Epidemiological model of the spread of COVID-19 in Hawaii's challenging fight against the disease

Monique Chyba, Yuriy Mileyko, Oleksandr Markovichenko, Richard Carney
Dept. of Mathematics
University of Hawai'i at Manoa
Honolulu, Hawai'i, United States
{chyba,ymileyko,markov,rscarney}@hawaii.edu

Alice E. Koniges
Hawai'i Data Science Institute
University of Hawai'i at Manoa
Honolulu, Hawai'i, United States
koniges@hawaii.edu

***Abstract*—Hawai'i and similar island populations can follow a different course of pandemic spread than large cities/states/nations and are often neglected in major studies. We provide a detailed epidemiological model of the spread of COVID-19 in Hawai'i and explore effects of different intervention strategies in both a prospective and retrospective fashion. We use a modified compartmentalized extended Susceptible-Exposed-Infected-Recovered (SEIR) model with a simple step function time dependence calibrated using the current data. We model asymptomatic carriers and actual mitigation strategies such as social distancing, contact tracing and quarantine policy. We find different outcomes for different scenarios: predicting retrospectively that if we successfully isolated 52% (alternately 38.8%) of the asymptomatic on days 2-4 (alternately 3-5) after exposure as we came out of the first lockdown, we would have reduced daily cases, hospitalisation and Intensive Care Unit (ICU) occupancy by about 74% (alternately 50%), where alternately refers to the second of two retrospective modeling scenarios. Going forward, we forecast that successful identification and isolation of 49% between days 2-4 of exposure as well as compliance from individuals to reduce the transmission rate by 14.4% provides a scenario where the daily cases would peak for a third time at a moderate triple digit rate of 193 in early December, potentially avoiding a third lockdown. Furthermore, because of the unique isolation of Hawai'i to incoming travelers fitting our specific data and using our methodology to predict outcomes serves as an important semi-controlled experiment to help others in applying epidemiological models to their populations.**

***Keywords*—** COVID-19; Compartmentalized Epidemiological Model; Contact Tracing; Pandemic Mitigation; Hawai'i.

I. INTRODUCTION

Hawai'i and other US Islands have recently been noted by the media as COVID-19 hotspots after a relatively calm period of low case rates. U.S. Surgeon General Jerome Adams came in person on August 25 to Oahu to address the alarming situation. In this paper, we capture the peculiarity of the situation in Hawai'i and provide detailed modeling of current virus spread patterns aligned with dates of lockdown and similar measures. We use this analysis to formulate predictive scenarios.

Hawai'i finds itself in a unique position due to its extremely isolated geographic location, mostly linear population distribution along the coast, and a heavy dependence on the tourism and hospitality sectors of the economy. While the first two factors appeared advantageous in the fight against the disease, the latter one creates a tempering effect on feasible long-term mitigation efforts, since too stringent an approach may lead to a catastrophic impact on the economy. We study the unique aspects of Hawai'i from both a social and data-driven modeling perspective to understand and recommend the critical intervention measures that make the most impact on spread of the disease while mitigating societal adversities.

This is not the first Hawai'i encounter with an invasive virus. In the past, measles, whooping cough, dysentery, and influenza decimated the native Hawaiian population. In the first recorded introduction of major diseases to the islands, measures were taken to prevent sailors from being in close contact with natives; ultimately, this failed due to complications demanding sailors stay on the islands for several days. Upon later visits, the westerners noticed the heavy impact of the disease upon the entire archipelago. Later on in the Kingdom's history, foreign ships brought about more diseases: cholera (1804), influenza (1820s), mumps (1839), measles and whooping cough (1848-9) and smallpox (1853). King Kamehameha V, noticing the loss of his people, established the Kingdom's first quarantine station, which later moved from Honolulu to Moloka'i. Not only were a large portion of Native Hawaiian lives lost, but schools were left empty and the economy disrupted due to the great mortality [1]–[3]. Today, Hawaii remains vulnerable to disease because it is geographically isolated and does not have hospital and other facilities capable of treating large numbers of infected non-residents, nor does it have the ability to shift excess COVID-19 cases to neighboring hospitals or care centers other than perhaps military ships.

Today facing the COVID-19 pandemic, the state government has taken several measures to mitigate spread, including a stay-at-home order and an incoming arrival 14-day quarantine, a reflection of the past. As with minority populations in other states, certain populations (in our case self-identified Pacific Islanders exclusive of native Hawaiians) are impacted at a significantly larger rate, both in terms of testing positive for the disease compared to their population percentage and presumably with respect to the economical loss since this population depends heavily on the tourist industry for economic stability [4] [5]. The March stay-at-home order brought applause when the epidemic was stomped flat but as a result Hawai'i remained extremely vulnerable to the disease exemplified by the current alarming situation in which the islands saw a very significant second wave of infections. The state's seven day average case rate per 100,000 of populations went from months at the bottom of the US list to holding a clear spot in the top 15 as of the ending days of August 2020 [6].

