependent upon parameters, such as physician ordering patterns for management of COVID as well as non-COVID patients during peak pandemic that were estimated for this study. This study assumed that existing laboratory staff levels would be sufficient to accommodate the additional workload. A major limitation of this study was the use of proprietary vendor-provided simulation software that has not been described in peer-reviewed publications and had a limited evaluation under baseline conditions for this study. At this time, local emergency medicine, hospital admissions and laboratory workload during the COVID-19 pandemic has not exceeded capacity or

exceeded the baseline workload described in this study. It remains a limitation that the impact of elevated workload has not been assessed. In spite of these caveats, our simulation findings have been helpful to identify instrumentation capacity issues that could affect our ability to delivery timely test results during a pandemic surge in our organization. We anticipate that currently employed simulation software from many different vendors could facilitate pandemic planning of laboratory resources.

In conclusion, the simulation models provided an in-depth perspective of the impact of hospital laboratory resources during various degrees of pandemic-induced stress. This study allowed us to anticipate and plan to direct specimens to the site best able to accommodate increased volumes (i.e. the SPH site). The study also suggests that to accommodate the acute care COVID hospital beds and the field hospital test volume that pre-pandemic community patient workload at the SPH site may need to be reduced.

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A. Bajkov, statistical analysis; D. Haugrud, provision of study material or patients.

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Figure 1. Simulation for the RUH site of incrementally increased COVID bed occupancy on the percentage maximal test throughput for Panel A chemistry, Panel B IA and Panel C ISE tests. Lines: Black: pre-COVID baseline condition; Dark Blue: baseline+ 25% COVID beds filled; Dark Green: baseline+ 50% COVID beds filled; Light Green: baseline+ 75% COVID beds filled; Maroon: baseline+100% COVID beds filled; Orange: baseline+ 100% COVID beds and field hospital filled.

