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A Decision Guidance System for COVID-19 Comprehensive Mitigation with Pareto-Optimal Health, Cost and Productivity Outcomes

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***Abstract*—This paper reports on the design and development of a decision guidance system to make actionable recommendations on a COVID-19 comprehensive mitigation protocol that is Pareto-Optimal in terms of health outcomes, mitigation cost and productivity loss. The comprehensive mitigation protocol includes personal protection and social distancing; use of smart applications for symptom reporting and contact tracing; targeted testing based on identification of individuals with possible exposure and/or infection via symptom reporting and contact tracing; random surveillance testing, and; shelter, quarantine and isolation procedures. The decision guidance system (1) gets, as input, expert-generated configurations of epidemiological parameters and assumptions on population behavior, (2) precomputes a database of discretized Pareto-optimal mitigation protocol alternatives based on which it (3) provides decision makers an iterative methodology of (a) Pareto-optimal KPI graphing and trade-off analysis (between health, cost and productivity outcomes), (b) detailed comparison of selected Pareto-optimal mitigation protocol alternatives, and (c) what-if analysis for selected protocol alternatives, including disease progression over the time horizon and sensitivity analysis to refine and converge on the mitigation protocol to be used.**

***Index Terms*—COVID-19, coronavirus, mitigation protocol, decision guidance, Pareto-optimal recommendations**

I. Introduction

The total number of COVID-19 cases exceeded 28M, and the death toll exceeded 500,000 in the US alone, as of beginning of March, 2021 [7], [12]. According to [6], the total economic cost of the pandemic to the US through Fall 2021 is estimated at $16 trillion, or 90% of the gross domestic product (GDP). This includes $4.4 trillion in losses due to premature death [9]; $2.6 trillion in losses for long-term care [11]; $1.6 trillion in losses for mental health symptoms, and; $7.6 trillion for lost economic output over 20 years [1], [19].

Social distancing, wearing masks, and comprehensive testing and tracing have all been shown to be effective components of a holistic and comprehensive mitigation approach to reduce the impact of the pandemic [16], [20]. Deciding on the best composition of such comprehensive mitigation strategy is, obviously, a critical challenge. As a step in this direction, this paper focuses on making actionable recommendations on a comprehensive mitigation protocol for COVID-19 that balances health, productivity, and cost outcomes, and is Pareto-optimal.

There has been extensive work on epidemiological modeling, e.g., see a recent comprehensive review of [4], [10]. Dynamic models based of the Susceptible- Exposed- Infected-Recovered (SEIR) compartments and their extensions are most commonly used to understand infectious diseases' dynamics [5], [8], [10]. Recently, the authors of [15] extend the standard SEIR compartmental model to assess social distancing mitigation on COVID-19 transmission dynamics using factors specific to COVID-19, resulting in the Susceptible, Unsusceptible, Exposed, Infected, Hospitalized, Critical, Dead, Recovered (SUEIHCDR) dynamic model, described as a system of differential equations.

The work in [18] makes recommendations on COVID-19 screening strategies, in terms of frequency of asymptomatic testing, to open a university campus. It is based on a variant of the SEIR model, extended with an isolation pool due to asymptomatic testing of the university population. However, to the best of our knowledge, these prior models do not take into account a comprehensive parameterized protocol of interrelated mitigation strategies.

To bridge this gap, the recent work [2] proposes a discrete dynamic model, extending the SUEIHCDR model of [15] with a comprehensive mitigation protocol parameterized with (1) personal protection and social distancing mitigation ratios, (2) population ratios with smart apps for symptoms reporting and contact tracing, (3) the number of tests per individual marked by each of the apps, (4) the ratio of the population marked by the apps and negatively-tested that are required to stay in quarantine/isolation due to low test sensitivity, and (5) the frequency of surveillance testing on a random round-robin basis. The model in [2] estimates Key Performance Indicators (KPIs) including (1) health outcomes, in terms of all compartments, (2) the mitigation cost and its break-down, and (3) productivity loss in terms of percentage of non-circulating population.

However, while this model (as all predictive models) allows running trial and error scenarios for various instances of the mitigation protocol and comparing the results, it falls short of systematic decision guidance to make actionable recommendations to public policy decision makers on Pareto-optimal mitigation protocols. This is exactly the focus of this paper.

More specifically, the key contribution of this paper is the design and development of a Decision Guidance (DG) system to make actionable recommendations on a comprehensive mitigation protocol that is Pareto-optimal in terms of (1) health outcomes - the total number of infections over the time horizon, (2) mitigation cost, and (3) productivity loss.

From the base input, the DG system gets a domain-expert-produced configuration of epidemiological parameters, including (1) transition rates among and duration within compartments (such as Susceptible, Exposed, Infected, Recovered, Hospitalized, Critical and Dead); (2) sensitivity and specificity of COVID-19 tests; (3) time horizon under consideration and initial state of compartments and population.

From the scenarios generation template, the DG system gets discretized parameters of the mitigation protocol, including (1) mitigated daily beta - the number of individuals exposed to COVID-19 by a single infected individual, assuming all in population are susceptible, after social distancing and personal protection mitigation is enacted; (2) individual compliance ratios; (3) the ratios of Enhanced Contact Tracing (ECT) and Symptoms Reporting (SR) apps on mobile devices within population; (4) number of tests administered as triggered by marking an individual by ECT or SR app; (5) surveillance testing window within which the entire asymptomatic population is tested on a random round-robin basis.

Based on the basic and scenario-generation input, the DG system runs the epidemiological model extended with mitigation on each generated scenario, and then computes a Pareto-Front of mitigation protocol instances, i.e., for every cost point, it computes an optimal mitigation protocol instance that minimizes the total number of infections.

We envision that health policy decision makers will be key users; we refer to them as *decision makers*. Decision makers input the basic assumptions on (1) mitigated daily beta (effected by number of close contacts, on average, an individual has per day with others, and probability of a susceptible individual exposure to COVID-19 in close contact with an infected individual); and (2) compliance ratio by individuals.

Given that input, the DG system provides decision makers an iterative methodology of (1) Pareto-optimal KPI graphing and trade-off analysis (between health, cost and productivity outcomes); (2) detailed comparison of selected Pareto-optimal mitigation protocol alternatives; (3) what-if analysis for selected protocol alternatives, including (a) computing and presenting KPIs, (b) graphing and analyzing disease progression over time horizon, and; (c) graphing and analyzing sensitivity of decision makers' assumptions and choices. The proposed system follows the methodology of decision guidance systems proposed in [3], [14] and the recommendation process methodology proposed in [17].