Compartmentalized SEIR models of the COVID-19 provide the basis for much of the current epidemiological modeling efforts worldwide, however variants in the compartmental choices and corresponding variables allow for parameter matching and optimizations, thus providing useful predictive information specific to our Island population [7] [8]. In this paper, we adapt and use these models on Oahu data. Oahu is the most populated island in the chain, providing an appropriate data set for interpretation of our models as well as guidance for the entire state. We focus specifically on Oahu, the most-affected by COVID-19 Island as of now, since each island (or group of islands in the case of Maui) has its own mayor and thus restrictions

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and governmental actions may vary slightly within the entire state as they are determined not only uniformly by the Governor but also by the Mayors and local governments of the outer islands.

Our simulations demonstrate that to control the spread of COVID-19 both actions by the State in terms of testing, contact tracing and quarantine facilities as well as individual actions by the population in terms of behavioral compliance to wearing a mask and gathering in groups are vital. They also explain the turn for the worst Oahu took after a very successful stay-at-home order back in March.

It is time critical that models for COVID-19 transmission are applied across a variety of US regions with populations exhibiting different characteristics. Results are presented for Italy [9] and Austin, Texas [10] highlighting the impact of proper timing for efficient mitigation measures. Tuning our model to Hawai‘i specific data ensures proper assessment of the local spread of the disease that may not be feasible via larger and more common studies. Also, the controlled environment plays a role in assessing the effectiveness of current and future mitigation strategies. Our methodology is directly applicable to other States and counties with similar accessible data. Observed qualitative behavior of the transmission rate for the States of Alaska, Oregon and Montana, as well as the corresponding numbers for the daily cases, are comparable to Hawai‘i's [11] [12]. Our work suggests that a lack of individual compliance prevented a significant decrease in the number of daily cases in these states, and indicates that they are likely to see the daily case numbers increase further following the recent increase in transmission rate. There is a need to either expand asymptomatic isolation or request more severe compliance from the population.

II. Mathematical Model and Parameters

A. SEIR Compartmentalized Model

To model the spread of COVID-19, we employ a compartmentalized model inspired by [13], which is based on a standard discrete SEIR model. As in the standard SEIR model, we partition a given population into four compartments: Susceptible (not currently infected), Exposed (infected with no symptoms), Infected (infected with symptoms), Removed (recovered or deceased). However, to better capture the dynamics of the infection, we divide the whole population into two population groups: the general community and healthcare workers (healthcare workers play a vital role and are exposed in different ways than the general community, see for instance [14] [15]). We shall denote these groups by C and H, respectively. These groups interact with each other, and each of them consists of the aforementioned compartments. Hence, variables representing the compartments may be decorated with a sub-index c or h, to indicate the appropriate group. In addition, compartments Exposed and Infected (in each population group) are split into multiple stages to better reflect the progression of the disease.

The dynamics of each population group have two distinguished parts: the dynamics of Susceptible individuals, and the dynamics of the rest of the compartments. The former is governed by the *hazard rate*, $\lambda(t)$, which depends on time and essentially determines the probability, $1 - e^{-\lambda(t)}$, of an individual becoming exposed at time t. The hazard rate is different for different population groups and takes into account interactions between the groups, thus coupling their dynamics.

The equations for the dynamics of the two population groups are essentially the same and are given below. Only the hazard rate and the parameters determining transition rates into quarantine may be different between the two groups.

$$S(t+1) = e^{-\lambda(t)} S(t) \tag{1}$$

$$E_0(t+1) = (1 - e^{-\lambda(t)}) S(t) \tag{2}$$

$$E_i(t+1) = (1 - p_{i-1})(1 - q_{a,i-1}) E_{i-1}(t), \quad i = 1, \dots, 13 \tag{3}$$

$$E_{q,i}(t+1) = (1 - p_{i-1})(q_{a,i-1} E_{i-1}(t) + E_{q,i-1}(t)), \quad i = 1, \dots, 13 \tag{4}$$

$$I_0(t+1) = \sum_{i=0}^{13} p_i (1 - q_{a,i}) E_i(t) \tag{5}$$

$$I_1(t+1) = (1 - q_{s,0}) I_0(t) \tag{6}$$

$$I_2(t+1) = (1 - q_{s,1}) I_1(t) + (1 - r)(1 - q_{s,2}) I_2(t) \tag{7}$$

$$I_j(t+1) = r(1 - q_{s,j-1}) I_{j-1}(t) + (1 - r)(1 - q_{s,j}) I_j(t), \quad j = 3, 4 \tag{8}$$

$$I_{q,0}(t+1) = \sum_{i=0}^{13} p_i (q_{a,i} E_i(t) + E_{q,i}(t)) \tag{9}$$

$$I_{q,1}(t+1) = I_{q,0}(t) + q_{s,0} I_0(t) \tag{10}$$

$$I_{q,2}(t+1) = I_{q,1}(t) + q_{s,1} I_1(t) + (1 - r)(q_{s,2} I_2(t) + I_{q,2}(t)) \tag{11}$$

$$I_{q,j}(t+1) = r(q_{s,j-1} I_{j-1}(t) + I_{q,j-1}(t)) + (1 - r)(q_{s,j} I_j(t) + I_{q,j}(t)), \quad j = 3, 4 \tag{12}$$

$$R(t+1) = R(t) + r I_4(t) + r I_{q,4}(t) + (1 - p_{13}) E_{13}(t) + (1 - p_{13}) E_{q,13}(t) \tag{13}$$

Below is a detailed description of the variables, all of which depend on time, t, measured in days.