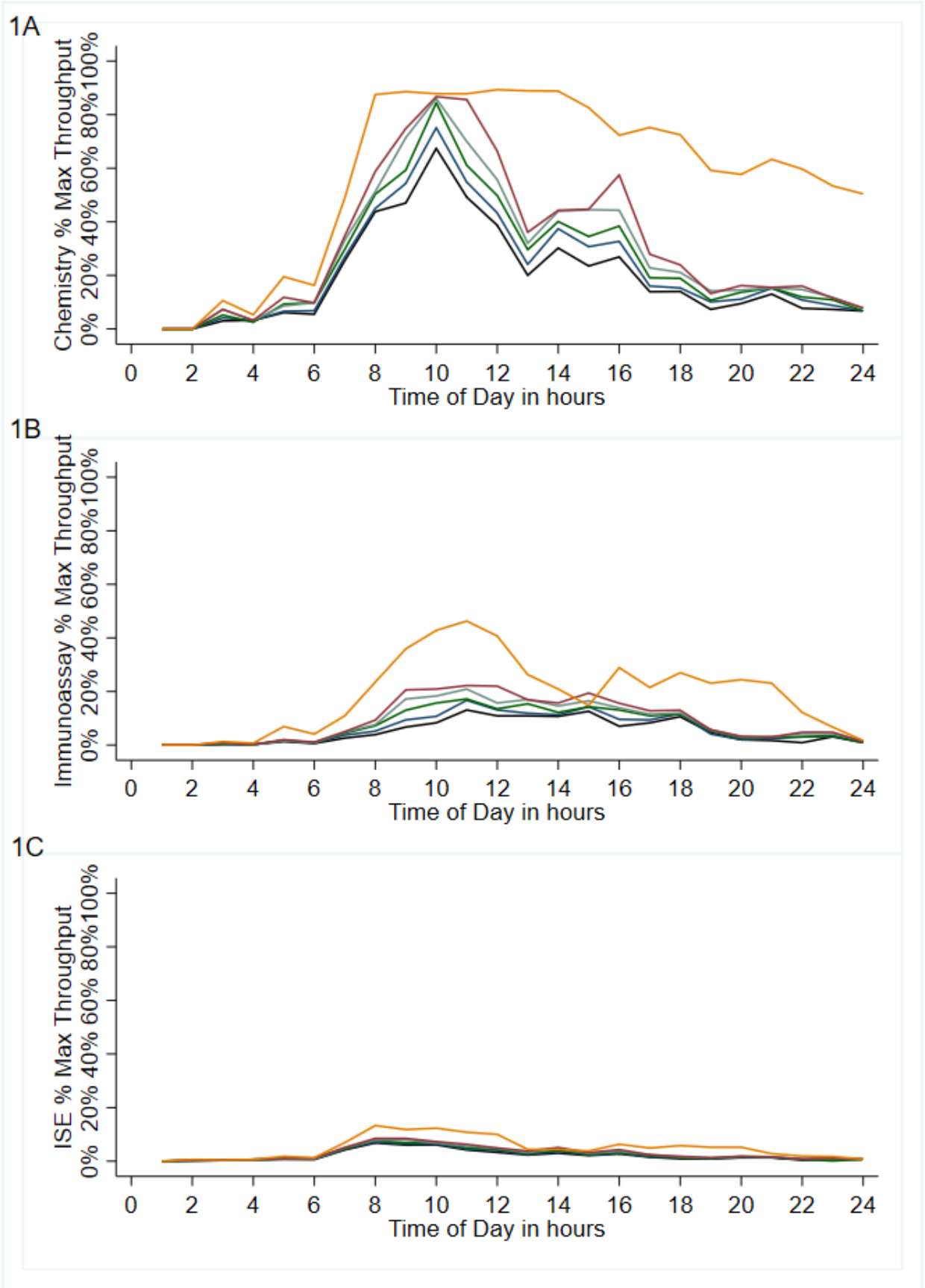

1A
Chemistry % Max Throughput
0% 20% 40% 60% 80%100%
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of Day in hours
1B
Immunoassay % Max Throughput
0% 20% 40% 60% 80%100%
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of Day in hours
1C
ISE % Max Throughput
0% 20% 40% 60% 80%100%
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of Day in hours

Figure 2. Simulation for the SPH site of incrementally increased COVID bed occupancy on the percentage maximal test throughput for Panel A chemistry, Panel B IA and Panel C ISE tests. Lines: Black: pre-COVID baseline condition; Dark Blue: baseline+ 25% COVID beds filled; Dark Green: baseline+ 50% COVID beds filled; Light Green: baseline+ 75% COVID beds filled; Maroon: baseline+100% COVID beds filled; Orange: baseline+ 100% COVID beds and field hospital filled.

