Sg2 COVID-19 Surge Demand Calculator: How Accurate Has It Been?

SURGE DEMAND CALCULATOR MODEL ENHANCEMENTS.

Hospital leaders, planners and local governments value the Sg2 model due to its ability to accurately predict inpatient surge(s) to inform planning and resource allocation efforts in response to COVID-19. Based on feedback from model users as well as new modeling considerations for the later stages of the pandemic, such as clinical advancements in the treatment of COVID-19 patients, Sg2 has added updates to the model to more accurately model second- and third-wave surges. Sg2 recently released the Sg2 COVID-19 Surge Demand Calculator v6.1 with new features that allow users to model additional changes over time in transmission rates and demographics for a given market, and flexible, custom hospital-related inputs based on trends observed within an organization's clinical setting.

CHANGES IN SURGE MODELING FROM THE SPRING TO THE FALL.

Key considerations and inputs for modeling COVID-19 hospitalization surges have changed since spring 2020.

Cumulative Infection Rate and Immunity Levels: The total number of SARS-CoV-2–infected people has climbed steadily across the US, though at varying rates by market. The US still has a significant way to go before potentially reaching herd immunity, estimated to be between 60% and 70%. But as the population develops immunity over time, transmission will modestly slow even before that point. While in summer 2020 an estimated 10% of the US population was infected by the SARS-CoV-2 virus, market-specific immune rates, as estimated by susceptible-infectious-recovered (SIR) modeling and confirmed in population-based seroprevalence studies, show wide variation depending on the level of surge they experienced. Markets with large, primary surges reported upwards of 30% of the population infected, while markets with minimal surge had seroprevalence rates below 10%. To accurately model surges for second and third waves, it is important to factor in the most current level of immunity in a given market, as this will impact the speed of transmission, modestly slowing transmission rates the higher the immunity level. Over the course of the pandemic, the SIR model factors in the cumulative total infected population and adjusts the impact of the reproduction number based on that factor. While our understanding of SARS-CoV-2 immunity is still evolving, a growing body of evidence shows that the vast majority of people infected with SARS-CoV-2 have immunity for at least the short-term, up to at least 2 years.

Sources: Stadlbauer D et al. Repeated cross-sectional sero-monitoring of SARS-CoV-2 in New York City. *Nature*. November 2, 2020; Rosenberg ES et al. Cumulative incidence and diagnosis of SARS-CoV-2 infection in New York. *Ann Epidemiol*. 2020;48:23–29.e4; Anand S et al. Prevalence of SARS-CoV-2 antibodies in a large nationwide sample of patients on dialysis in the USA: a cross-sectional study. *Lancet*. 2020;396(10259):1335–1344.

Clinical Advances Affecting Average Daily Census: Advancements in clinical care for COVID-19 patients have impacted hospital utilization per infected person over the course of the pandemic. Specifically, ICU and ventilator rates and average length of stay have been reduced with the adoption of new treatments such as Remdesivir, antibodies and steroids. These changes require modeling inputs differently over time to accurately project future average daily census (ADC). The updated model allows the user to continue to customize the inputs for ICU, ventilator and ALOS based on their organization's practice patterns and has the added feature of allowing the user to change these inputs over time to capture the changes in bed utilization.

Hospitalization Rate Trends Over Time: Widespread transmission of SARS-CoV-2 shifted to younger, healthier populations during the summer and fall and has resulted in fewer hospitalizations per infected persons. The updated model allows the user to input a change in overall hospitalization rate over time to reflect this phenomenon.

Bed Capacity Considerations: Modeling bed capacity for second and third waves requires customizing the occupancy rates to current hospital trends and local staffing shortages to more accurately predict when capacity thresholds are surpassed. Occupancy rates for non–COVID-19 conditions have fluctuated over the course of the pandemic and alter the supply of beds available to care for COVID-19 patients. In the springtime, much of the US shut down scheduled surgeries and decanted their ICUs in preparation for COVID-19 surges, resulting in many hospitals operating at a 40% to 50% occupancy rate for non–COVID-19 conditions. Fast forward to the fall, and many hospitals' occupancy rates for non–COVID-19 conditions have risen to 70% or higher. In addition, growing nursing shortages over the course of the pandemic have resulted in organizations operating at lower total bed counts than in the spring.