- **Variable $S(t)$.** The number of susceptible individuals.
- **Variables $E_i(t)$.** The number of asymptomatic infected individuals i days after exposure who are not quarantined.
- **Variables $E_{q,i}(t)$.** The number of quarantined asymptomatic infected individuals i days after exposure.
- **Variables $I_j(t)$, $i = 0, 1$.** The number of symptomatic infected individuals i days after the onset of symptoms who are not quarantined.
- **Variables $I_j(t)$, $j = 3, 4, 5$.** The number of symptomatic infected individuals at the nominal stage i of the illness. Note that a person can stay at a given stage for several days.
- **Variables $I_{q,j}(t)$, $j = 0, 1$.** The number of quarantined symptomatic infected individuals, with j representing either the number of days after the onset of the symptoms ($j = 0, 1$), or the stage of the illness ($j = 2, 3, 4$).
- **Variable $R(t)$.** The number of removed (recovered or deceased) individuals.

Splitting exposed individuals into multiple stages, E_i, allows us to capture possible differences in the progression of the asymptomatic phase of the disease. Importantly, it allows us to take into account that, according to the Centers for Disease Control and Prevention (CDC) as well as other sources, about 40% of people who contract SARS-CoV-2 remain asymptomatic, and the incubation period for those who do develop symptoms is somewhere between 2 to 14 days after exposure, with the mean incubation period between 4 and 6 days [16]–[18]. Individuals who do not develop symptoms after 14 days are assumed recovered. The use of the quarantine sub-compartments,

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$E_{q,i}$, allows us to capture the effect of contact tracing and the reduced transmission rate for quarantined individuals.

Similarly, having multiple stages for infected individuals better reflects progression of the symptomatic phase of the disease. The first two stages represent the first two days of symptoms, but the next three should be understood as phases of the immune system fighting the disease. There is a substantial variability (due to age as well as other factors) in the number of days any given person can spend at each stage. Our model implicitly assumes that the symptomatic phase of the illness lasts at least 5 days (in the unlikely case that each stage lasts just one day). From the variables above, we can compute hospitalization count and the total number of ICU beds (it is assumed 8% of people with symptoms are hospitalized, and of those, 20% enter the ICU.)

As we mentioned, a crucial part of the dynamics relates to the hazard rate. For the general community, group C, we have

$$\lambda_c(t) = \beta\Big[(I_c + \varepsilon E_c) + \gamma((1-\nu)I_{c,q} + \varepsilon E_{c,q}) + \rho[(I_h + \varepsilon E_h) + \gamma((1-\nu)I_{h,q} + \varepsilon E_{h,q})]\Big]/N_c, \quad (14)$$

where we suppressed the dependency on t on the right for convenience. Subscripts c and h indicate the general community and healthcare workers, respectively, and subscript q indicates quarantined individuals. Variables E and I here represent the sum over all the stages within these compartments. N_c denotes the mixing pool for the general community, computed as

$$N_c(t) = S_c + E_c + I_c + R_c + \rho(S_h + E_h + I_h + R_h). \quad (15)$$

For the healthcare worker group, we have

$$\lambda_h(t) = \rho\lambda_c + \beta\eta\Big[(I_h + \varepsilon E_h) + \kappa\nu(I_{h,q} + I_{c,q})\Big]/N_h, \quad (16)$$

where $N_h(t) = S_h + E_h + I_h + R_h$.

B. Parameters and Initial Conditions

The model parameters have been chosen to reflect the spread of COVID-19 on Oahu, taking into account the fit for the daily cases and active hospitalizations. Most parameters remain fixed over time. However, parameter β, capturing the basal transmission rate due to various interactions among individuals, as well as parameters reflecting the rates of quarantine can change over time along with active mitigation measures. Specifically, we use several different values of β that capture changes in COVID-19 policy on Oahu (specific values can be seen in Table II). Table I provides the description of the model parameters and their values.

The values of the basal transmission rate β change over time, as shown in Table II, and are obtained by minimizing the sum of squared differences between the recorded number of daily cases and the number given by the model (the latter is calculated as the number of individuals about to be quarantined). The optimization is done using the Levenberg–Marquardt algorithm [19], which is well suited for solving the nonlinear least squares problem. The Jacobian of the objective function, required by the algorithm, is computed exactly by implementing the dynamics of the derivatives of our variables with respect to β.

