Multi-criteria performance analysis based on Physics of Decision - Application to COVID-19 and future pandemics

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Abstract—The purpose of this study is to present a novel perspective on decision support based on the conventional SEIR pandemic model paradigm considering the risks and opportunities as physical forces deviating the expected performance trajectory of a system. The impact of a pandemic is measured by the deviation of the social system's performance trajectory within the geometrical framework of its Key Performance Indicators (KPIs). According to the overall premise of utilizing Ordinary Differential Equations to simulate epidemics, the deviations are connected to several alternative interventions. The model is essentially built on two sets of parameters: (i) social system parameters and (ii) pandemic parameters. The ultimate objective is to propose a multi-criteria performance framework to control pandemics that includes a combination of timely measures. On the one hand, the current study optimizes prospective strategies to manage the potential future pandemic, while on the other hand, it explores the COVID-19 epidemic in the state of Georgia (USA).

1 INTRODUCTION

TRANSMISSION of infectious diseases has long been a cause of worry and a hazard to public health. It has presented severe risks to the survival of humans and social development. Following pandemic crises such as the Cholera (1817-1923), Spanish Flu (1918-1919), COVID-19 (2019-present), and others [1], [2], implementing pandemic preparedness measures has become a top concern for worldwide public health. Pandemic prevention and containment techniques fall into three major categories: antiviral (chiefly a drug or treatment effective against viruses), vaccination (treatment with a vaccine to produce immunity against disease), and non-pharmaceutical (isolation of the infected cases, quarantine, closure of school and workplaces, and travel restrictions) [3]. A critical step in controlling a "non-pharmaceutical" infectious disease outbreak is attempting to reduce the epidemic peak, which reduces the danger of overburdening healthcare systems and allows for more time for the development of a vaccine and treatment [4]. A thorough assessment of the pandemic-contaminated area and the pandemic itself can provide insight into the scope of the pandemic threat and potential control strategies. The proposed study considers a pandemic-contaminated region as a system and a pandemic as a potential that may affect system KPIs in a multi-dimensional performance space. The Physics-of-Decision (POD) paradigm proposed in [5] is used in this study. Risks and opportunities, according to the original POD framework, may be viewed as physical forces applied to the system trajectory that could push or pull it in its performance space by varying the system's KPIs [6].

The primary goal of this study is to present a tentative Decision Support System (DSS) by tuning a well-known Susceptible-Exposed-Infected-Recovered (SEIR) pandemic model to the POD framework through Ordinary Differential Equations (ODEs). To this aim, by putting the POD principles into practice, researchers may be able to study various strategies that might impact the performance of the considered system and assist them in successfully intervening in the control of future pandemics.

The paper is structured as follows. Section 2 focuses on current research efforts and scientific contributions that are related to the topic at hand. Section 3 first introduces the pandemic modeling through ODEs then tunes the presented model into the POD framework. Section 4 provides a specific POD framework process for a Decision Support System. Section 5 shows the value of the POD as a strategies management framework for the COVID-19 pandemic in the State of Georgia (USA) and to control potential future pandemics efficiently. Finally, section 6 provides conclusive remarks and proposes areas for further research.

- *N. Moradkhani, Centre Génie Industriel, IMT Mines Albi - University of Toulouse, Albi, France. E-mail: nafe.moradkhani@mines-albi.fr*
- *F. Benaben, Centre Génie Industriel, IMT Mines Albi - University of Toulouse, Albi, France. E-mail: frederick.benaben@mines-albi.fr*
- *B. Montreuil, Physical Internet Center, ISyE, Georgia Tech, Atlanta, USA. E-mail: benoit.montreuil@isye.gatech.edu*
- *M. Lauras, Centre Génie Industriel, IMT Mines Albi - University of Toulouse, Albi, France. E-mail: matthieu.lauras@mines-albi.fr*
- *J. Jeany, Scalian Lab, Toulouse, France. E-mail: julien.jeany@scalian.com*
- *L. Faugère, Physical Internet Center, ISyE, Georgia Tech, Atlanta, USA. E-mail: louis.faugere@gatech.edu*

2 BACKGROUND AND RELATED WORKS

Effective management of emerging pandemic infectious disease issues in the absence of treatment or vaccine is primarily dependent on government preventive strategies [7]. Scientific understanding is scarce regarding these strategies in the field of infectious disease control. There is also little information on whether theories and measurements created for risk perception studies on chronic diseases, for example, can be used for infectious diseases [8]. Such information, however, is critical for the successful management of newly developing infectious illnesses, because the capacity to promote health-protective behavioral change is conditional on the understanding of major drivers of such behavior [9]. In recent years, epidemiological models have been the subject of significant research. Compartmental models, such as the SEIR model (see subsection 3.2), have been utilized often for epidemic analysis among the many models. The early dynamics of disease transmission, from initial infected cases through the potential of the intervention to limit disease spread, are the primary focus of epidemic modeling approaches [10].