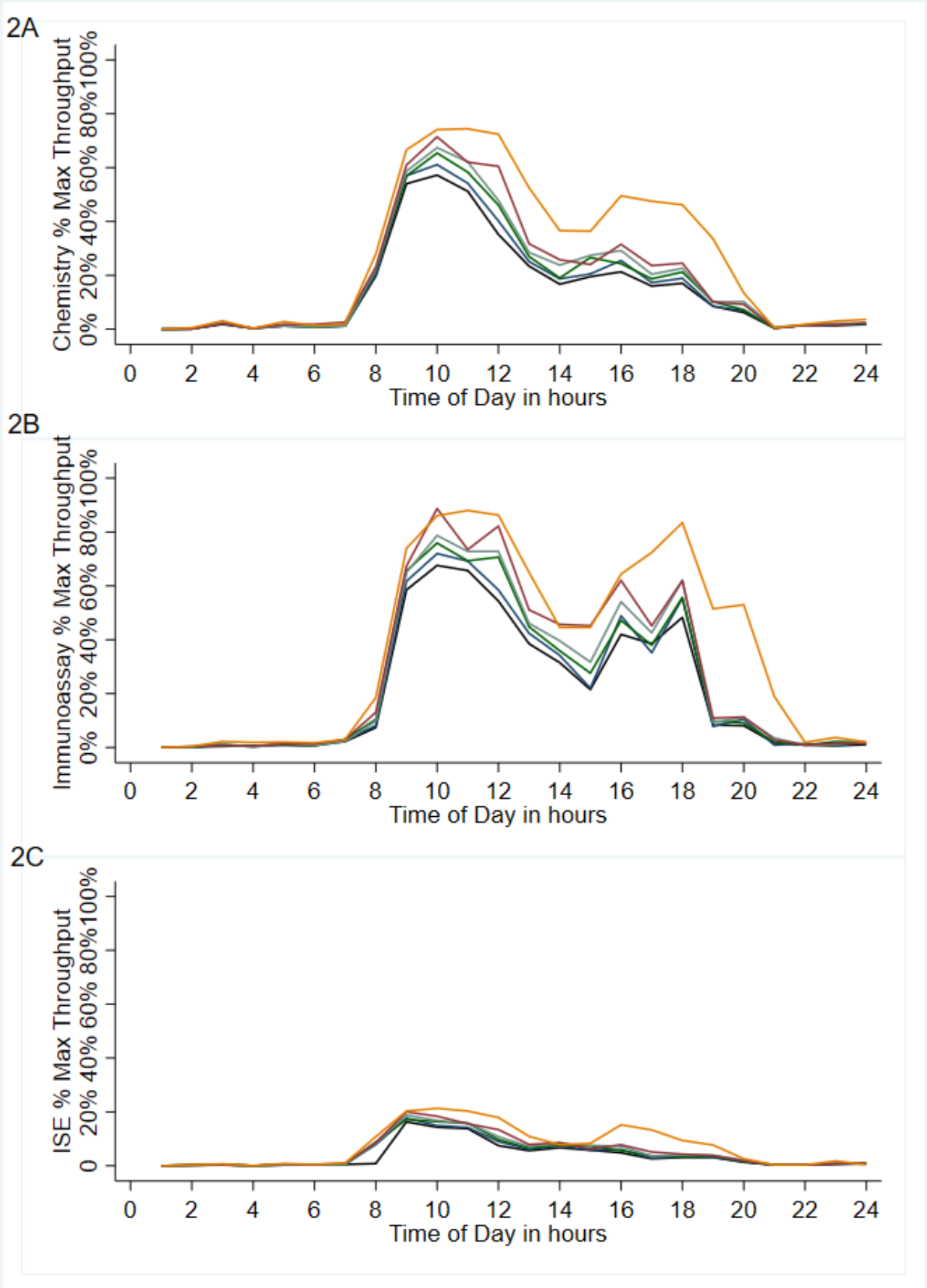
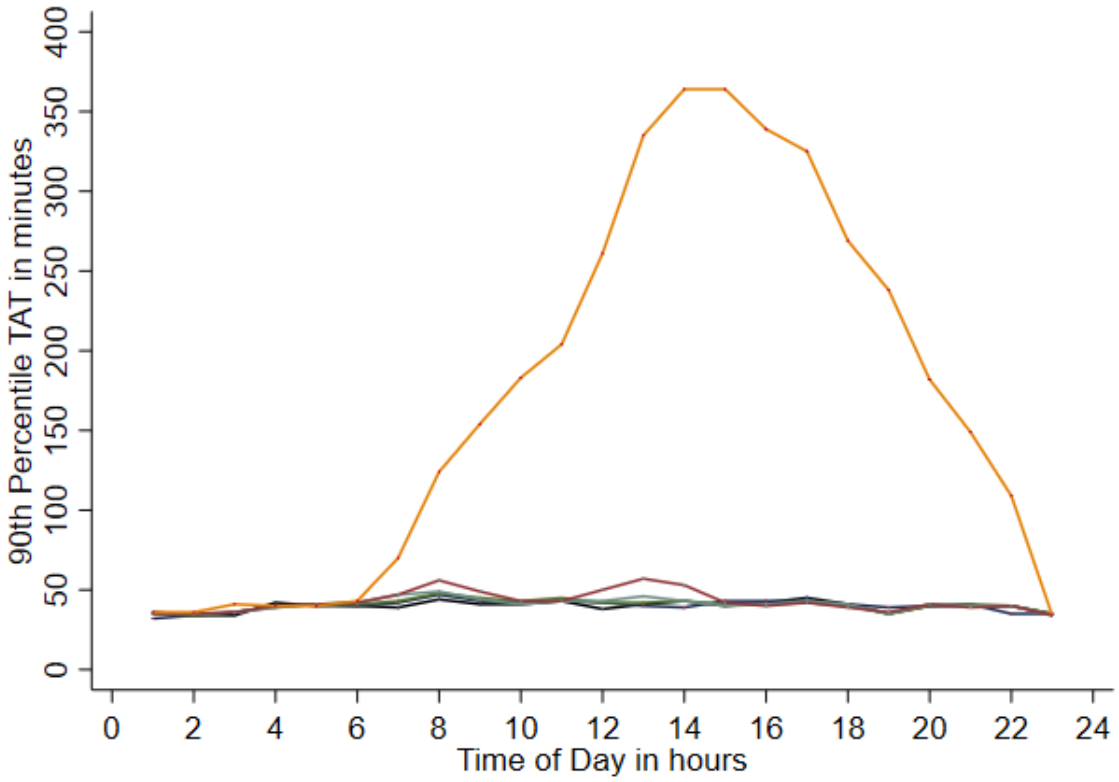