This paper is organized as follows. Section II reviews COVID-19 epidemiological model extended with a comprehensive mitigation protocol from [2], which we leverage in the DG system. Section III describes the proposed methodology and Decision Guidance system functionality. Section IV describes the high-level architecture of the DG system, and implementation details of its components. Section V demonstrates the methodology and the DG system use through an example of prototypical population of 10,000 persons over the time horizon of 150 days. Finally, Section VI concludes and briefly outlines future research.

II. Review of Epidemiological Model Extended with a Comprehensive Mitigation Protocol

For the DG system reported in this paper, we leverage the model from [2], which we briefly overview in this section. This models adapts Susceptible- Unsusceptible- Exposed- Infected- Hospitalized- Critical- Dead- Recovered (SUEIHCDR) model of COVID-19 from [15], by extending the first four compartments with non-circulating (shelter, quarantine or isolation) and circulating sub-compartments. The epidemiological model is extended with a comprehensive mitigation protocol that is parameterized with (1) personal protection and social distancing mitigation ratios, (2) population ratio that have smart apps for symptoms reporting and contact tracing, (3) the number of tests per individual requested as a result of being marked by the smart apps, (4) the ratio of marked (by ECT and/or SR apps) individuals that are requested to stay in non-circulation despite having a negative-test, and (5) the testing frequency of asymptomatic individuals on a random round-robin basis. Technically, the model (1) uses Bayesian probability analysis to estimate the conditional probabilities of being in non-circulating sub-compartments as a function of mitigation protocol parameters and (2) computes transition ratios among the compartments as part of a discrete dynamic model. The model computes Key Performance Indicators (KPIs) including (1) health outcomes, in terms of all compartments, (2) the mitigation cost and its break-down, and (3) productivity loss in terms of percentage of non-circulating population.

III. Decision Guidance for COVID-19 Mitigation: Methodology and System Functionality

The main DG system dashboard, displayed in Figure 1, supports the methodology of deriving actionable recommendations on COVID-19 mitigation protocols. The key methodology involves an iteration of the following steps supported by the DG system.

1) Domain-expert configuration: epidemiological parameters and scenario templates
2) Decision makers' assumptions
3) Pareto-Optimal KPI Graphing and Tradeoff Analysis
4) Detailed comparison of selected Pareto-optimal options
5) What-if Analysis for the selected options
    - Computing and presenting KPIs

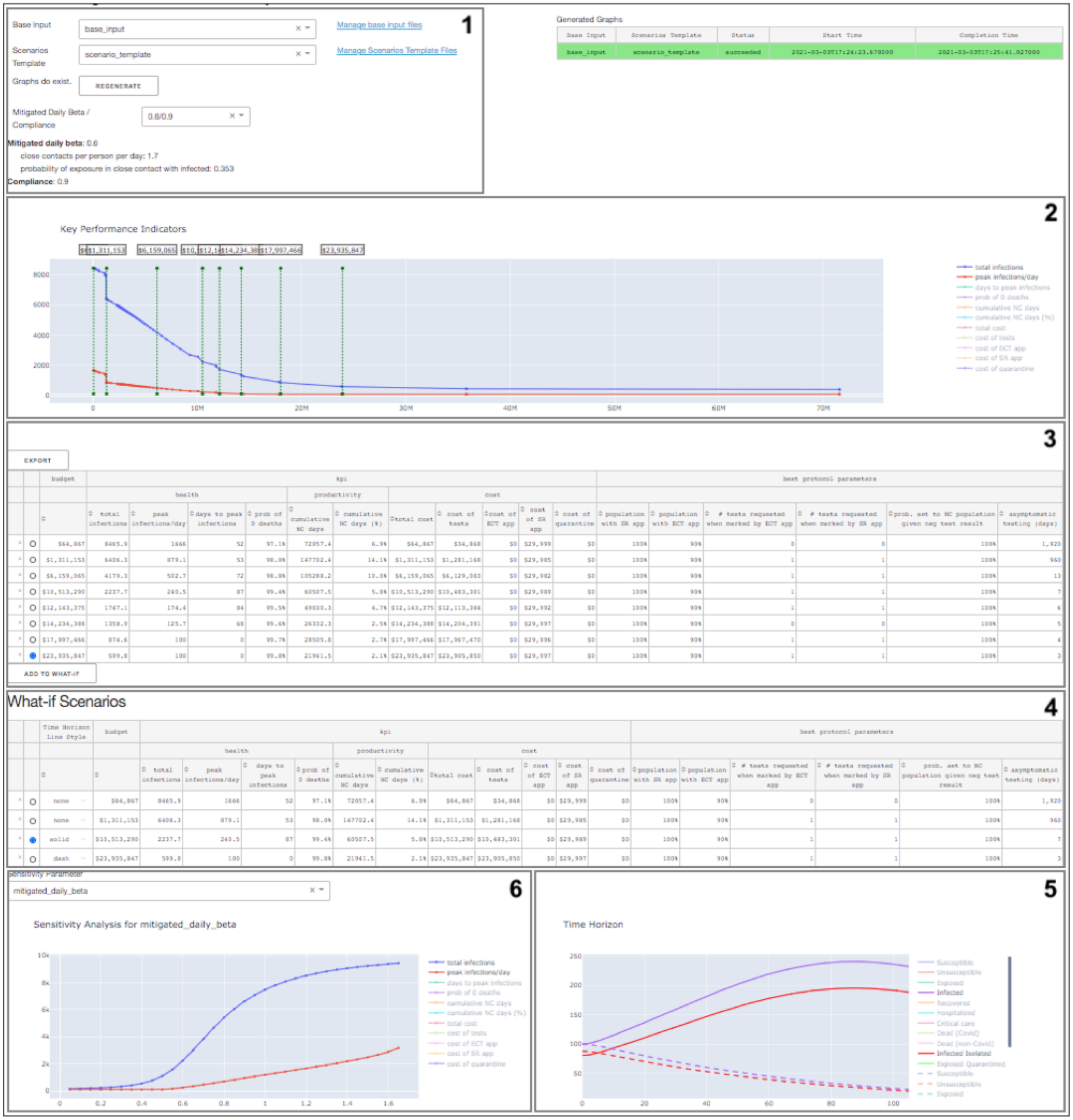

Fig. 1. DG System for COVID-19 Comprehensive Mitigation

- Graphing and analyzing disease progression over time-horizon
- Graphing and analyzing sensitivity of assumptions

A. Inputs and Assumptions

The DG system input include the *Base Input* and *Scenario Template*.