It is useful to regard parameters p_i, $q_{a,i}$, and $q_{s,i}$ as probabilities, which is their role in stochastic SEIR epidemiological models [20]. The values of p_i are chosen to reflect the observations that, if symptoms do develop, it takes between 2 to 14 days, with a mean between 4 and 6 days [16]. We also take into account the estimate that about 40% of all infections remain asymptomatic. In the stochastic setup, the probability to remain asymptomatic is given by $\prod_{i=0}^{13}(1-p_i)$, and the expected length of incubation period, given that symptoms do develop, is calculated using the formula

$$\sum_{i=0}^{13} \frac{(i+1)p_i \prod_{j=0}^{i-1}(1-p_j)}{1-\prod_{i=0}^{13}(1-p_i)}. \quad (17)$$

TABLE I
VARIABLE AND PARAMETERS FOR OAHU MODEL

Parameter, meaning	Value
β, basal transmission rates	optimized to fit data
Factors modifying transmission rate	
ε, asymptomatic transmission	0.75
ρ, reduced healthcare worker interactions	0.8
γ, quarantine	0.2
κ, hospital precautions	0.5
η, healthcare worker precautions	0.5
Population fractions	
p_i, i =0,...,13, onset of symptoms after day i	0.000792, 0.00198, 0.1056, 0.198, 0.2376, 0.0858, 0.0528, 0.0462, 0.0396, 0.0264, 0.0198, 0.0198, 0.0198, 0
$q_{a,i}$, i =0,...,13, asymptomatic quarantine after day i	0 before June 10, then $q_5 = q_6 = q_7 = 0.05$
$q_{s,i}$, i =0,...,4, symptomatic quarantine after day/stage i	C: 0.1, 0.4, 0.8, 0.9, 0.99; H: 0.2, 0.5, 0.9, 0.98, 0.99
r, transition to next symptomatic day/stage	0.2
ν, symptomatic hospitalization	0.08

As we mentioned earlier in the paper, the choice of $q_{a,i}$ reflects the testing and contact tracing efforts in Hawaii. The values of $q_{s,i}$ reflect the sentiment that symptomatic individuals are likely to quarantine, especially after a couple of days of symptoms.

Similarly, parameter r can be viewed as the probability of transitioning from one stage of the illness to the next (with the final stage being recovery or death). Taking into account that the reported length of illness ranges from 2 weeks (for mild cases) to 6 weeks (for severe cases), and that there is a high prevalence of mild and moderate cases, the value of r is chosen to yield an expected length of illness of 17 days. It is calculated using the following formula:

$$2 + \sum_{n=3}^{\infty} \frac{n(n-1)(n-2)}{2} r^3(1-r)^{n-3} = 2 + \frac{3}{r}. \quad (18)$$

a) Initial Conditions.: The initial values of most variables are zero. The only non-zero values are the number of susceptible individuals in the general community and the healthcare worker community, $S_c(0) = 937711$, $S_h(0) = 15000$, as well as a single not quarantined symptomatic individual, $I_{c,0}(0) = 1$.

III. MODEL FIT AND FORECASTING

Our simulations demonstrate the critical impact of testing and timely contact tracing with adequate quarantine facilities on the number of hospitalizations and required ICU beds. This information is vitally important to immediate disease mitigation strategy.

We also highlight in our work that individual behavior is vital to control the spread of the virus; if we rely solely on testing/contact tracing and quarantine facilities, we would need an unrealistically high success rate to overcome the transmission rate.

A. Fitting the curve from March 6 to August 31, 2020

In this section, we summarize specifics of the model and parameters necessary for an accurate data fit of Oahu data from March 6th to August 27. We use data from the Hawaii Data Collaborative [21] for the count of daily cases as well as active hospitalisations and active ICU beds. The basal rate of transmission β of SARS-CoV-2 in our model is adjusted in time to reflect non-pharmaceutical measures taken by state of Hawai'i during this pandemic. On March 25, the governor imposed a stay-at-home order which was then progressively lifted throughout the months of May and June. The exact timeline of events can be found here [22], but we focus on five major events as transition points for adjusting the β. Due to an alarming spike in daily cases, U.S. Surgeon General Jerome Adams visited Hawaii for a couple of days starting on August 25 to address the situation with Hawaii government and talk to the public. On August 27, a new stay-at-home order was imposed. This second lockdown is complemented with improved access to testing with a goal of improving contact tracing and to once again stop the spread.

The primary goal of our work is to fit model to current data by selecting appropriate parameter values and then to employ the model in a predictive fashion to improve the mitigation strategy. In general, fitting parameters in an SEIR model is often a combination of mathematics and sociology, since changes in the transmission rate generally occur with a certain time lag based on governmental restrictions and population response [23]. Except for the basal transmission rate, our model parameters are fixed to correspond to available information about the virus and the disease. The basal transmission rates are obtained by optimizing the fit to the data using the Levenberg–Marquardt algorithm and are shown in Table II. A more detailed description of our complete model and parameters is given in Section II.

TABLE II
OPTIMIZED TRANSMISSION RATES TO FIT OAHU DATA. THEY REFLECT THE STATE AND OAHU NON-PHARMACEUTICAL MITIGATION MEASURES.

Transmission rates		
March 6 - April 2	April 2 - May 20	May 20 - May 30
$\beta = 0.3657$	$\beta = 0.0491$	$\beta = 0.1133$
May 30 - June 10	June 10 - Aug 11	Aug 11 - Aug 27
$\beta = 0.2109$	$\beta = 0.1694$	$\beta = 0.1086$

Figure 1 displays the model, run with the transmission rates from Table II, versus the real data. The dots are the recorded daily case counts and the solid line gives the model daily counts.