This study looks at a simplified version of the SEIR pandemics model implemented through ODEs in which no one has preexisting immunity, and every infected one has immunity after recovery. The objective is to characterize the pandemic model to investigate the possible interventions to control the outbreak through finding the most desirable solutions considering the limits of their execution. International travel restrictions [11], contact reduction [12], isolation of sick persons from the outset [13], and the use of masks [14] are some of the most common measures for controlling a non-pharmaceutical pandemic. The current research delves into the SEIR model to distinguish the model's inputs from its outputs, and it looks at the mentioned pandemic control strategies with the assumption that changes in system inputs generate changes in its outputs. Some modified SEIR models such as [15], [16], and [17] attempt to thoroughly assess various intervention techniques. The inputs of the pandemic model are divided into two categories: virus and society. The influence of virus-related elements and the characteristics of the pandemic-affected region as a society on the epidemic, are examined in this study. To investigate a behavioral dynamic epidemic model for multidimensional policy analysis that includes endogenous viral transmission, various simulation-based assessments of outbreak reactions and tactics are established [18]. Understanding the interaction between factors in nonlinear systems attempts to investigate "what-if" possibilities based on the community and region's capabilities. The wearing masks as an example among the non-pharmaceutical intervention measures has been studied in [19] for the COVID-19 epidemic. In the SEIR model, population transmission through dynamic flows has been established using various ODEs. Various pandemics are represented by different input values for the equations, as mentioned in [20].

The foundation of system diagnostics is the characterization of the system and the relationship between its parameters. Controlling the system, necessitates the identification of such linkages and their impact on the system's performance. The varied circumstances of the system across time are defined by system states [21]. Over the last few decades, the field of risk management has produced a number of acknowledged outcomes that are now regarded as reliable contributions [5]. According to [22], risk is defined as a mix of the severity of the system's consequences on the one hand and the likelihood of occurrence on the other. The Physics of Decision (POD), which is based on physical principles and mathematical equations, is a novel performance management technique in the field of risk management [5]. The POD framework is a multi-criteria, time-dependent approach for performance analysis that quantifies the impact of various pandemic control methods. When compared to earlier researches, the innovation of this approach is the ability to measure the influence of multiple strategies (simultaneously) on system performance in a multi-dimensional framework and then determine the optimum strategies while keeping the execution restrictions in mind.

3 Physics-Based Decision Support System

The term "Risk" is used in many ways and is given different definitions depending on the field and context. Common to most definitions of risk is uncertainty and undesirable outcomes. From a reciprocal perspective, those uncertainties that could bring benefits if they were to occur are known as "Opportunities" [23]. The definition of opportunity is: "an uncertainty that could have a positive effect leading to benefits or rewards". The opportunity could be seen as just another form of risk: a risk with negative impacts is a threat, whereas a risk with a positive impact is an opportunity [24].

Decision Support Systems (DSSs) are at the heart of risk/opportunity management projects [25]. The necessity of such systems is critical to deal with the complexities due to massive data and interconnectivity between the system's components and its environment [26].

In this section, the *Physics Of Decisions* (POD) is presented and illustrated as an innovative approach for decision support in context of instability and uncertainty. POD considers that risks and opportunities can be created by spontaneous or intentional changes in the system's parameters or in its environment parameters. These changes may push or pull the system in its *performance space* by varying system's KPIs. **Essentially, these variations' consequences are observed through the deviation of the system *"trajectory"* within the multidimensional *performance space* of its KPIs**.

3.1 Preliminaries, Basic Concepts, and Notation

System characterization and identification are fundamental problems in systems theory. The problem of characterization is concerned with the mathematical representation of a system. A model of a system can be expressed as a function $\mathbf{F}$ from an input space $\mathscr{U}$ into an output space $\mathscr{Y}$ [27]. The function $\mathbf{F}$ is defined implicitly by the specified input-output pairs. The method of representing time-depended systems by vector differential or differential equations is well established in systems theory and applies to a fairly large class of systems [28]. For example, the differential equation

$$\begin{aligned} \frac{dx(t)}{dt} \triangleq \dot{x}(t) = \Phi[x(t), u(t)], \qquad t \in \mathbb{R}^+ \\ y(t) = \Psi[x(t)]. \end{aligned} \tag{1}$$