Reinfections: The potential for reinfection from SARS-CoV-2 has been reported in the literature, and waning of antibodies to infection after 6 months has been observed in seroprevalence data. However, widespread reinfections, or reinfections resulting in hospitalizations, have not been observed to date. Furthermore, research on immunity to SARS-CoV-2 has evolved scientists' understanding of the multiple pathways, including T-cell mediated immunity, involved in long-term memory and protection from SARS-CoV-2 reinfection. As the pandemic enters its 10^{th} month in the US, it is unlikely that reinfection will play a role in second- and third-wave surges. However, over a longer period, as immunity gradually wanes, the ability to model reinfections may be of value.

Prominent Updates

- Multiple new inputs for scenario modeling of COVID-19 resurgence based on changes in social distancing and transmission rates, to include up to 30 changes in the reproductive rate
- Ability to account for population age-cohort adjustments based on in-migration to or out-migration from the market area
- Enhanced capability to model the changing overall hospitalization rates, as observed over the course of this pandemic, using up to 3 hospitalization rates, with flexible inputs for the start date of second and third hospitalization rates
- Capability to model local changes in the rates of hospitalizations requiring the ICU and ventilators, with a flexible input for start date of secondary rate
- Ability to model changes over time in ALOS for non-ICU patients, ICU patients and days for mechanical ventilation, with flexible input for secondary start date
- Ability to model the potential impact of COVID-19 reinfections, with the capability for the user to input average length of immunity and percentage reduction in hospitalization for secondary infection
- Enhanced user experience to streamline entry of reproductive rate changes on a secondary inputs tab

Release of Updated Validation Document (v3.0).

In follow-up to the previously released validation documents v1.0 and v2.0 (see below for summaries), Validation Document v3.0 is intended to demonstrate how the updated Sg2 COVID-19 Surge Demand Calculator v6.1 can be used to project potential winter surges based on data reported from Chicago, IL; Dallas, TX; Milwaukee, WI; New York City, NY; San Antonio, TX; and San Francisco, CA.

The scenarios presented in this paper leverage the new calculator enhancements to demonstrate how the new features and flexible inputs improve accuracy in modeling potential winter surges by region. Given local variance over time in infection spread, immunity levels and hospital utilization trends, the flexible hospital-related inputs allow for more accurate, localized projections for COVID-19 surges over time. For the purposes of scenario planning, this document will also offer insights into the potential best- and worst-case scenarios of what a winter surge may look like.

Lastly, an important factor to achieve an accurate 2-week projection is to frequently update the model using ADC data from local regions.

Summary of Validation Document (v1.0).

In May 2020, Sg2 released Validation Document v1.0, reviewing the accuracy of the Sg2 COVID-19 Surge Demand Calculator v3.2 hospitalization projections for Albany, GA; Chicago, IL; New York City, NY; San Antonio, TX; and San Francisco, CA. The analysis demonstrated that the Sg2 model was able to satisfactorily match actual data from these 5 regions.

A comparison of the Sg2 Surge Demand Calculator against other models frequently cited by the White House and the state of New York found the other models overestimated census and bed need projections. These models used projected hospitalization rates that applied cited case-positive hospitalization rates from the international literature to the projected total infected population rate estimates. Sg2 derived its lower hospitalization rate using actual COVID-19 hospitalization data from Lombardy, Italy; New York City; San Francisco; Chicago; and Albany, GA, and comparing the data to the active infected population under the SIR curve for specific dates in the early phase of the pandemic. In addition, Sg2's model enabled more rigorous modeling of the impact and timing of social distancing measures that resulted in projections mirroring actual surges in markets across the US. Other factors that contributed to the accuracy in projections were the application of market-specific, age-adjusted COVID-19 hospital rates (see Appendix Table 1) and custom inputs for average length of stay that captured differences in case mix and local practice patterns.