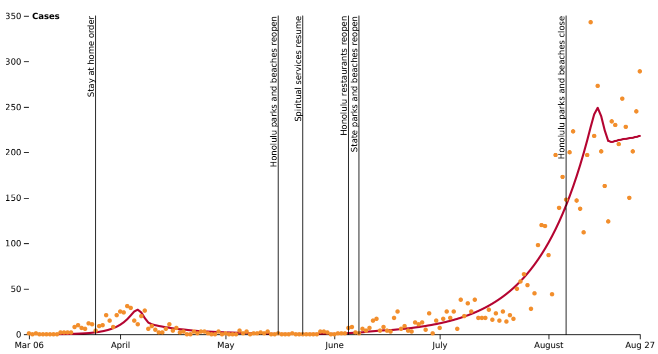

Fig. 1. Daily cases. Dots are the actual data and the plain line represents the model. We also delineate the various mitigation measures that took place during that period.

An important quantifier in COVID-19 is the number of hospitalization and ICU beds. This is a concrete number (as opposed, say, to unknown carriers) that is historically used to document the amount of disease. Additionally, since we have seen hospitals throughout the world being overwhelmed by the number of COVID-19 patients, it is a critical element of mitigation strategy. Figure 2 shows our model values for active hospitalizations (left) and active ICU beds (right) along with the corresponding recorded values. Note that the model values are slightly smaller than the best data fit would yield, however this results from the fact that hospitalisation and ICU data are available for the entire State only, while the model is fitted to the daily cases on Oahu. Also, the data are shown starting July 18, since the numbers for earlier dates have not been released by the Department of Health.

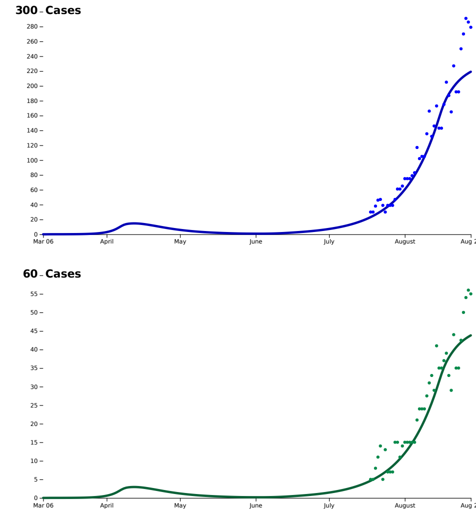

Fig. 2. Data fit for data on active hospitalization (blue) and ICU beds (green). Real data are dots and model predictions are lines.

B. Impact of testing, contact tracing, and quarantine measures

1) Revisiting the Past: In this section, we retrospectively predict the impact on the number of hospitalisations and ICU beds if proper testing/contact tracing and quarantine measures would have been in place on June 10, corresponding to the date when many of the Hawai'i stay-at-home restrictions were lifted.

Some level of testing and contact tracing were in place, but precise data have not been shared publicly and it has turned into a very controversial issue for the State that we will not discuss here. We therefore assume minimal contact tracing and limited testing which we believe is the most accurate representative of the situation. In Figures 1 and 2, we assume that starting June 10, 15% of the asymptomatic people are going into quarantine as the result of testing and contact tracing. More precisely, we assume we catch about 14.3% of asymptomatic population as follows: 5% after day 5 of being exposed, then 5% of the remaining after day 6 of exposure, and then another 5% of the remaining after day 7. We will denote this scenario as $5 : 0.05, 6 : 0.05, 7 : 0.05$ (days 5,6 and 7, each at 5%).

There are several factors which affect the number of asymptomatic individuals going into quarantine, thus slowing down the spread of the virus: improved testing with more rapid turn around, increased contact tracing, and dedicated quarantine facilities.

a) Impact of early asymptomatic quarantine.: Faster detection of asymptomatic individuals can be achieved through a more rapid turnaround on testing as well as through increased contact tracing. Our model parameters reflect this combined effect. Table III shows the impact of the earlier detection on the total number of cases from June 10 to August 27 as well as on the cumulative number of active hospitalisations and active ICU patients for the two and a half month period. These cumulative numbers are computed by summing up the number of all hospitalized (ICU) patients for each day. Table IV shows the same comparison but with a higher percentage of detected asymptomatic individuals going into quarantine.

The financial impact of these measures are addressed in more details in Section IV but just improving time to trace asymptomatic from days 5,6,7 to days 2,3,4 under this minimal contact tracing scenario would save about $2.6 million.

TABLE III
IMPACT OF DELAY IN ASYMPTOMATIC DETECTION ON THE SPREAD OF COVID-19

Testing/Contact Tracing	Total Cases	Cum act Hospt.	Cum act ICU
5:0.05, 6:0.05, 7:0.05	6517	4721	944
3:0.05, 4:0.05, 5:0.05	5658	4163	833
2:0.05, 3:0.05, 4:0.05	5102	3799	760

Note: Cum Act Hospt. (Cum act ICU) refers to the cumulative number of active hospitalizations (ICU patients).