The *Base Input* file has parameters which are depicted in Table I, and include: (1) time horizon, (2) initial population, groups, and sub-compartment information (number of individuals and transition rates between groups), (3) Costs, including those of tests, isolation, and SR and ECT apps, and (4) tracking windows. These are generally provided by domain experts.

The *Scenario Template* file includes all the possible protocol parameters that the decision maker would like the model to use. These protocol parameters include details regarding the scenario(s) - possible mitigation and compliance levels, smart app settings, and possible asymptomatic testing windows; the smart app settings include: the ratio of population that is utilizing the SR and ECT apps, the number of tests administered for an individual that is marked by either the SR app or the ECT app, and the probability an individual is sent to the NC sub-compartment given a negative test result. All the parameters that are included in the *Scenario Template* can be seen in Table II.

Lastly, the user selects a *mitigated daily beta and compliance* ratio from the drop-down menu, which is an assumption reflecting population behavior. Both the files and the *mitigated daily beta and compliance* ratio are chosen by the decision maker on the system, as shown in Figure 1.1.

B. Pareto-Optimal KPI Graphing and Tradeoff Analysis

After both input files and the *mitigated daily beta and compliance* ratio are chosen, the system will either generate graphs if unavailable or display the cached results, as seen in Figure 1.2. The model essentially uses the parameters from the *Base Input* file and iterates over the possible scenarios from the *Scenario Template*, and at each budget point, is selects the Pareto-optimal scenario. Once the model has completed, the Key Performance Indicator (KPI) Tradeoff graphs are shown on the system. The decision maker can now toggle between various *mitigated daily beta and compliance* ratio combinations on the graph, and the system will update the KPI Tradeoff graphs accordingly. The chart has the KPIs on the y-axis for each budget point on the x-axis. The KPIs include total infections, peak infections/day, days to peak infections, prob of 0 deaths, cumulative NC days, total cost, cost of tests, cost of ECT app, cost of SR app, cost of quarantine; the details of each KPI is shown in Table III. Initially, only total infections, and peak infections per day are shown, but others can be displayed by clicking their entries on the legend. At any time, the decision maker has the option to swap the *Base Input* and/or the *Scenario Template* files, and the graphs will update immediately (assuming graphs were previously generated).

Input Parameter	Definition
General Setting	
Time Horizon	Number of days in simulation, from 0, …, n
Outbreak Infected Ratio	Ratio of the total population that is infected needed to define an outbreak
Max NC Population Ratio	Max allowed ratio of the total population that is non-circulating during the time horizon
Initial Compartments	
pop	Aggregate number of individuals from all groups {U, S, E, I, R, H, C, D, M} initially
U, S, E, I, R, H, C, D, M	Number of individuals in each group initially
Transition Ratios	
$s \to u$, $s \to e$	Transition rates from s to u and e, respectively
$u \to m$	Transition rate from u to m
$e \to i$, $e \to m$	Transition rates from e to i and m, respectively
$i \to r$, $i \to h$, $i \to m$	Transition rates from i to r, h, and m, respectively
$h \to r$, $h \to c$, $h \to m$	Transition rates from h to r, c, and m, respectively
$c \to h$, $c \to d$, $c \to m$	Transition rate from s to u
Mitigation	
Compliance	Ratio of the total population that is compliant with the protocol
% High Risk Sheltering	Ratio of the total population that is high risk; to be requested to shelter
SD Interactions/Day	Average number of interactions per person per day with other individuals (as defined by the proximity tracking application
SD Mitigation Ratio	Percentage reduction to the average number of interactions per person per day as a result of social distancing
PP Exposure Given Probability	Probability that a random susceptible person becomes exposed due to an interaction with an infected individual
PP Cost/Person/Day	Cost of personal protection normalized per person per day
ECT App Ratio in Population	Ratio of population having exposure tracking apps
ECT Tracking Window	Number of days prior to infection that should be assessed to alert potentially exposed individuals of their status
ECT Wait Before Test	Number of days after potential exposure that an individual should wait prior to taking a test if they have been notified of potential exposure through the app and are not symptomatic - if symptomatic then test is given immediately
ECT Cost/Unit	Cost of the ECT app normalized per person per time horizon
SR App Ratio in Population	Ratio of population having symptoms reporting apps
SR Probability Symptom Given	Probability that SR app reports symptomatic given individual is in u, s, e, i; unique values for each compartment
SR Cost/Unit	Cost of the SR app normalized per person per time horizon
SR Ratio of Probability Known Symptomatic	Ratio of probability of a symptomatic individual realizing they are symptomatic without the use of the SR app
Cost/Unit	Cost of 1 test
Wait for Results	Number of days needed to receive test results
Tracking Window	Number of days within which the test is still considered relevant
# Tests/SR detection	Number of tests given to individual marked symptomatic by the SR app
# Tests/ECT detection	Number of tests given to individual marked symptomatic by the ECT app
Asymptomatic Testing Window	Number of days in which entire asymptomatic population is testing via round robin method
Prob NC given Neg Test	Probability of keeping an individual in the NC population given negative test results, values varies based on what triggered the need for test (ECT, SR, asymp)
Misc	
Infection duration	Duration of COVID-19 infection
Exposure duration	Time it takes for individual to be infected
Quarantine cost	Cost of quarantine

TABLE I
INPUT PARAMETERS FOR THE MODEL

Input Parameter	Definition
m	Mitigated Daily Beta
c	Compliance
Asymptomatic Testing	Number of days within which the entire asymptomatic population is tested on a random round-robin basis
Smart App Settings	
SR app ratio	Percentage of population utilizing SR app
ECT app ratio	Percentage of population utilizing ECT app
Tests/SR detection	Number of tests requested when marked by SR app
Tests/ECT detection	Number of tests requested when marked by ECT app
Prob NC given Neg Test	Percentage of individuals kept in NC population given negative test result

TABLE II
SCENARIO TEMPLATE

KPI	Definition
Health Outcomes	
Total Infections	Total individuals infected over the time horizon
Peak Infections/Day	Maximum number of individuals infected on a single day
Days to Peak Infection	Number of days to reach Peak Infections/Day
Probability of 0 deaths	Probability of 0 deaths during the time horizon
Productivity Outcomes	
Cumulative NC days	Cumulative number of days people are quarantined
Cumulative NC days (%)	Days in quarantine (all individuals) / (time horizon * total individuals)
Mitigation Cost Outcomes	
Total Cost	Total cost of best protocol over time horizon
Cost of Tests	Cost of testing over time horizon
Cost of ECT apps	Cost of tracking apps over time horizon
Cost of SR apps	Cost of symptom reporting apps over time horizon
Cost of Quarantine	Cost of quarantine (of all individuals) over time horizon

TABLE III
KEY PERFORMANCE INDICATORS (KPIS)

C. Comparison of selected Pareto-optimal options

On the KPI Comparison Chart in Figure 1.2, decision makers choose one or more points on the chart to further investigate, triggering entries on the Pareto-optimal Comparison Table, as seen in Figure 1.3. Each entry on the table shows all the KPIs (health, productivity, and cost outcomes) and the best Pareto-optimal parameters found within that budget. This table allows decision makers to view and compare the KPIs and Pareto-optimal mitigation protocol parameters at various budget points.