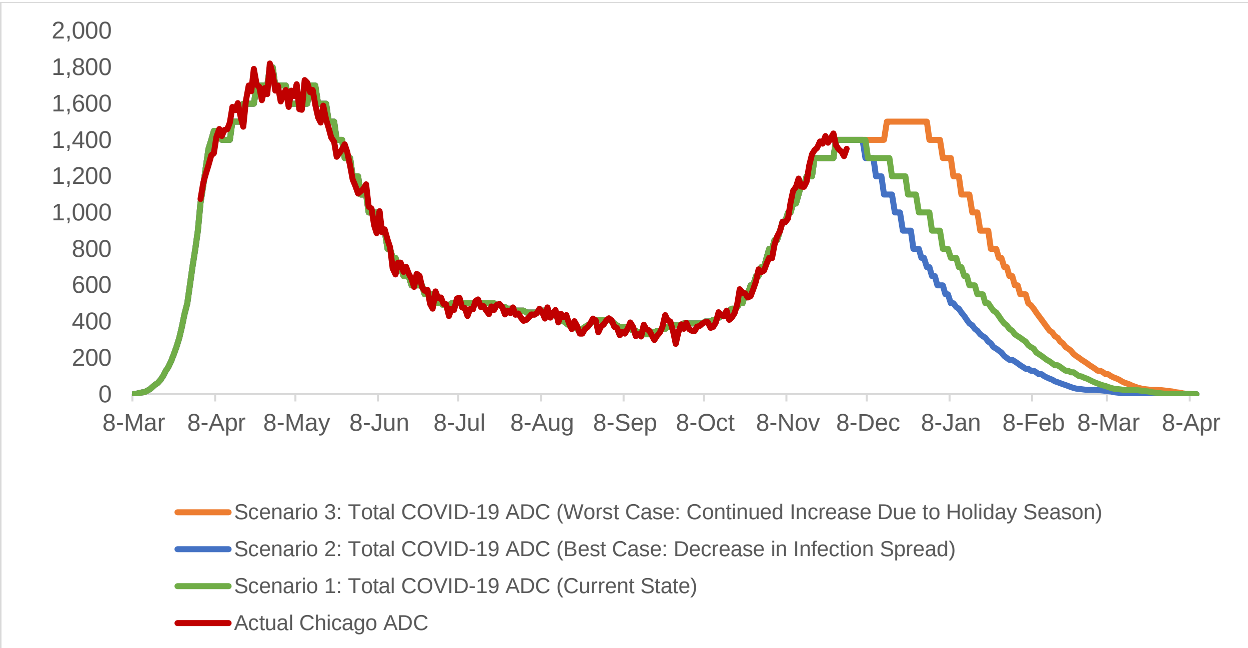
Summary of Validation Document (v2.0).

In follow-up to the summer release of the updated Surge Demand Calculator, Sg2 released Validation Document v2.0 to demonstrate how the Sg2 COVID-19 Surge Demand Calculator v5.1 continues to match actual data reported from Chicago, IL; Dallas, TX; Milwaukee, WI; New York City, NY; San Antonio, TX; and San Francisco, CA. In addition, the document offers insight into how new features in the model can be leveraged for scenario planning as the nation begins to consider the impacts of school reopening policies and Labor Day activities.

CHICAGO, IL (V6.1)

The Sg2 model was able to accurately model the actual ADC peak magnitude and timing that Chicago experienced, as well as the ongoing trajectory of virus within the region.

ADC Surge Scenario Impact for COVID-19



Source: City of Chicago. COVID-19 hospital capacity metrics. Chicago Data Portal. Accessed December 2020.