TABLE IV
IMPACT OF DELAY IN ASYMPTOMATIC DETECTION ON THE SPREAD OF COVID-19

Testing/Contact Tracing	Total Cases	Cum act Hospt.	Cum act ICU
5:0.1, 6:0.1, 7:0.1	5760	3953	791
3:0.1, 4:0.1, 5:0.1	4346	3088	618
2:0.1, 3:0.1, 4:0.1	3551	2590	518

b) Impact of the volume of asymptomatic quarantine.: The actual percentage of detected asymptomatic individuals is affected by the amount of testing done, by the amount of contact tracing resources available, and in large part, by quarantine facilities. Quarantine facilities are particularly important for the Oahu modeling, since a large number of residents live in multi-generational and non-family member shared households. Table V shows how various fractions of quarantined asymptomatic individuals affect the total number of cases, hospitalizations, and ICU occupancy, while the dates of quarantine remain the same. Note that the quarantine fraction of 0.1 on each of the three days leads to the overall 27% detection of asymptomatic cases, 0.2 reaches 48.8%, and 0.3 reaches 65%.

TABLE V
IMPACT OF VOLUME OF ASYMPTOMATIC DETECTION ON THE SPREAD OF COVID-19

Testing/Contact Tracing	Total Cases	Cum act Hospt.	Cum act ICU
5:0.05, 6:0.05, 7:0.05	6517	4721	944
5:0.1, 6:0.1, 7:0.1	5760	3953	791
5:0.2, 6:0.2, 7:0.2	4499	2865	573
5:0.3, 6:0.3, 7:0.3	3573	2175	435

Together, Tables IV and V show that both the detection day of asymptomatic individuals as well as the volume of quarantined asymptomatic individuals have a significant impact on the hospitalisation and ICU occupancy. Our model suggests a larger benefit when asymptomatic individuals are caught early. Combining both of the above factors, we create various scenarios to predict how the total hospitalisation and ICU beds would have been affected. Figure 3 compares the fit based on real data with two scenarios where testing and contact tracing is assumed to be $3 : 0.15, 4 : 0.2, 5 : 0.1$ and $2 : 0.15, 3 : 0.3, 4 : 0.2$, which represents earlier detection of exposed individuals and in larger quantities. While the two scenarios yield continuously decreasing numbers of daily cases, with the second scenario achieving single digits by the end of the year, this does not represent a proper forecasting due to unrealistic assumptions. We address the forecasting question in detail in the next section.

Notice that the gain from this last scenario compared to the control simulation would amount to a savings of about $10 million.

2) Forecasting: The data fitting and parameter matching specific to our Oahu data allows us to better understand the effects of the various parameters as well as the transmission rate fits. We

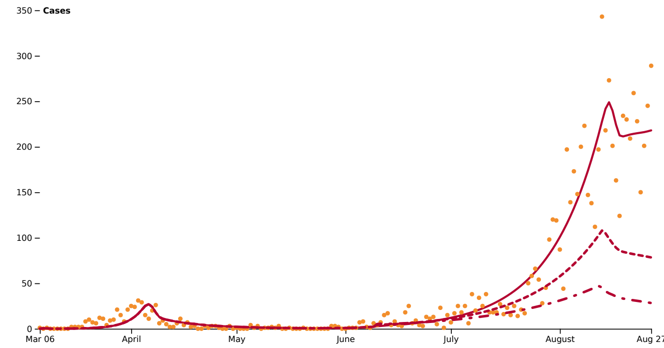

Fig. 3. Comparison of the daily cases real data fit (plain line) to two alternate scenario assuming $3 : 0.15, 4 : 0.2, 5 : 0.1$ (dash line) and $2 : 0.15, 3 : 0.3, 4 : 0.2$ (dotdash line) respectively for testing/contact tracing and quarantine.

TABLE VI
HOSPITALISATION AND ICU VARIATIONS FOR DIFFERENT SCENARIOS

Testing/Contact Tracing	Total Cases	Cum act Hospt.	Cum act ICU
5:0.05, 6:0.05, 7:0.05	6517	4721	944
3:0.15, 4:0.2, 5:0.1	3249	2269	454
2:0.15, 3:0.3, 4:0.2	1667	1208	242

then use this to provide forecasting scenarios that are dependant on testing/contact tracing and quarantine measures. These forecasting scenarios are critical to guiding Hawaii decision makers.

All of our predictive scenarios start on Aug 27 using a transmission rate of $\beta = 0.1086$ from Aug 27 to Aug 30. The transmission rate is then adjusted for each scenario depending on various societal events: stay-at-home order (we assume β slightly higher than during the first stay-at-home order due to community spread); Labor day holiday weekend (increase in transmission rate for a few days); lifting the stay-at-home order on October 5 (varies depending on population behavior), Thanksgiving holiday (variable spike over a few days). At the same time, parameters for testing and contact tracing are gradually adjusted starting August 30 to attain the target values by October 5.

a) Scenario 1.: The first scenario assumes very aggressive testing/contact tracing and facility quarantine but moderate compliance in individual behavior. The target parameter values for testing and contact tracing are taken as $2 : 0.4, 3 : 0.4, 4 : 0.4$, which assumes catching a total of 78% of asymptomatic individuals between days 2 and 4 of exposure. Table VII provides the transmission rates for the various periods. In this scenario, we assume the population will behave similarly to what happened after June 10 once the stay-at-home order is lifted.