D. What-if Analysis

Decision makers choose and transfer some rows from the Pareto-optimal Comparison Table to the What-If Scenarios Table in Figure 1.4, by selecting its radio-button and clicking the 'ADD TO WHAT-IF' button.

The What-if Analysis Table allows the decision maker to:

- modify mitigation protocol parameter(s) to observe the resulting changes in the KPIs
- view disease progression over time horizon, as shown in Figure 1.5
- graph and analyze sensitivity of assumptions, as show in in Figure 1.6

In this table, decision makers can view how modifying one or more protocol parameters changes the resulting KPIs. Decision makers can simulate modifications to compare mitigation protocol alternatives. From the Time Horizon Chart, decision makers can observe how one or more KPIs vary by day over the time horizon. To view it for a row, decision makers select the line style, which can be none, solid, dash, dot, or dashdot to differentiate between the rows on the graph.

The Sensitivity Analysis Chart shows, for a protocol alternative under consideration, how changes in a particular parameter affects the KPIs. To display it, decision makers select the radio button for a row, and then select one of the available parameters: (1) Mitigated Daily Beta, Compliance, Test Wait for Result, Initial Infected Exposed Percent, and Initial Recovered.

E. State Diagram

Figure 2 shows all the states in the system and the events that must take place to go from one state to another. As mentioned previously in this section, the decision maker must choose a *Base Input*, *Scenario Template*, and a Mitigated Daily Beta and Compliance pair to generate the KPI Tradeoff Chart as show in state (1). The decision maker is able to toggle various KPIs to observe on this chart. From this point, if they choose to further investigate, they can chose one or more points from the graph to display the the Pareto-Optimal Comparison Table (2). Here they can select a row, and add it to the What-if Scenarios Table (3) by then clicking the "ADD TO WHAT-IF" button. Now they can modify the protocols in a row and immediately see the changes this causes to the KPIs. They can also visualize the data in two ways: in the Time-Horizon Chart (4), or the Sensitivity Chart (5), each of which is depicted in the diagram. They see the time-horizon by selecting a line style for one or more rows to show the changes to the SUEIHCDR categories in the Time-Horizon Chart (4). They can select or de-select rows to see in the chart. To see the Sensitivity Chart (5) they select the radio button for a row, and an entry in the Sensitivity Parameter drop-down. They can the select a different KPI row, or sensitivity parameter to immediately see the new chart.

IV. DG SYSTEM ARCHITECTURE & IMPLEMENTATION

A. Architecture

The high-level architecture of the DG system is depicted in Figure 3. It has three main components: (1) a Dashboard Web Application written in Python, (2) a Pareto-front Database layer stored in MongoDB, and (3) a Scenario Generator Daemon that performs time-consuming computations. The core of the system consists of Python modules which generate all scenarios. From these scenarios the system computes the Pareto-front of the mitigation protocols, which correspond to

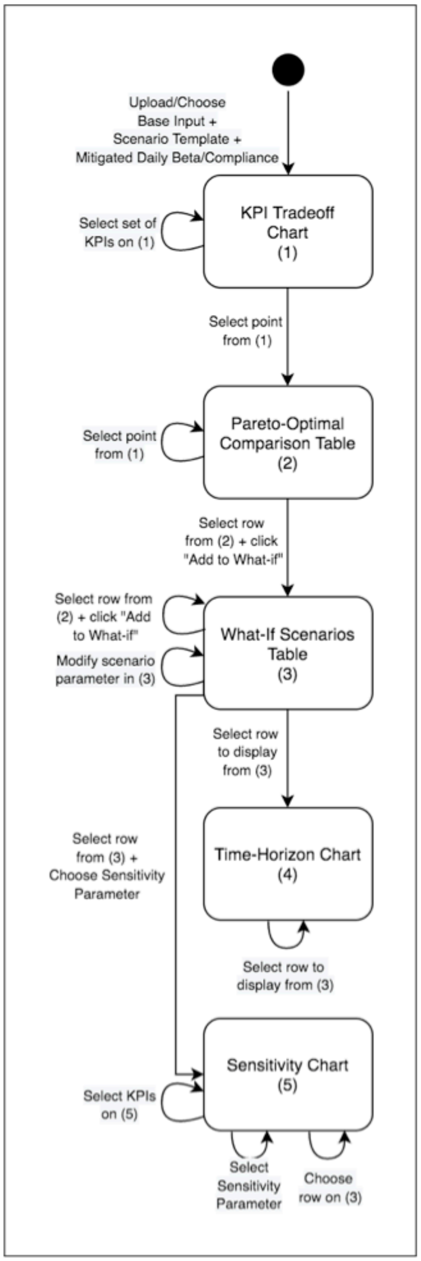

Fig. 2. State Diagram

the KPI Trade-off graphs. They are also used to perform What-if Analysis for the selected options, graphing and analyzing disease progression over the time-horizon, and performing sensitivity analysis.

Dashboard Web Application The web application is written Python, making extensive use of the Plotly Express and Dash packages from Plotly Software [13]. Plotly and Dash allow the creation of web applications that display complex, interactive graphs and charts. They are distributed under the MIT license.

Pareto-front Database Producing the model data is relatively time-consuming for an interactive application (typically on the order of minutes), so we store the results in a database. We chose MongoDB, since the both the input and generated

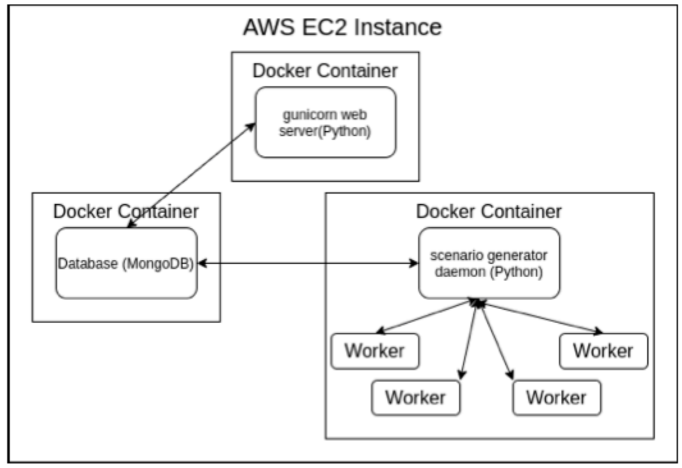

Fig. 3. Software Components of the DG system

model data are represented as JSON. MongoDB allows for the efficient storage and rapid retrieval of JSON documents in binary (BSON) format.