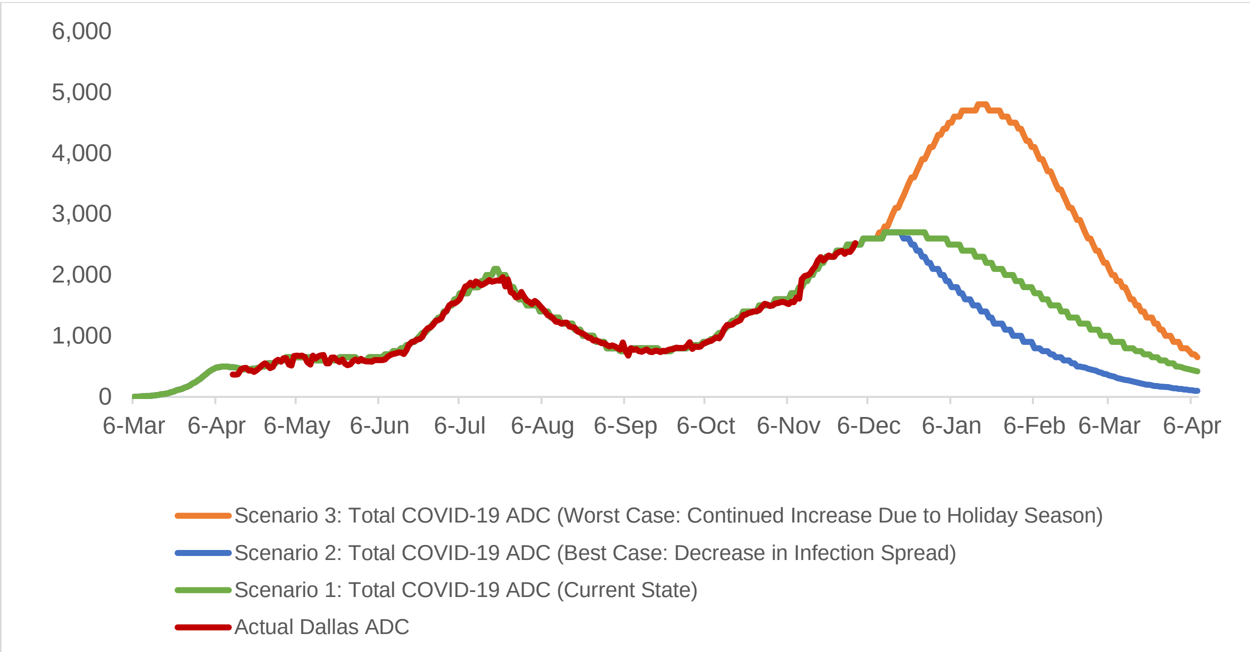
Starting R_0: 2.2 (See Appendix Table 2 for guidance regarding starting reproductive rates.)

- Accuracy of the model:
  - Peak timing and magnitude were predicted with accuracy.
  - Average of 5% variance between actual Chicago ADC and Sg2 projected total COVID-19 ADC
- Fall/winter scenario planning:
  - Scenario 1 is the assumed surge scenario based on current state and infection spread based on an R_0 of 2.1. In this scenario, the surge is anticipated to come close to the surge the region experienced during spring.
  - Scenario 2 is defined by a presumed 10% decrease in infection spread (resulting R_0: 1.8). In this scenario, the ongoing surge will continue to increase, similar to Scenario 1, but will last a shorter period.
  - Scenario 3 assumes continued infection spread due to indoor gatherings and holiday season activities (resulting R_0: 2.4). In this scenario, Chicago's winter surge will remain prolonged through December before gradually declining mid-January.

DALLAS, TX (V6.1)

The Sg2 model accurately modeled both the initial ADC peak magnitude and timing that Dallas experienced and the resurgence that occurred with reopening the economy.

ADC Surge Scenario Impact for COVID-19



Note: Actual Dallas ADC from July 23, 2020, to July 28, 2020, may be incomplete due to transition in the reporting process.
Source: Texas Health and Human Services. COVID-19 hospitalizations by trauma service area. Accessed December 2020.