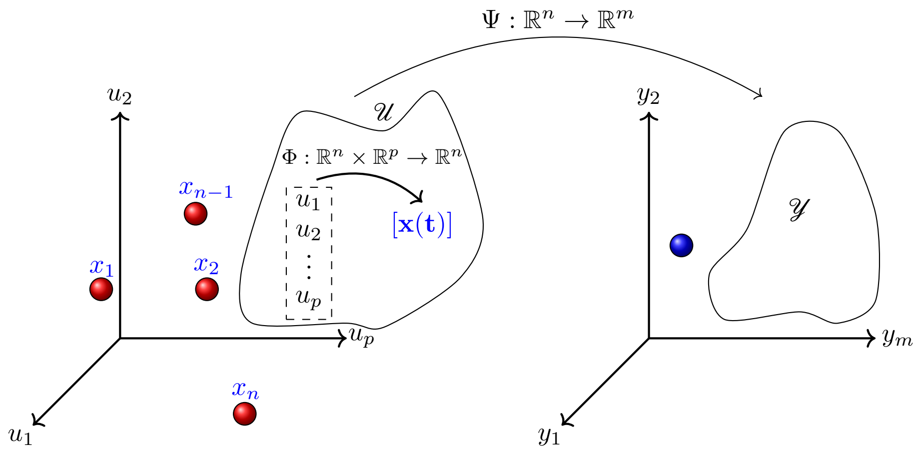

Fig. 1. Mathematical representation of input-state-output of a system

Where $u(t) \triangleq [u_1(t), u_2(t), \cdots, u_p(t)]^T$, $x(t) = [x_1(t), x_2(t), \cdots, x_n(t)]^T$, and $y(t) = [y_1(t), y_2(t), \cdots, y_m(t)]^T$, represents a p input, m output system of order n with $u_i(t)$ representing the inputs, $x_i(t)$ the state variables, and $y_i(t)$ the outputs of the system. Φ and Ψ are static nonlinear maps defined as $\Phi : \mathbb{R}^n \times \mathbb{R}^p \to \mathbb{R}^n$ and $\Psi : \mathbb{R}^n \to \mathbb{R}^m$. The vector $x(t)$ denotes the state of the system at time t and is determined by the state at time $t_0 < t$ and the input u defined over the interval $[t_0, t)$. The output $y(t)$ is determined by the state of the system at time t. Equation (1) is referred to as the input-state-output representation of the system [27], [28]. This paper is concerned with discrete-time systems which can be represented by differential equations corresponding to the differential equation given in (1). These take the form

$$\begin{aligned} x(k+1) &= \Phi[x(k), u(k)], \\ y(k) &= \Psi[x(k)]. \end{aligned} \tag{2}$$

where $u(.)$, $x(.)$, and $y(.)$ are discrete-time sequences. Fig. 1 illustrates a time-dependent input-states-output system.

3.2 Pandemic modeling through Ordinary Differential Equations

Quantitative studies on mechanisms of disease transmissions provide a foundation for pandemic prevention and control. The Epidemic Dynamics formulates mathematical models based on the occurrence and progressions of diseases to its surroundings to characterizing the infectious agents, describing the transmission processes, analyzing origins of the diseases and factors involved in the transmissions, and predicting the prevalence of the diseases and their patterns [10]. Dynamic models for infectious diseases are mostly based on compartment structures [10]. To formulate a dynamic model for the transmission of an epidemic disease, the population in a given region is often divided into several different groups or compartments. Such models describing the dynamic relations among these compartments are called **compartment models**. The population is assigned to compartments with labels – for example, **S**, **I**, or **R**, (**S**usceptible, **I**nfectious, or **R**ecovered). The population may progress between compartments. The order of the labels usually shows the flow patterns between the compartments; for example, **SEIS** means **S**usceptible, **E**xposed, **I**nfectious, then **S**usceptible again. The numbers of individuals are presented in the compartments S, E, I, and R, at time t, as **S(t)**, **E(t)**, **I(t)**, and **R(t)**, respectively [29]. This section introduces the generic version of pandemics model including Susceptible, Exposed, Hospitalized, Recovered, and Dead as common compartments of different pandemics shown in Fig. 2.

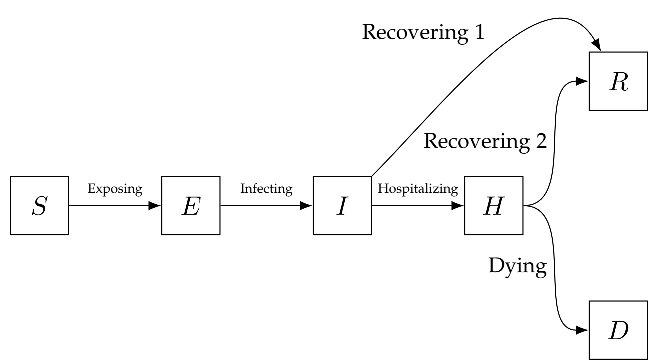

Fig. 2. Flow chart of the SEIR model

This model postulates rules on how populations in each category move to the next categories. Based on Fig. 2, the transitions of the population through the flows from left to right are as follows:

(i) Exposing flow $\Rightarrow$ The individuals move from S to E through this flow (Fig. 2) at the exposure rate, *i.e.*, the population in category S decreases concerning time **t** and the population in E correspondingly increases at the same rate. The exposure rate grows with **I**, the number of infected individuals. A standard hypothesis is that exposure rate is the product of the transmission rate (or *contact rate* (**cr**)) and the probability of infection given that contact occurred (*infectious rate* (**ir**)) divide by latency due to *infectious duration* (**id**) [30].

$$\text{Exposing flow} = \frac{ir \times cr}{id} S \times I. \tag{3}$$

(ii) Infecting flow $\Rightarrow$ The Exposed individuals progress to the Infected category through this flow after the *latent period* (**lp**), the period at which exposed hosts become infected [30].

$$\text{Infecting flow} = \frac{E}{lp}. \tag{4}$$

(iii) Hospitalizing flow $\Rightarrow$ The individuals with lower immunity in case of virus infection, called severe infected group, progress to the Hospitalized compartment with the rate of *fraction hospitalized* (**fh**).

$$\text{Hospitalizing flow} = fh \times I. \tag{5}$$

(iv) Recovering 1 flow $\Rightarrow$ The lightly Infected individuals (non-severe cases), those who don't need to be Hospitalized, progress to the *Recovery* compartment directly after the *infectious duration* (**id**).

$$\text{Recovery 1 flow} = \frac{1 - fh}{id} I. \tag{6}$$

(v) Recovering 2 and Dying flows $\Rightarrow$ The *Hospitalized* individuals, depending on the *fatality rate* (**fr**) of the virus, either recover (*Recovering 2* flow) or die after *infectious duration* (*Dying* flow). The hospitalized fatality rate (**hfr**) is calculated by dividing the *fatality rate* (**fr**) of the virus by the *fraction hospitalized* (**fh**), hfr=(fr)/(fh).

$$\begin{aligned} \text{Recovery 2 flow} &= \frac{1 - hfr}{id} H, \\ \text{Dying flow} &= \frac{hfr}{id} H. \end{aligned} \tag{7}$$

The basic reproductive number (denoted $\mathscr{R}_0$), in epidemiological modeling, is the expected number of cases directly caused by one case in a community where everyone is susceptible. In the majority of commonly used epidemic models, a pandemic can spread in a population if $\mathscr{R}_0 > 1$, but not if $\mathscr{R}_0 < 1$. The basic reproductive number for the SEIR model is shown in equation 8, assuming that the latency period is a random variable with exponential distribution with parameter α (i.e., the average latency period is α^{-1}, or lp^{-1}), β, γ, and μ are the rates of infection (the number of contacts per person per time (cr/id), multiplied by the probability of disease transmission in a contact between a susceptible and an infectious subject (ir)), recovery, and mortality, respectively [30].

$$\mathscr{R}_0 = \frac{\alpha}{\mu + \alpha} \frac{\beta}{\mu + \gamma} \tag{8}$$

Since the natural mortality rate is not included in the presented SEIR model in Fig. 2 ($\mu = 0$). According to the "Recovery 1" and "Recovery 2" flows in Fig. 2 and equations 6 and 7, the γ is obtained using equation 9.

$$\gamma = \frac{1 - fh}{id} + \frac{1 - hfr}{id} = \frac{2 - (fh + hfr)}{id} \tag{9}$$

Finally, the reproductive number of the presented model is obtained through equation 10.

$$\mathscr{R}_0 = \frac{\beta}{\gamma} = \frac{(cr/id) \times ir}{(2 - (fh + hfr)/id} = \frac{cr \times ir}{2 - (fh + hfr)} \tag{10}$$

Given that the disease spreads in a closed environment; the paper considers there is no emigration nor immigration and neither birth nor death in the population so that the total population remains a constant N for all t, that is:

$$S(t) + E(t) + I(t) + H(t) + R(t) + D(t) = N \tag{11}$$

Instead of establishing the system for a specific total number of the population, the paper simplifies the equation 11 by dividing the sides of the equation by total population N to be efficient for any population size. Therefore, the following proportions are obtained.

$$\begin{aligned} & s(t) = \frac{S(t)}{N}, e(t) = \frac{E(t)}{N}, i(t) = \frac{I(t)}{N}, \\ & h(t) = \frac{H(t)}{N}, r(t) = \frac{R(t)}{N}, d(t) = \frac{D(t)}{N}, \\ & s(t) + e(t) + i(t) + h(t) + r(t) + d(t) = 1 \end{aligned} \tag{12}$$