TABLE VII
TRANSMISSION RATES FOR SCENARIO 1

Transmission rates		
Aug 30 - Sep 11 $\beta = 0.09$	Sep 11 - Sep 14 $\beta = 0.12$	Sep 14 - Oct 5 $\beta = 0.09$
Oct 5 - Dec 1 $\beta = 0.17$	Dec 1 - Dec 5 $\beta = 0.2$	Dec 5 - Dec 31 $\beta = 0.17$

b) Scenario 2.: The second scenario assumes a more realistic testing/contact tracing and facility quarantine but higher compliance in individual behavior starting after lifting the stay-at-home order on October 5. The target parameter values for testing and contact tracing are taken as $2 : 0.2, 3 : 0.2, 4 : 0.2$, which assumes catching a total of

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49% of asymptomatic individuals between days 2 and 4 of exposure. Table VIII provides the transmission rates for the various periods. We assume the population will behave in a more compliant way than what happened after June 10 once the stay-at-home order is lifted. The transmission rate is thus reduced from 0.1694 to 0.145.

TABLE VIII
TRANSMISSION RATES FOR SCENARIO 2

Transmission rates		
Aug 30 - Sep 11 $\beta = 0.09$	Sep 11 - Sep 14 $\beta = 0.12$	Sep 14 - Oct 5 $\beta = 0.09$
Oct 5 - Dec 1 $\beta = 0.145$	Dec 1 - Dec 5 $\beta = 0.2$	Dec 5 - Dec 31 $\beta = 0.145$

c) Scenario 3: The third scenario is identical to scenario 2 but with more a relaxed testing/contact tracing and facility quarantine, reflected by the target testing/contact tracing parameter values of $3 : 0.2, 4 : 0.2, 5 : 0.2$, which still assumes catching a total of 49% of asymptomatic individuals, but now between day 3 and 5 of exposure.

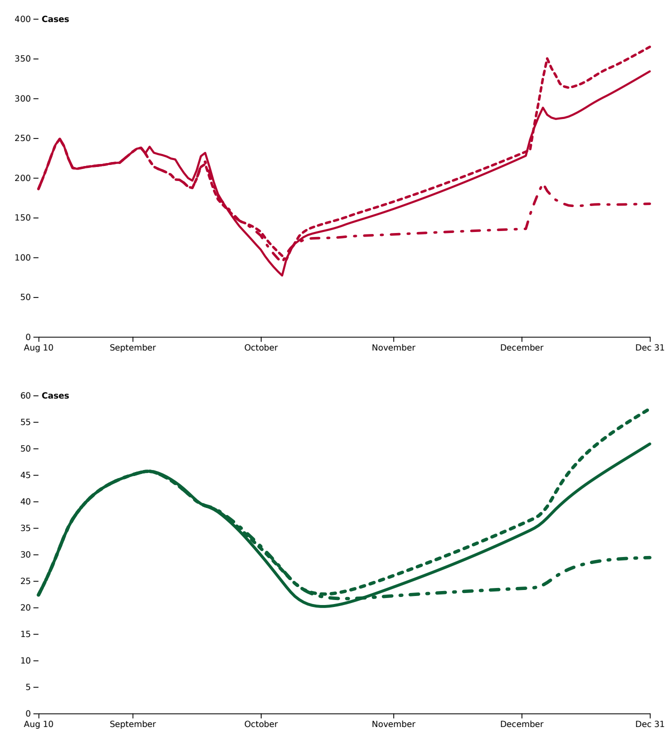

Fig. 4. In red we have the daily cases, and green ICU beds. Scenario 1: plain line. Scenario 2: dot-dash line. Scenario 3: dash line. Scenario 1 is better at first but scenario 2 is provides the best outcome over the long run.

TABLE IX
HOSPITALISATION AND ICU VARIATIONS AS OF DECEMBER 31

Testing/Contact Tracing	Total Cases	Cum act Hospt.	Cum act ICU
Scenario 1	25141	21043	4209
Scenario 2	19318	18162	3632
Scenario 3	26471	22434	4487

In Figure 4 we compare the three scenarios. The plain line corresponds to scenario 1, the dot-dash line is scenario 2 and the dash one is scenario 3. The number of active hospitalisation cases is qualitatively identical to ICU beds, with the first spike around 228 and the dashed line reaching about 287 on December 31. It is important to note that the line for scenario 2 starts to decrease in early 2021, while the number of daily cases for scenarios 1 and 3 see keeps increasing, with a peak of 594 daily cases on April 3 for scenario 1, and a peak of 541 daily cases on April 23 for scenario 3.