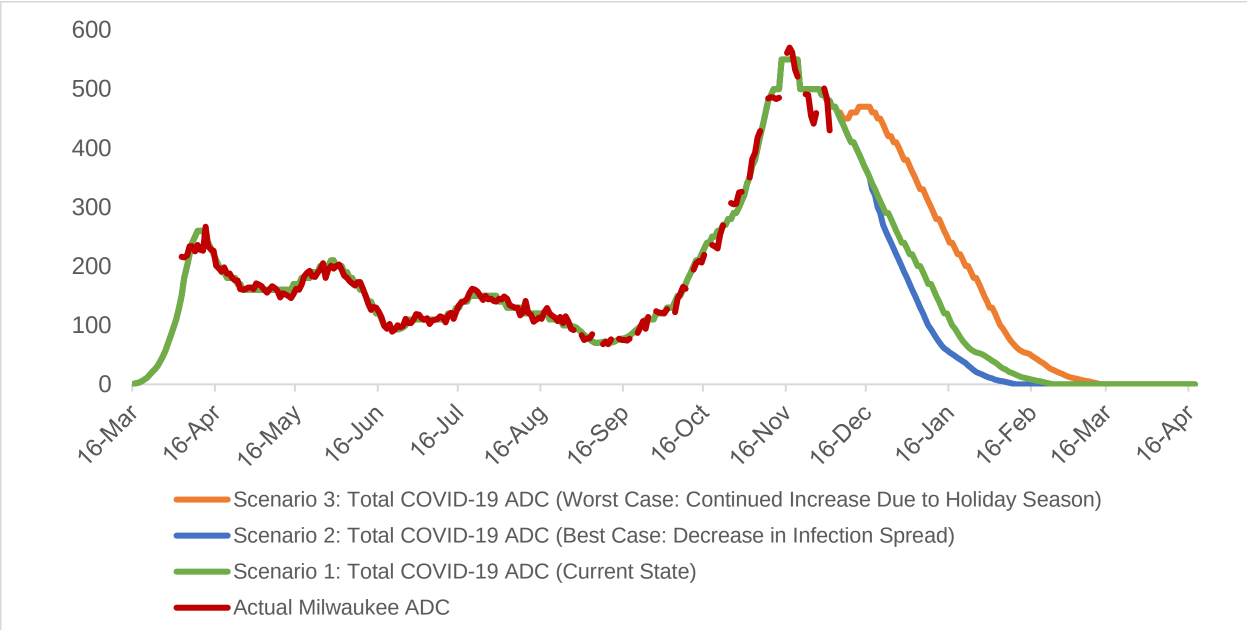
Starting R_0: 1.8

- Accuracy of the model:
  - Peak timing and magnitude were predicted with accuracy.
  - Average of 6% variance between actual Dallas ADC and Sg2 projected total COVID-19 ADC
- Fall/winter scenario planning:
  - Scenario 1 is the assumed surge scenario based on current state and infection spread based on an R_0 of 1.4. In this scenario, the surge is anticipated to exceed the surge the region experienced during summer and will remain prolonged before gradually declining starting in January.
  - Scenario 2 is defined by a presumed 10% decrease in infection spread (resulting R_0: 1.2). In this scenario, the ongoing surge will continue to increase until mid-December before starting its decline.
  - Scenario 3 assumes continued infection spread due to indoor gatherings and holiday season activities (resulting R_0: 1.7). In this scenario, Dallas will experience a substantial surge that exceeds the surge the region experienced during summer, to almost 5,000 ADC.

MILWAUKEE, WI (V6.1)

The Sg2 model continues to accurately match and follow the COVID-19 hospitalization data reported by Milwaukee.

ADC Surge Scenario Impact for COVID-19



Source: County of Milwaukee. Milwaukee County COVID-19 Dashboard. Accessed December 2020.