Based on Fig. 2 and equations (3) - (7), there are six parameters involved in the flows. The vector u presents those parameters as inputs for derived equations.

$$u = [lp, id, fr, ir, cr, fh]^T = [u_1, u_2, u_3, u_4, u_5, u_6]^T \tag{13}$$

The rate of change in the compartments in Fig. 2 from left to right according to the transmission of individuals are represented in equation 14 through Ordinary Differential Equations (ODEs) based on equations and the input vector u (13).

$$\begin{aligned} \frac{ds}{dt} &= -\frac{u_4 u_5}{u_2} si, \\ \frac{de}{dt} &= \frac{u_4 u_5}{u_2} si - \frac{e}{u_1}, \\ \frac{di}{dt} &= \frac{e}{u_1} - \frac{(1 - u_6)}{u_2} i - u_6 i, \\ \frac{dh}{dt} &= u_6 i - \frac{(1 - \frac{u_3}{u_6})}{u_2} h - \frac{h}{u_2} \times \frac{u_3}{u_6}, \\ \frac{dr}{dt} &= \frac{(1 - \frac{u_3}{u_6})}{u_2} h + \frac{(1 - u_6)}{u_2} i, \\ \frac{dd}{dt} &= \frac{h}{u_2} \times \frac{u_3}{u_6}. \end{aligned} \tag{14}$$

The ordinary differential equations (ODEs) system in equation 14, together with some initial conditions (values of the input variables of the model (vector u) at initial starting time $t_0 = 0$), make up an Initial Value Problem, or IVP. IVPs are ubiquitous in modeling systems that evolve in time. They encapsulate how a future state of a system is determined by the present state (the initial data) plus certain rules on how quantities evolve (the ODEs) [31]. As soon as the preliminary infected (or exposed) cases appear in the region, the pandemic starts to spread. The ODEs in equation 14 are supplemented with some initial conditions. For example, some percentage of the whole population (α) is infected (or exposed) and the rest are susceptible to be infected.

$$\begin{aligned} &s(0) = 1 - \alpha, e(0) = 0, i(0) = \alpha, \\ &h(0) = 0, r(0) = 0, d(0) = 0. \end{aligned} \tag{15}$$

The modeling through ODEs has been completed. The following are some remarks on specific hypotheses.
(i) The simple version of the presented SEIR model in this section considers that the recovered individuals gain permanent immunity. However, for bacterial diseases, such as encephalitis, and gonorrhea, the recovered individuals don't gain permanent immunity and can be reinfected [10].
(ii) The paper considers there is not an emigration or immigration, and neither birth nor death in the population and the population size remains a constant N for all t.
(iii) The presented model considers all the individuals are susceptible to be infected. It might be a portion of the population is immune to the virus and so not susceptible to it. Besides, depending on the type of the virus, due to the sensitivity of the virus to some parameters such as age category, the health status of the population in the region; some individuals might be more susceptible and some not.
(iv) The exposed compartment could be distinguished to individuals with and without symptoms and the Infected group, in addition to the light and severe groups, could include infected individuals that don't carry the virus.
(v) The severely infected individuals could be hospitalized and ICU sections. The model doesn't consider differentiation between these two groups, while it might be the limit capacity for the ICU bed in hospitals.

In addition to the above remarks, there may be other hypotheses for the epidemic model that are not considered in this study. This paper considers one of the simplest cases that is common to most epidemics. It's important to point out that the paper does not cover all the possible versions of epidemics models. This is mostly due to the fact that the study's focus is on the model's application rather than its relevance.

3.3 Physics of Decision theory and its tuning to pandemic performance management

The Physics Of Decision (POD) framework introduced in section 2 is a mathematical representation of a system considering internal system connections and communication of the system with its environment. The next step after characterization and identification of the system is to evaluate the system performance. The three modes are considered to assess the system performance: (i) **Inertia** mode: The performance could change due to its normal behavior and the associated consumption. In this mode, the system is not facing any perturbation. (ii) **Passive** mode: In addition to the performance changes of Inertia, the performance might change because there is (are) perturbation(s) in the system or its environment, (iii) **Active** mode: In addition to the performance changes of Inertia, the performance could change because the system is facing some perturbations (passive changes) and also because of some taken decisions to manage the consequences of those perturbations. In the case of a pandemic crisis, the change of population size due to migration, or natural birth/death is considered *Inertia*, the sudden change of the population because of the pandemic issues is considered *Passive*, and the change of the population due to some intervention in comparison to the *Passive* mode is considered as *Active* mode. The POD framework defines two spaces in which a system can be positioned.