IV. SIMULATIONS ANALYSIS

A zoom on Figure 1 for dates between March 6 and May 30 demonstrates the efficiency and good timing of the first stay-at-home order, Hawai'i even being referred at the time as the safest state. Starting in mid-June we see the daily cases increasing and following an exponential trend for a 40 day period to become one of the worst states in dealing with the pandemic. Our simulations attempt to provide an explanation to this observation and produce some forecasting scenarios to help decision makers as we will come out of the second stay-at-home order around October 5.

In Section III-B, we show that with an increased structure of testing/contact tracing and quarantine facilities, we could have dramatically impacted the outcome as of August 27. Our results show that earlier detection of asymptomatic individuals has the most effect on the behavior of the model. From Figure 3 and Table VI, assuming we traced and quarantine successfully 52% of the asymptomatic population after days 2, 3 and 4 (more dominantly after day 3 of being exposed), we would have seen a reduction of 4850 total daily cases, 3513 cumulative active hospitalisation and 702 cumulative active ICU beds which is equivalent to a reduction of about 74% for total daily case, and for both hospitalisation and ICU beds. We can only speculate why these measures were not in place back in June, it was likely due to a combination of different challenges that have been well addressed in the newspapers. For instance, per an article in the Star advertiser on July 8, one of Hawaii's largest COVID-19 testing laboratories supply of chemicals needed to run test locally was restricted and reduced testing capabilities by about 70%. This was a consequence of surge in coronavirus cases across the country and supplies were distributed in priority to states where the intensive care units were overrun. Lack of contact tracing and quarantine facilities for people testing positive have also been issues that prevented the State to successfully keep the count under control. It is easy to downplay quarantine facilities compared to testing and contact tracing, however in Hawaii's a disproportionate fraction of individuals affected by the spread of the virus are Pacific Islanders and they very often live in multi-generational housing that does not permit for isolation. Recently the State has made agreements with hotels to turn them into quarantine facilities.

The forecasting portion of Section III-B raises a very important point. Figure 4 and Table IX demonstrate how different transmission rates and testing/contact tracing, quarantine facilities affect the future of the curve. The take away from these results is that to succeed in controlling the curve, we need a combination of aggressive testing/contact tracing, quarantine facilities as well as compliance from individual to keep the transmission rate to lower levels. Scenario 1 assumes almost perfect success in quarantining exposed individuals but transmission rates comparable to what we had after the State lifted the first stay-at-home order. The second scenario assumes better compliance from the population (lower transmission rate β) and aggressive but doable contact tracing; it provides the best outcome. The scenario 3 with same transmission rate as scenario 2 but shifting the contact tracing by one day shows significantly more cases. The conclusion is that to control the curve long term we need both: aggressive contact tracing and high compliance from the population. Unless the State can enforce such measures, we will be back into a third stay-at-home order in about a couple from months from lifting the second one. Note that for scenario 2, the maximum daily cases will not exceed 193 and the peak will occur in early December due to an assumed increase in non-compliance during the Thanksgiving

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holiday, while for scenario 3 we are looking at 541 cases in early April, and we reach 594 cases in late April for scenario 1. Those results are aligned with other work that has been published for instance in [24] [25].

V. Conclusion and Future Work

The goal of our model is not primarily to predict the single most likely outcome for the COVID-19 outbreak on Oahu, but rather is to compare the benefits and costs of implementing various mitigation strategies. We conclude that, provided contact tracing was in place with quarantine facilities as well as explicit guidance for the public on how to behave and compliance to those, we would be now under 50 daily cases and a second stay-at-home would not have been necessary. The State absolutely needs to be prepared when lifting the second stay-at-home order.

A. Economic Impact

It is possible to associate some numbers to the quantitative study we have done. Indeed, calculating the differences between two scenarios for the total hospitalization and ICU beds, we can assign a cost reduction for Oahu over the period June 10 to August 27. Numbers need, however, to be taken with a grain of salt since we are only providing estimates.

We are assuming the cost of a hospitalization day to be $2,000 and we average the daily cost at the intensive care to $4,200. The last number accounts for the fact that a fraction of patients are in need of ventilators and that the first two days in ICU are more costly than the rest of the stay. As mentioned above in the discussion the best scenario in Table VI reduces the total hospitalisation and ICU beds by 74% which amount to almost $10 million. Contact tracing, as well as quarantine facilities also have a cost, but it will be quite lower. Comparing the forecasting scenario, we obtain that as of December 31, scenario 2 saves more than $12 million compared to scenario 3 and scenario 1 saves almost $4 million compared to scenario 3. Those amounts increase quite dramatically after December 31, 2020.

B. Tourism and Vaccines

The State of Hawai'i is, since March 26, 2020, in an effective isolation bubble following the mandatory 14-day traveler quarantine that has not yet been lifted. The interisland quarantine was lifted on June 16 and then partially reinstated on August 11. This is the reason why travelers are not explicitly included in our work; they are currently virtually nonexistent (counts dropped to the lower hundreds from a historical norm of about 30,000 a day). Once tourism is open again, it will be added to the model and new simulations can take place. The form of re-instating tourism is still undetermined, and we expect it will be gradual and measured. Furthermore, if and when a vaccine is developed, our compartmental model can be used to account for the additional sub-population of the vaccinated.

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