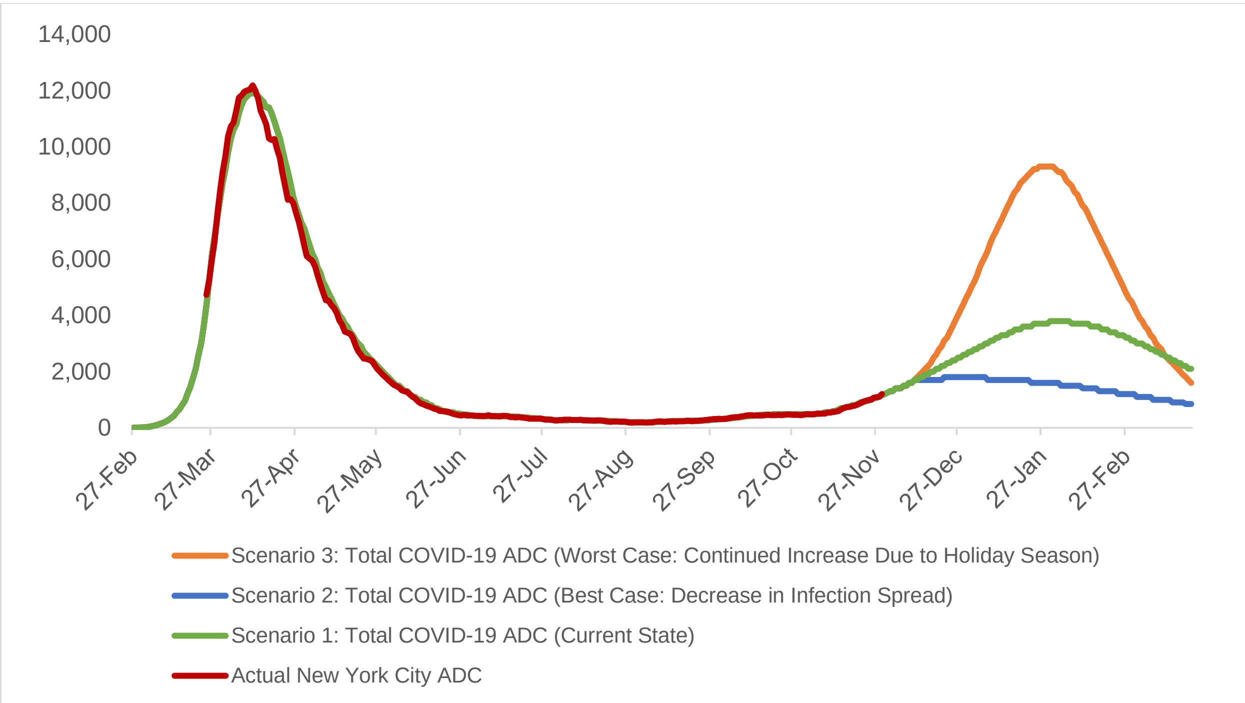
Starting R_0: 1.9

- Accuracy of the model:
  - Peak timing and trajectory of virus spread were predicted with accuracy.
  - Average of 5% variance between actual Milwaukee ADC and Sg2 projected total COVID-19 ADC
- Fall/winter scenario planning:
  - Scenario 1 is the assumed surge scenario based on current state and infection spread based on an R_0 of 1.7. This scenario follows the COVID-19 ADC that Milwaukee experienced and is tracking with the current decline in cases.
  - Scenario 2 is defined by a presumed 10% decrease in infection spread (resulting R_0: 1.6). In this scenario, the decline will be slightly faster than in Scenario 1.
  - Scenario 3 assumes continued infection spread due to indoor gatherings and holiday season activities (resulting R_0: 2.0). In this scenario, COVID-19 hospitalizations will remain slightly prolonged until mid-December before declining.

NEW YORK CITY, NY (V6.1)

The Sg2 calculator modeled the timing of the peak ADC in New York City as well as ongoing COVID-19 ADC trajectory with accuracy.

ADC Surge Scenario Impact for COVID-19



Source: NYC Health. COVID-19: data; New York State. Pressroom: Official news from the Office of the Governor. All websites accessed December 2020.