The ***Description Space*** describes the parameters of the system and the scope of their variation. The **p**-input vector **u(t)** represents the input system parameters (subsection 3.1). *Description Space* generally refers to what is happening in and around the monitored system. The parameters of the *Description Space* refer to the "System" and are known as ***"Attributes"***. A monitored system with particular attributes could be affected by several circumstances. These circumstances are known as "Potentials". A potential could have positive or negative impacts on the system (Risks and Opportunities). The parameters of systems' potentials are known as **"Characteristics"**. State variable **x(t)** is one set of input parameters including *Attributes* (system's parameters) and *Characteristics* (potentials' parameters) that describes the mathematical ***"states"*** of a system under function $\boldsymbol{\Phi}$ (See Fig. 3 and equation 2).

The ***Performance Space*** under function $\boldsymbol{\Psi}$ describes the system performance with an $\boldsymbol{m}$-output vector $\boldsymbol{y(t)}$. The output vector $\boldsymbol{y(t)}$ is determined by the system state in the *Description Space* (vector $\boldsymbol{x(t)}$) at time $\boldsymbol{t}$.

The relationship between the two spaces is determined by the map function $\boldsymbol{\Psi}$ of the state variables, $\boldsymbol{x(t)}$ (one set of input parameters including Attributes and Characteristics) to the outputs, $\boldsymbol{y(t)}$. This map function could be known (e.g., is formulated with equations from inputs to outputs), or it could be unknown but estimable (e.g., through simulation analysis, approximation function, Neural Network, etc.).

The *Description Space* in Fig. 3 represents a system with a $\boldsymbol{p}$-input vector composed by one vector of Attribute (system) and $\boldsymbol{r}$ vector of potentials (system's environment). The vector of each potential is represented with its characteristics:

(i) $\boldsymbol{\theta_i}$ characteristics for potential $\boldsymbol{P_i}$ (on-axis) and the $\boldsymbol{\delta_i}$ possible state variables for each $\boldsymbol{P_i}$ at specific time $\boldsymbol{t}$ shown with colored points in Fig. 3 (oval marked with "Environment"),

(ii) $\boldsymbol{\theta}$ Attributes (on-axis) of the system $\boldsymbol{S}$ and $\boldsymbol{\delta}$ possible state variables for these Attributes at specific time $\boldsymbol{t}$ shown with colored points in Fig. 3 (oval marked with "System").

Equation 16 presents the number of inputs $\boldsymbol{p}$ of the input vector $\boldsymbol{u}$ and the number of possible system states $\boldsymbol{n}$ for the generic version of the POD framework presented in Fig. 3.

$$\begin{aligned} |\boldsymbol{p}| &= \sum_{i=0}^{r} \boldsymbol{\theta_i} + \boldsymbol{\theta}, \\ |\boldsymbol{n}| &= \prod_{i=1}^{r} \boldsymbol{\delta_i} \times \boldsymbol{\delta}. \end{aligned} \tag{16}$$

According to the state variables of Attributes and Characteristics, $\boldsymbol{\delta}$ and $\prod_{i=1}^{r} \boldsymbol{\delta_i}$ respectively, $\boldsymbol{n}$ possible initial