Scenario Generator Daemon Generating the model from the input files can take several minutes, so it needs to be done asynchronously from the web application. The generator daemon is a Python program that polls the database for generation requests, passes them to worker processes, and writes the results back into the database. The web application displays the generated models, and periodically checks for completed work. A table displays a global log of the requests and their status (one of *new*, *running*, *succeeded*, or *failed*).

The graphs, tables, and controls are all implemented using Dash modules. Although the page the user sees has many interactive features, Dash requires the developer only to write Python and make calls to the API. The primary modules used by the DG system are the *dash_core_components.Graph* and *dash_table.DataTable*. The former produces the interactive graphs, and the latter produces the interactive tables. A variety of other Dash components make up the other widgets on the web pages such as drop-downs, links, markdown, text-areas, file uploads, confirmation dialogues, and buttons.

In some cases, it is helpful to store data in the user's browser. For example, the Graph object does not allow points to be manipulated from outside the Graph component itself. This is a problem since we would like to be able to clear all the points, or remove one, when the user deletes a row from the Pareto-optimal Comparison table. To work around this, we store the selected points in a Store object, which allows us to keep the points in browser memory, and manipulate them as needed. The KPI Tradeoff chart is rendered from these stored points.

The Generated Graphs table reports to the user which combinations of *Base Input* and *Scenario Template* files have generated scenarios in the database. To keep this table up-to-date, we use the *dash_core_components.Interval* class, which calls a thread asynchronously that periodically polls the Pareto-front Database, and updates the user interface when new files are uploaded and scenarios generated.

B. Implementation

There are three places where significant computations are performed, as depicted in Figure 4, and described in detail below.

1) When the user generates scenarios.
2) When the user adds a row to the What-If Scenarios table, or modifies the protocols in an existing row.
3) When the user selects a row in the What-If Scenarios table to display in the Sensitivity graph, or updates the sensitivity parameter in the drop-down menu.

Generation of Scenarios: The user has selected *Base Input* and *Scenario Template* files, and clicked the "Generate" button. The scenario generator daemon does the following:

1) The selected base input file and scenario template file are retrieved from the database.
2) All combinations of these scenario parameters are substituted into the *Base Input* file, as described in Section III.
3) Each combination is run through the COVID-19 state-transition model for the number of days defined in the *Base Input* file. The KPIs are aggregated; note that these include the total cost of each mitigation approach, and the total number of infected individuals from the population.
4) The data is aggregated to the Mitigated Daily Beta and Compliance level. For each distinct cost C in the outputs from the previous step, the protocol instance with the lowest number of infected people within budget C is selected for display.
5) The optimal protocol instance for each total cost is saved to the database, along with all associated KPIs, for future display and calculations.

Update What-if Table: The user has copied a row from the Pareto-optimal Comparison table to the What-if Scenario table, or has updated a protocol parameter for an existing row in the latter table. This causes a refresh of the table display:

1) Each row is processed. The Mitigated Daily Beta, Compliance, and protocol parameters (current or modified) are substituted into the model input.
2) A single iteration of step 2 from the previous algorithm is executed with the protocol parameters. The new KPI values are written to the What-if table, and the complete time series for the KPIs, for each row, are saved in memory, for use by the Time-Horizon graph.

Generate Sensitivity Graph: when a user selects a row in the What-if table, and chooses a sensitivity parameter in the drop-down menu, the effect of varying that parameter is calculated. This is done by *discretizing* the selected parameter and running the scenarios as follows:

1) The code picks a lower bound, an upper bound, and a step value, which are dependent on the selected sensitivity parameter.
2) Iterate the steps from the lower bound to the upper bound. For each step, run through the scenario generation with all other parameters fixed to the selected Mitigated Daily Beta, Compliance, and what-if table protocol parameters. This is shown in the following pseudocode:

$lb = get\_lowerbound()$
$ub = get\_upperbound()$
$step = get\_step()$
$cur = lb$
$KPI = []$
while $cur <= ub$: **do**
  $KPI = KPI + run\_model(cur, \ldots)$
  $cur += step$
end while
return KPI

---

3) Update the Sensitivity graph with the calculated values.

V. System Demonstration

This section provides an example of how a decision maker evaluates different mitigation protocols by comparing their total costs and effectiveness, and converges to choosing the recommended alternative.

In Figure 5 the decision maker selects a *Base Input* and *Scenario Template*. Table IV shows a sample input that was used for the model. Figures 5-10. These will have already been created and loaded by a domain expert such as an epidemiologist, and a user will have clicked the 'GENERATE' button, to produce the KPI Comparison graphs. The decision maker assumes that the *mitigated daily beta* will be 0.6 and the *compliance* will be 0.9, and selects that combination from the drop-down menu. The description below the drop-down explains what the *mitigated daily beta* means: the number of close contacts per person per day is 1.7, and the likelihood of close contact resulting in exposure is 0.353.

The KPI Tradeoff Chart is in Figure 6. It shows the KPIs for the best mitigation protocol, in terms of the total number of infections, for all possible cost points. By default, the graphs for the total number of infections and the peak infections/day are shown. Several other KPIs are listed in the chart legend. Clicking one causes its graph to appear on the chart.

The decision maker selects several points on the chart for comparison: the lowest cost protocol (\$64, 487), the point at which additional costs seem to provide little benefit (\$23, 935, 847), and several interesting points in between, such as when a small budget increase results in a significant reduction in total infections (\$1, 311, 153). Each time they select a point, it is added to the Pareto-optimal Comparison Table, which is in Figure 7. The decision maker examines this table to compare all the health, productivity, and cost KPIs, as well at the protocols. They decide to take a closer look at the protocols corresponding to budgets \$64, 867, \$1, 311, 153, \$10, 513, 290, and \$23, 935, 847.