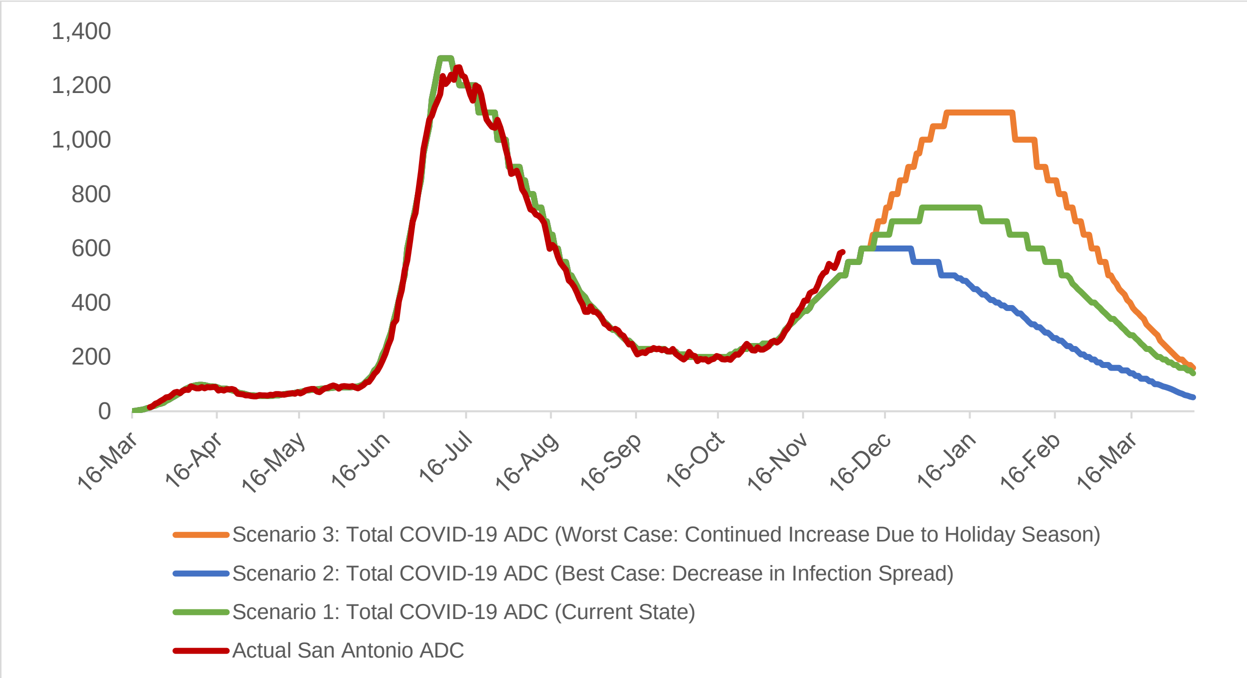
Starting R_0: 2.6

- Accuracy of the model:
  - Peak timing and trajectory of the virus spread were predicted with accuracy.
  - Average of 5% variance between actual New York City ADC and Sg2 projected total COVID-19 ADC
- Fall/winter scenario planning:
  - Scenario 1 is the assumed surge scenario based on current state and infection spread based on an R_0 of 1.8. In this scenario, the COVID-19 ADC will slightly increase during winter.
  - Scenario 2 is defined by a presumed 10% decrease in infection spread (resulting R_0: 1.6). In this scenario, the ongoing increase in the census will only slightly increase before beginning its decline from early December.
  - Scenario 3 assumes a worst-case scenario of continued infection spread due to indoor gatherings and holiday season activities (resulting R_0: 2.2). In this scenario, the COVID-19 ADC is expected to rise to about 9,000 by late January before declining.

SAN ANTONIO, TX (V6.1)

The Sg2 model accurately fits the actual surge trajectory for San Antonio.

ADC Surge Scenario Impact for COVID-19



Note: From early November, the Sg2 model slightly underestimates the actual ADC data from San Antonio due to transfers to the local hospitals from outside the service area.
Source: City of San Antonio. COVID-19 trends. Accessed December 2020.