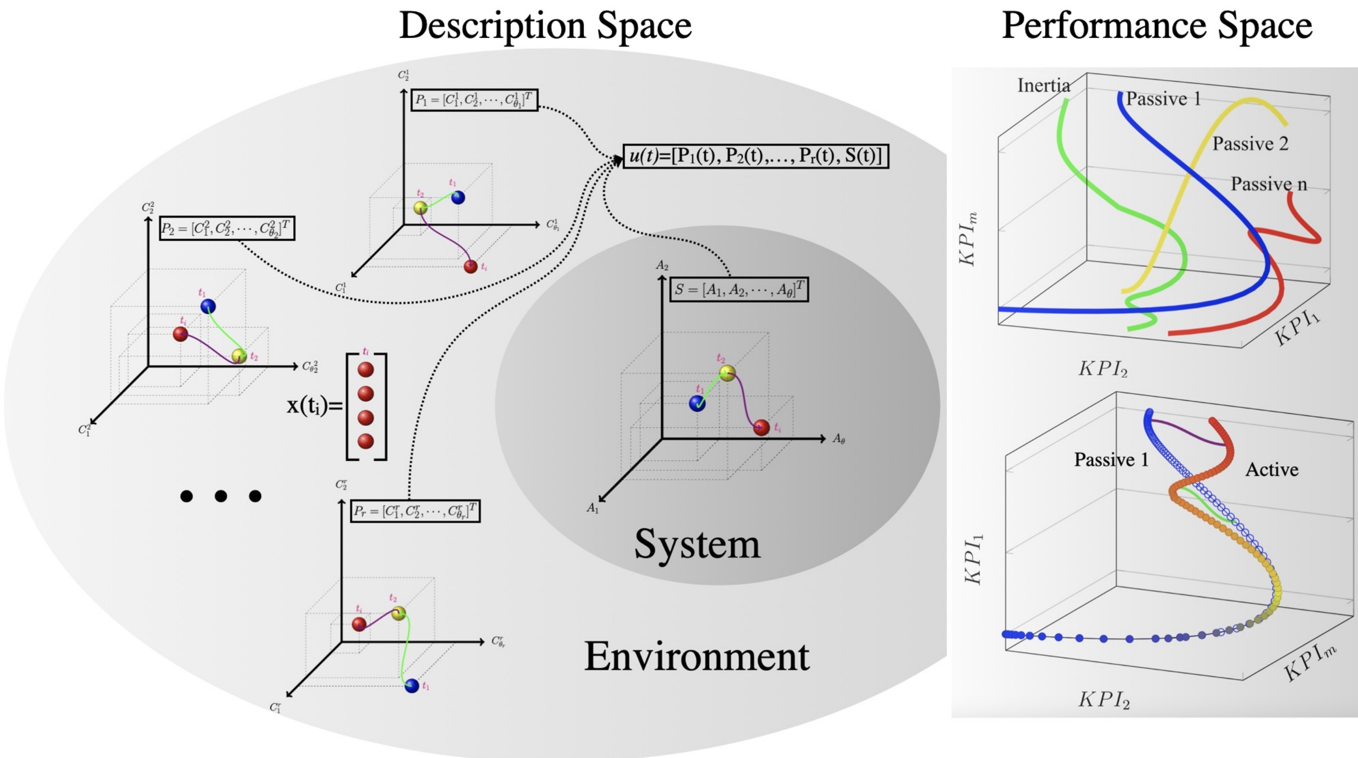

Fig. 3. Description and Performance Spaces of POD framework

system states exist at time t in the *Description Space* ($x(t) = [x_1(t), x_2(t), \cdots, x_n(t)]$).

The *Performance Space*, according to Fig. 3, describes:
(i) on the top, in the case of "no perturbation", the **"Inertia"** trajectory is shown in green. Besides, the n possible **passive** trajectories have been depicted according to n possible initial system states in the *Description Space*. In this case, the system goes through its own **"passive"** trajectories in the system's KPIs space according to the δ given colored points for the Attributes of the system S and δ_i given colored point of Characteristics for each potential P_i,
(ii) on the bottom, **"active"** trajectory, in the sense that one movement at specific time t_i from one colored point to another one has been made through green edge in order to deviate the *passive* trajectory (blue trajectory as one of possible n passive trajectories). The same process continues at $t_j (j > i)$ from the new state of the system to another state through another edge (e.g., purple edge).

The system might be destabilized by unforeseen changes. These changes are due to the existence of perturbations that create a passive trajectory. The passive trajectory is determined by the instance in question, with the most likely case being chosen. The changes related to decisions mainly refer to the varying of system parameters including *Attributes* and *Characteristics* (changing the system state by moving the colored points through edges) and consequently, deviation from the system's passive trajectory. Any deviation from that trajectory is considered an active one for the system.

Subsection 3.2 presented the ODEs modeling for the pandemic that disease spread in a closed environment. In the perspective of the presented POD framework in this section, the system is the ***"region"*** contaminated by a ***"pandemic"***. The ***"Attributes"*** are related to the parameters of the region and there is only one ***"Potential"*** which is a pandemic and means, $r = 1$ in equation 15 (at the same period, the potentials except pandemic could be other similar negative potentials (risks) such as hurricanes, earthquakes, etc., or positive potentials (opportunities) such as the development of agriculture and industry, increasing social security, improving the standard of living acts, etc.).

According to Fig. 2 (or equation 13), all the compartments (or left sides of ODEs) could be a KPI in the POD *performance space* ($m = 6$). Besides, the system's inputs, represented in vector u (equation 12), are parameters of the:

(i) Potential ⇒ pandemic, including the following *Characteristics*: latent period, infectious duration, fatality rate, and infectious rate of the virus,

$$P_1 = [C_1^1, C_2^1, C_3^1, C_4^1] = [u_1, u_2, u_3, u_4]. \tag{17}$$

(ii) System ⇒ region, including contact rate and hospitalized fraction as attributes

$$S = [A_1, A_2] = [u_5, u_6] \tag{18}$$

In other words, in the POD framework for the presented ODEs of pandemic, $r = 1$, $\theta_1 = 4$, and $\theta = 2$ (see equation 16).