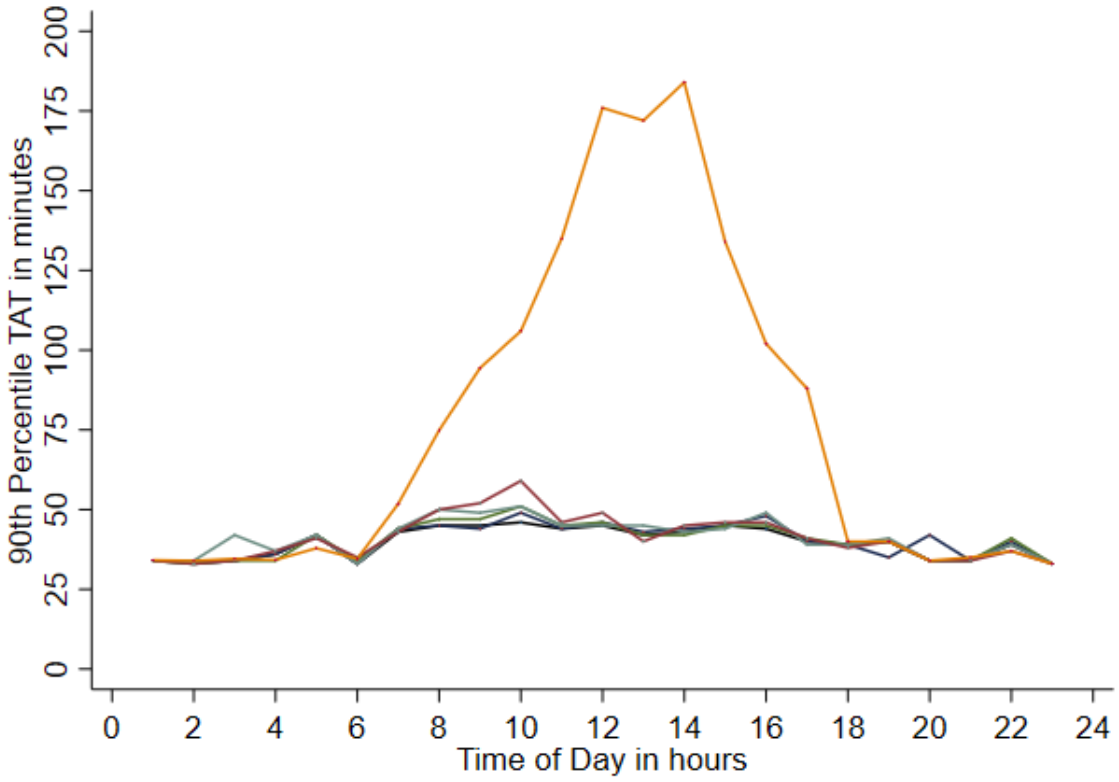