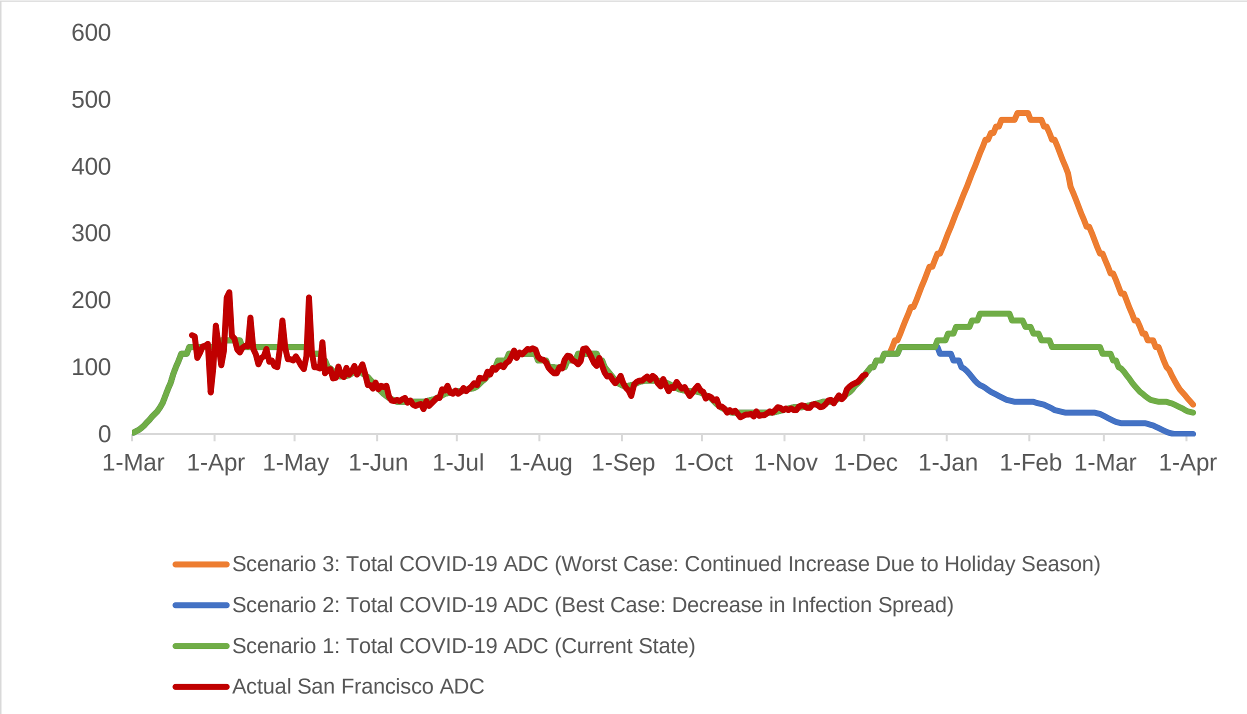
Starting R_0: 1.5

- Accuracy of the model:
  - Peak timing, magnitude and trajectory of COVID-19 census were predicted with accuracy.
  - Average of 6% variance between actual San Antonio ADC and Sg2 projected total COVID-19 ADC
- Fall/winter scenario planning:
  - Scenario 1 is the assumed surge scenario based on current state and infection spread based on an R_0 of 1.7. In this scenario, the surge is anticipated to increase to about 800 COVID-19 ADC early January before gradually declining.
  - Scenario 2 is defined by a presumed 10% decrease in infection spread (resulting R_0: 1.5). In this scenario, the surge will increase to about 600 mid-December and is anticipated to decrease shortly thereafter.
  - Scenario 3 assumes continued infection spread due to indoor gatherings and holiday season activities (resulting R_0: 1.8). In this scenario, the surge for San Antonio is anticipated to come close to the summer surge but is not expected to exceed it.

SAN FRANCISCO, CA (V6.1)

Since early May, the Sg2 model has been able to model the COVID-19 ADC with accuracy.

ADC Surge Scenario Impact for COVID-19 and PUI Cases



PUI = patient under investigation.
Source: DataSF. COVID-19 data and reports. Accessed December 2020.

Starting R_0: 1.8

- Accuracy of the model:
  - At the onset of the pandemic, San Francisco experienced fluctuations in COVID-19 ADC. However, the Sg2 model continued to predict the ADC trajectory with sufficient accuracy.
  - Average of 9% variance between actual San Francisco ADC and Sg2 projected total COVID-19 ADC
- Fall/winter scenario planning:
  - Scenario 1 is the assumed surge scenario based on current state and infection spread based on an R_0 of 1.6. In this scenario, San Francisco is expected to increase to COVID-19 ADC similar to that experienced during spring.
  - Scenario 2 is defined by a presumed 10% decrease in infection spread (resulting R_0: 1.4). In this scenario, the surge will nevertheless increase; however, the peak will not be prolonged into winter.
  - Scenario 3 assumes continued infection spread due to indoor gatherings and holiday season activities (resulting R_0: 1.9). In this scenario, the COVID-19 ADC surge is expected to exceed the previous peaks experienced by the region. The census is anticipated to reach almost 500 if the R_0 increases to 1.9.

Sg2 COVID-19 SURGE DEMAND CALCULATOR VALIDATION—APPENDIX

Table 1. Population-Based Non-ICU and ICU Hospitalization Rates

Age Group	% Symptomatic Cases Requiring Hospitalization	% Hospitalized Cases Requiring Critical Care
0 to 9	0.1%	5.0%
10 to 19	0.3%	5.0%
20 to 29	1.2%	5.0%
30 to 39	3.2%	5.0%
40 to 49	4.9%	6.3%
50 to 59	10.2%	12.2%
60 to 69	16.6%	27.4%
70 to 79	24.3%	43.2%
80+	27.3%	70.9%

Table 2. Sg2 COVID-19 Surge Demand Calculator Starting Infection Rate (Reproductive Rate, R_0) for Local Community Viral Spread—Reproductive Rates and Suggested Uses

R_0	2.5	2.4	2.3	2.2	2.1	2.0	1.9	1.8	1.7	1.6	1.5
Total Infection Rate (%)	91%	90%	89%	87%	85%	83%	77%	73%	70%	67%	64%
Relative Population Density	High urban density					Moderate urban density (urban/suburban mix)			Low urban density (rural)		
Relative Use of Public Transportation	High reliance on public transportation					Increased reliance on automobile transportation			No real public transportation use		

Note: R = reproduction number, a mathematical term that indicates how contagious an infectious disease is (R_0 or R naught).

Sg2 health care intelligence