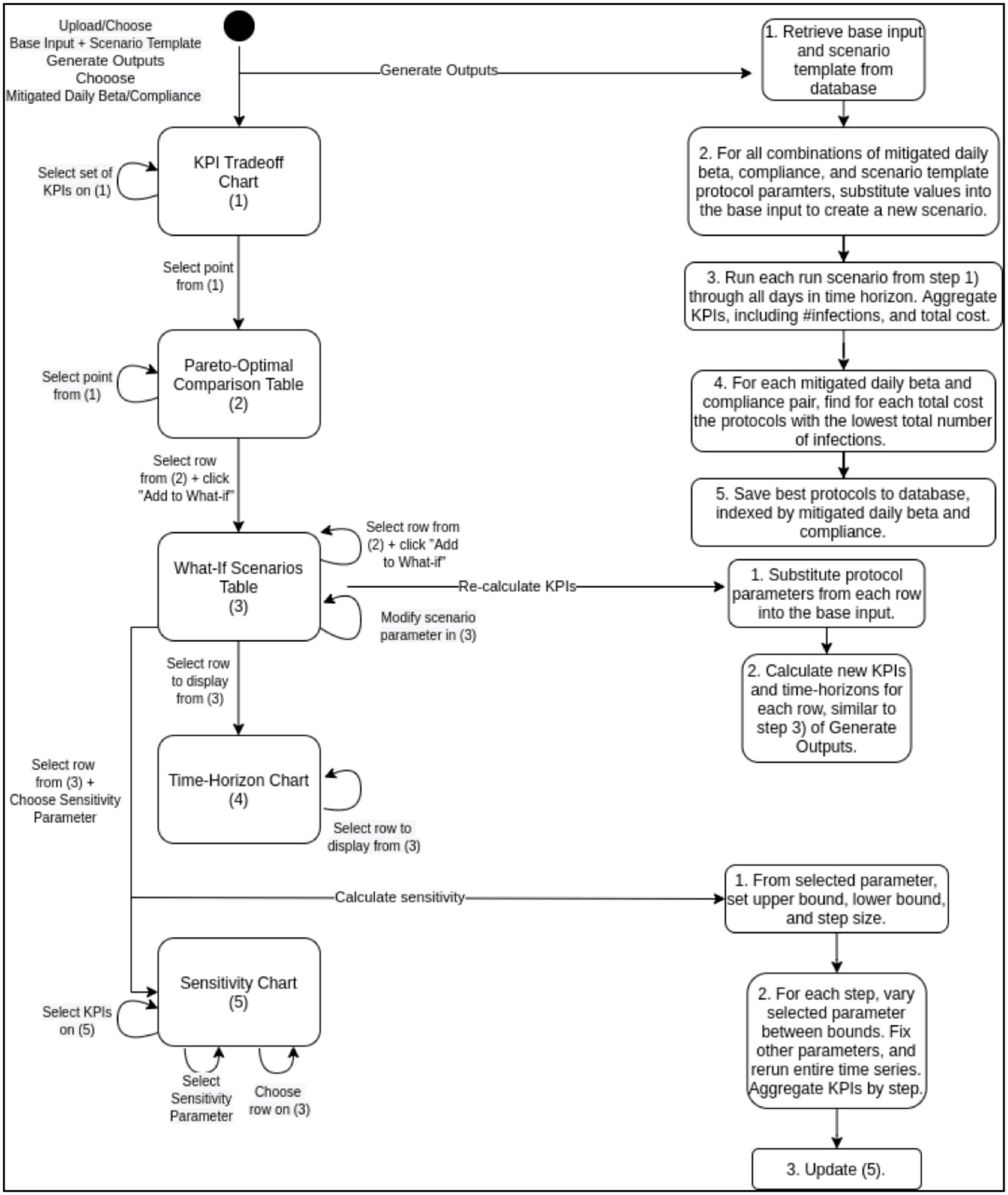

Fig. 4. Data Flow of the DG System

Input Parameter	Example Value
General Settings	
Interval	day
Time Horizon	150
Outbreak Infected Ratio	0.05
Max NC Population Ratio	0.3
Initial Compartments	
pop	10,000
u	0
s	9,360
e	40
i	100
r	500
h	0
c	0
d	0
m	0
Transition Ratios	
u → m	5.5e-06
e → i	0.25
e → m	5.5e-06
i → r	0.0999
i → h	0.0002
i → m	5.5e-06
h → r	0.08
h → c	0.02
h → m	5.5e-06
c → h	0.08
c → d	0.02
c → m	5.5e-06
Mitigation	
Compliance	0.9
% High Risk Sheltering	0
SD Interactions/Day	1.7
SD Mitigation Ratio	0
PP Exposure Given Probability	0.411764706
PP Cost/Person/Day	0
ECT App Ratio in Population	0.9
ECT Tracking Window	10
ECT Wait Before Test	4
ECT Cost/Unit	$0
SR App Ratio in Population	1.0
SR Probability Symptom Given	0.01
SR Ratio of Probability Known Symptomatic	0.5
SR Cost/Unit	$3
Wait for Results (days)	1
Tracking Window	10
# Tests/SR detection	1
# Tests/ECT detection	1
Asymptomatic Testing Window (days)	7
Prob NC given Neg Test	prox: 1, symp: 1, asymp: 0
Prob positive given s	symp: 0, asymp: 0
Prob positive given u	symp: 0, asymp: 0
Prob positive given e	symp: 0.475, asymp: 0.375
Prob positive given i	symp: 0.99, asymp: 0.75
Base s → u	0.0001
Misc parameters	
Infection duration	10
Exposure duration	4
Quarantine cost	$0

TABLE IV
SAMPLE INPUT PARAMETERS FOR THE MODEL

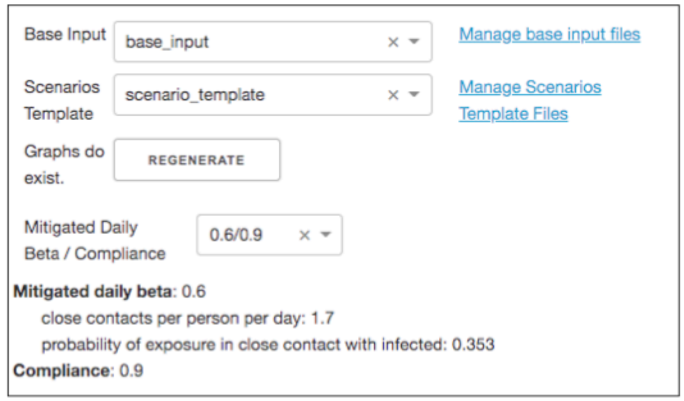

Fig. 5. Input for DG System

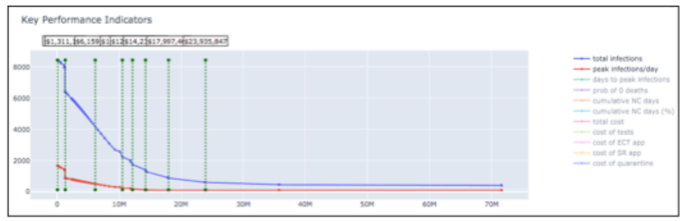

Fig. 6. KPI Tradeoff Chart of DG System

For each of these rows, the decision maker selects its radio button, and clicks the 'ADD TO WHAT-IF BUTTON'. This moves the row to the What-if Scenarios Table, shown in Figure 8. It would be possible at this point for them to modify the protocol parameters for a row, and immediately see the KPI changes; but the decision maker does not do this yet.