2A
Chemistry % Max Throughput
0% 20% 40% 60% 80%100%
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of Day in hours
2B
Immunoassay % Max Throughput
0% 20% 40% 60% 80%100%
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of Day in hours
2C
ISE % Max Throughput
0 20% 40% 60% 80%100%
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of Day in hours

Figure 3. Influence of incremental increase of COVID bed occupancy on the 90th percentile turnaround time by hour of day for all tests at Panel A: RUH site and Panel B: SPH site. Lines: Black: pre-COVID baseline condition; Dark Blue: baseline+ 25% COVID beds filled; Dark Green: baseline+ 50% COVID beds filled; Light Green: baseline+ 75% COVID beds filled; Maroon: baseline+100% COVID beds filled; Orange: baseline+ 100% COVID beds and field hospital filled.

3A


90th Percentile TAT in minutes
0
50
100
150
200
250
300
350
400
0
2
4
6
8
10
12
14
16
18
20
22
24
Time of Day in hours

3B


90th Percentile TAT in minutes
0
25
50
75
100
125
150
175
200
0
2
4
6
8
10
12
14
16
18
20
22
24
Time of Day in hours

Simulation Condition	Total Bed Number			Predicted Total Tests/day		
	RUH & JPCH	SPH	Field Hospital	RUH & JPCH	SPH	Field Hospital
Baseline (Pre-COVID)	606	250		8104	21123	
Baseline + 25% COVID Additional beds/hospital	606+64	250+91		8104+1196	21123+1709	
Baseline + 50% COVID Additional beds/hospital	606+128	250+182		8104+2393	21123+3401	
Baseline + 75% COVID Additional beds/hospital	606+192	250+273		8104+3589	21123+5093	
Baseline + 100% COVID Additional beds/hospital	606+256	250+364		8104+4768	21123+6802	
Baseline + 100% COVID Additional beds/hospital +100% Field Hospital beds	606+256	250+364	550	8104+4768	21123+6802	10340

Table 1. Simulation conditions of total bed number and predicted tests per day by site.

Workload	Bed Number	Tests/Day	Chemistry Module Mean change in 90th centile TAT/h (99% CI) in minutes	Immunoassay Module Mean change in 90th centile TAT/h (99% CI) in minutes	ISE Module Mean change in 90th centile TAT/h (99% CI) in minutes
RUH Baseline	606	8,104			
RUH Baseline + 25% additional COVID beds	670	9,300	-0.2 (-10 to 5)	-0.5 (-6 to 6)	-0.3 (-5 to 5)
RUH Baseline + 50% additional COVID beds	734	10,497	1.1 (-4 to5)	0.0 (-4 to 4)	0.2 (-5 to 4)
RUH Baseline + 75% additional COVID beds	798	11,693	1.6 (-4 to 8)	-0.1 (-7 to 5)	-0.4 (-5 to 5)
RUH Baseline + 100% additional COVID beds	862	12,872	3.4 (-4 to 18)	-0.8 (-7 to 5)	-0.1 (-5 to 4)
RUH Baseline + 100% additional COVID beds + 550 bed COVID Field Hospital	1,412	23,212	129.7 (-2 to 327) p <.001	50.5 (-7 to 186) p <.001	33.5 (-7 to 162) p <.001

Table 2: Mean changes in turnaround time per hour with increasing workload at the RUH site. The number of beds and daily test volume is shown for each workload condition. The mean 90th centile turnaround time each hour for the baseline workload was subtracted from the mean 90th centile turnaround time each hour for the increasing workload conditions for each analyzer module, to detect if increasing workload resulted in increased test turnaround time. Values for each module were assessed by ANOVA and pairwise comparison with Tukey's post hoc analyses and found statistically significant changes p <.001) with the addition of the field hospital and no statistically significant changes among the other workload groups.

Workload	Bed Number	Tests/Day	Chemistry Module Mean change in 90th centile TAT/h (99th CI) in minutes	Immunoassay Module Mean change in 90th centile TAT/h (99th CI) in minutes	ISE Module Mean change in 90th centile TAT/h (99th CI) in minutes
Baseline	250	21,123			
SPH Baseline + 25% additional COVID beds	341	22,832	0.1 (-5 to 3)	-0.4 (-6 to 4)	0.3 (-3 to 8)
SPH Baseline + 50% additional COVID beds	432	24,524	0.3 (-3 to 5)	-0.2 (-7 to 12)	0.3 (-3 to 10)
SPH Baseline + 75% additional COVID beds	523	26,216	0.3 (-3 to 5)	0.3 (-6 to 9)	1.0 (-2 to 9)
SPH Baseline + 100% additional COVID beds	614	27,925	0.3 (-3 to 5)	0.7 (-7 to 15)	1.2 (-4 to 18)
SPH Baseline + 100% additional COVID beds + 550 bed COVID Field Hospital	800	38,265	30.9 (-2 to 102) p <.001	55.2 (-7 to 154) p <.001	27.9 (-3 to 102) p <.001

Table 3: Mean changes in turnaround time per hour with increasing workload at the SPH site. The number of beds and daily test volume is shown for each workload condition. The mean 90th centile turnaround time each hour for the baseline workload was subtracted from the mean 90th centile turnaround time each hour for the increasing workload conditions for each analyzer module, to detect if increasing workload resulted in increased test turnaround time. Values for each module were assessed by ANOVA and pairwise comparison with Tukey's post hoc analyses and found statistically significant changes p <.001) with the addition of the field hospital and no statistically significant changes among the other workload groups