After observing protocol alternatives in the What-if Scenarios Table, the decision maker thinks the last two alternatives are the most promising, and would like examine and compare them more closely. To do that, they would like to see the progression of the disease over the time-horizon, in terms of the infected and infected isolated compartments. They select a solid line for the third alternative, and a dashed line for the fourth alternative. These then appear in the Time-Horizon Chart, shown in Figure 9. The decision maker observes that for the protocol represented by the dashed line, the number of infections is lower, and is decreasing over the time horizon. Whereas in the protocol represented by the solid line, the number of infections gradually increases to the peak of 241 individuals (corresponding to 2.41% of the population) on day 87 of the time horizon. However, cost of the solid-line protocol (the third in the What-if Scenarios Table) is significantly lower than the dashed-line protocol (the fourth in the What-if Scenarios Table): $\$10,513,290$, vs. $\$23,935,847$. The decision maker observes that for the less expensive protocol, the number of isolated individuals per day peaks at approximately 200, which can be supported by accommodation of the isolation dormitory.

The decision maker is leaning toward selecting the protocol represented by the solid-line, but would like to understand the

budget	kpi											best protocol parameters					
	health				productivity		cost										
	total infections	peak infections/day	days to peak infections	prob of 0 deaths	cumulative NC days	cumulative NC days (%)	total cost	cost of tests	cost of ECT app	cost of SR app	cost of quarantine	population with SR app	population with ECT app	# tests requested when marked by ECT app	# tests requested when marked by SR app	prob. set to NC population given neg test result	asymptomatic testing (days)
$64,867	8465.9	1666	52	97.1%	72057.4	6.9%	$64,867	$34,868	$0	$29,999	$0	100%	90%	0	0	100%	1,920
$1,311,153	6406.3	879.1	53	98.0%	147702.4	14.1%	$1,311,153	$1,281,168	$0	$29,985	$0	100%	90%	1	1	100%	960
$6,159,065	4179.3	502.7	72	98.8%	105288.2	10.0%	$6,159,065	$6,129,083	$0	$29,982	$0	100%	90%	1	1	100%	13
$10,513,290	2237.7	240.5	87	99.4%	60507.5	5.8%	$10,513,290	$10,483,301	$0	$29,989	$0	100%	90%	1	1	100%	7
$12,143,375	1747.1	174.4	84	99.5%	49030.3	4.7%	$12,143,375	$12,113,384	$0	$29,992	$0	100%	90%	1	1	100%	6
$14,234,388	1358.9	125.7	68	99.6%	26332.3	2.5%	$14,234,388	$14,204,391	$0	$29,997	$0	100%	90%	0	0	100%	5
$17,997,466	874.6	100	0	99.7%	28505.8	2.7%	$17,997,466	$17,967,470	$0	$29,996	$0	100%	90%	1	1	100%	4
$23,935,847	599.8	100	0	99.8%	21941.5	2.1%	$23,935,847	$23,905,850	$0	$29,997	$0	100%	90%	1	1	100%	3

Fig. 7. Pareto-Optimal Comparison Table of DG System

Time Horizon Line Style	budget	kpi											best protocol parameters					
		health				productivity		cost										
		total infections	peak infections/day	days to peak infections	prob of 0 deaths	cumulative NC days	cumulative NC days (%)	total cost	cost of tests	cost of ECT app	cost of SR app	cost of quarantine	population with SR app	population with ECT app	# tests requested when marked by ECT app	# tests requested when marked by SR app	prob. set to NC population given neg test result	asymptomatic testing (days)
none	$64,867	8465.9	1666	52	97.1%	72057.4	6.9%	$64,867	$34,868	$0	$29,999	$0	100%	90%	0	0	100%	1,920
none	$1,311,153	6406.3	879.1	53	98.0%	147702.4	14.1%	$1,311,153	$1,281,168	$0	$29,985	$0	100%	90%	1	1	100%	960
solid	$10,513,290	2237.7	240.5	87	99.4%	60507.5	5.8%	$10,513,290	$10,483,301	$0	$29,989	$0	100%	90%	1	1	100%	7
dash	$23,935,847	599.8	100	0	99.8%	21941.5	2.1%	$23,935,847	$23,905,850	$0	$29,997	$0	100%	90%	1	1	100%	3

Fig. 8. What-if Scenarios Table of DG System

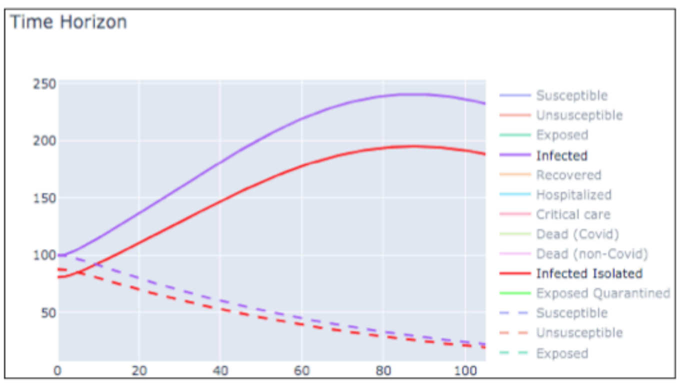

Fig. 9. Time-Horizon Chart of DG System

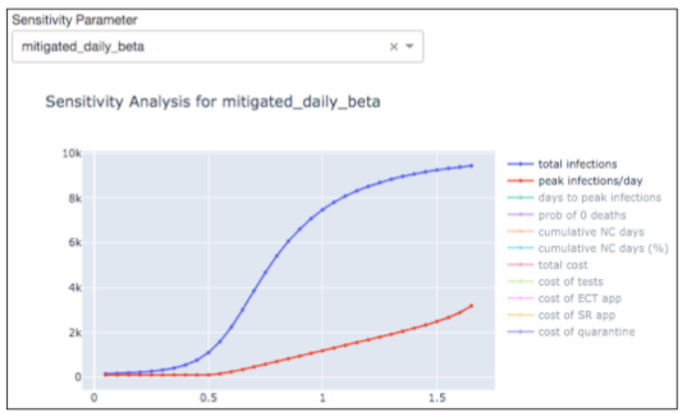

Fig. 10. Sensitivity Chart of DG System

sensitivity of the health and other outcomes to the assumptions, as the assumptions may not be fully accurate. To do this, they click the radio button for the solid-line protocol of $10,513,290, and then select the Sensitivity Parameter mitigated_daily_beta. This shows in Figure 10 the KPIs for a range of *mitigated daily beta* values. The decision maker can change a protocol parameter in the row for budget $10,513,290, at which point the KPIs are recalculated, and both the Time-Horizon Chart and the Sensitivity Chart are updated. While the total infections are highly sensitive to *mitigated daily beta*, the decision maker knows that 0.6 was already an over-estimation. The decision maker has the option to pick a more conservative *mitigated daily beta*, say 0.7, and redo the analysis.

The decision maker studies the sensitivity of other assumptions, using the Sensitivity Chart, including the wait time for test results, initial number of infected individuals, compliance ratio, and number of recovered individuals at the beginning of the time horizon. The decision maker decides to recommend the dashed-line protocol and make additional recommendations, including strong enforcement of compliance, and social distancing and personal protection recommendations. Also, they recommend only working with labs that return test results within one day, since waiting two days increases the total number of infections by about 35%.

The Dashboard Web Application can be accessed here http://54.147.155.77:8080/covid.

VI. Conclusion & Future Work

This paper reports on the development of the first, to the best of our knowledge, Decision Guidance system and methodology to make actionable recommendations on a comprehensive COVID-19 mitigation protocol, which are Pareto-optimal in terms of health outcomes, mitigation costs and productivity loss. Many interesting research questions remain open, including efficient algorithms for generation of Pareto-front of mitigation protocol alternatives not through discretization, but through the use of derivative-base optimization algorithms.

References

[1] An update to the economic outlook: 2020 to 2030, Jul 2020.

[2] Alexander Brodsky, Anita Tadakamalla, Shiri Brodsky, and Amira Roess. Modeling of covid-19 transmission dynamics extended with a comprehensive mitigation protocol to predict health, cost and productivity outcomes. Technical Report GMU-CS-TR-2021-1, Department of Computer Science, George Mason University, 4400 University Drive MSN 4A5, Fairfax, VA 22030-4444 USA, 2021.

[3] Alexander Brodsky and X Sean Wang. Decision-guidance management systems (dgms): Seamless integration of data acquisition, learning, prediction and optimization. In *Proceedings of the 41st annual Hawaii international conference on system sciences (HICSS 2008)*, pages 71–71. IEEE, 2008.

[4] Jinming Cao, Xia Jiang, Bin Zhao, et al. Mathematical modeling and epidemic prediction of covid-19 and its significance to epidemic prevention and control measures. *Journal of Biomedical Research & Innovation*, 1(1):1–19, 2020.

[5] Damian Clancy. Sir epidemic models with general infectious period distribution. *Statistics & Probability Letters*, 85:1–5, 2014.

[6] David M Cutler and Lawrence H Summers. The covid-19 pandemic and the $16 trillion virus. *Jama*, 324(15):1495–1496, 2020.

[7] Ensheng Dong, Hongru Du, and Lauren Gardner. An interactive web-based dashboard to track covid-19 in real time. *The Lancet infectious diseases*, 20(5):533–534, 2020.

[8] Chris Dye and Nigel Gay. Modeling the sars epidemic. *Science*, 300(5627):1884–1885, 2003.

[9] Jörg Eppinger and Magnus Rueping. Covid-19: Where we are, what we should do and what we should learn. 2020.

[10] Wayne M Getz, Richard Salter, Oliver Muellerklein, Hyun S Yoon, and Krti Tallam. Modeling epidemics: A primer and numerus model builder implementation. *Epidemics*, 25:9–19, 2018.

[11] Joshua R Goldstein and Ronald D Lee. Demographic perspectives on the mortality of covid-19 and other epidemics. *Proceedings of the National Academy of Sciences*, 117(36):22035–22041, 2020.

[12] Michelle L Holshue, Chas DeBolt, Scott Lindquist, Kathy H Lofy, John Wiesman, Hollianne Bruce, Christopher Spitters, Keith Ericson, Sara Wilkerson, Ahmet Tural, et al. First case of 2019 novel coronavirus in the united states. *New England Journal of Medicine*, 2020.

[13] Plotly Technologies Inc. Collaborative data science, 2015.

[14] William Jeffries and Alexander Brodsky. Composite alternative pareto optimal recommendation system with individual utility extraction (capors-iux). In *ICEIS (1)*, pages 328–335, 2018.

[15] Deanna M Kennedy, Gustavo José Zambrano, Yiyu Wang, and Osmar Pinto Neto. Modeling the effects of intervention strategies on covid-19 transmission dynamics. *Journal of Clinical Virology*, 128:104440, 2020.

[16] Halgurd S Maghded, Kayhan Zrar Ghafoor, Ali Safaa Sadiq, Kevin Curran, Danda B Rawat, and Khaled Rabie. A novel ai-enabled framework to diagnose coronavirus covid-19 using smartphone embedded sensors: Design study. In *2020 IEEE 21st International Conference on Information Reuse and Integration for Data Science (IRI)*, pages 180–187. IEEE, 2020.

[17] Mohamad Omar Nachawati, Alexander Brodsky, and Juan Luo. Unity decision guidance management system: Analytics engine and reusable model repository. In *International Conference on Enterprise Information Systems*, volume 2, pages 312–323. SCITEPRESS, 2017.

[18] A David Paltiel, Amy Zheng, and Rochelle P Walensky. Assessment of sars-cov-2 screening strategies to permit the safe reopening of college campuses in the united states. *JAMA network open*, 3(7):e2016818–e2016818, 2020.

[19] L Robinson. Covid-19 and uncertainties in the value per statistical life. *The Regulatory Review*, 8(5), 2020.

[20] Amin Yousefpour, Hadi Jahanshahi, and Stelios Bekiros. Optimal policies for control of the novel coronavirus disease (covid-19) outbreak. *Chaos, Solitons & Fractals*, 136:109883, 2020.