4 Physics of Decision Methodology

In the perspective of the POD framework, deviations from the system passive trajectory happen due to changes in the

TABLE 1
Physics of Decision process applied on the pandemic model presented in section 3.2

Input	u	Vector	Variation (Min, Avg, Max)	Movement Type	Consequence Type	Considered Potentiality
Latent Period	u_1	P_1	(3, **7**, 11) [days] [20], [32], [33]	Elusive	Inflicted	Mutation
Infectious Duration	u_2	P_1	(7, **12**, 17) [days] [20], [32], [33]	Elusive	Inflicted	Mutation
Fatality Rate	u_3	P_1	(1, **5**, 9) [percent] [20], [32], [33]	Elusive	Inflicted	Mutation
Infectious Rate	u_4	P_1	(40, **60**, 80) [percent] [32], [33]	Elusive	Managed	Mask/Social Distance
Contact Rate	u_5	S	(5, **10**, 15) [person/day]	Driver	Managed	Lockdown/Curfew
Fraction Hospitalized	u_6	S	(5, **10**, 15) [percent] [20], [33]	Driver	Managed	Partial Lockdown

system state in the *Description Space* (moving the colored point in Fig. 3). A movement of a colored point is considered a ***"strategy"***. According to the *performance space* in Fig. 3, the passive trajectory is formed by inputs of the pandemic (vector $\boldsymbol{P_1}$ in equation 17) and inputs of the region (vector $\boldsymbol{S}$ in equation 18).

The key objective of the POD management theory is to use the results of a model-based system on the paradigm of input-states-output to develop a management strategy. The main expected benefit of this vision is to enable decision-makers to manage the performance trajectory of a considered system by visualizing and combining the impact of risks and opportunities. This section develops an original process of the presented approach on a considered system that might face instabilities (Risks and Opportunities). This POD process is applied to the considered problem in the sequential steps presented as follows.

4.1 System Establishment

The first step of the POD process is understanding the observed system and its environment. First, the system which is supposed to be studied is determined; The boundaries of the system in terms of precise study must be clear. The environment of the selected system refers to its potentials (Risks and Opportunities). Once the system and its potentials are determined, the associate parameters of the system to the considered potentials must be appointed (*i.e.*, characterizing the $\boldsymbol{\theta}$ inputs of the system). Similarly, the inputs of the system's potentials have to be specified (*i.e.*, characterizing the $\boldsymbol{C_j^i}|\{\boldsymbol{i} \in [\boldsymbol{1}, \boldsymbol{r}] \wedge \boldsymbol{j} \in [\boldsymbol{1}, \boldsymbol{\theta_r}]\}$). Subsection 3.2 is dedicated to performing this step for the pandemic (potential) in a closed environment (system).

4.2 System Characterization

The established system includes the inputs of the system (*Attributes*) and its potentials (*Characteristics*). These inputs could be categorized into two groups in terms of their movement in the *Description Space*.

(i) The changes (*i.e.*, movements in the *Description Space*) of inputs more related to the potential are known as ***"elusive"*** changes. The elusive changes are considered out of control changes (or at least hard to perform). Table. 1 shows that the inputs $\boldsymbol{u_1}$ to $\boldsymbol{u_4}$ are connected to the virus's features (potential), and it is impossible to change them unless the virus itself has a mutation (e.g., fatality rate of the COVID-19 (1%-3.4%) is different from Ebola (50%) [34]). Roughly speaking, elusive changes look like impossible (or hard) strategies. The consequences resulted from elusive movements could be in two categories, **(i)** Inflicted consequences that are imposed on the system's outputs and unmanageable, **(ii)** Managed consequences that might be controlled through some potentialities (e.g., the infectious rate, $\boldsymbol{u_4}$, is related to the nature of the virus while the Mask and Social Distance potentialities could reduce it).

(ii) The changes more related to the system are known as ***"driver"*** changes. The driver changes (more possible strategies) mainly create deviations in the passive trajectories. In other words, driver changes (and also the elusive changes with "Managed" consequence) make the active trajectories (Fig. 3). The consequences of the driver changes are mainly managed consequences but are essentially related to the limits of the system (see section 4.3).

4.3 System Intending

The consequences of elusive and driver movements in the *Description Space* appear as a deviation in the trajectory of the system in the *Performance Space*. This step is related to **(i)** Which outputs (KPIs) the system manager is looking for to study (e.g., the number of Hospitalized and Dead cases in the SEIR model), **(ii)** What constraints might exist for the movement in the *Description Space*; In cases where the system must not be positioned in some states $\boldsymbol{x_i}$ forever or for a specific period in the *Description Space* (e.g., the region allowed to be in confinement only for one month, *i.e.*, the (cr) value can't be close to zero more than one month), **(iii)** Which movement is preferable to the other if there is any specific priority and/or preference (e.g., wearing mask potentiality to reduce infectious rate is more feasible than confinement potentiality to reduce contact rate), and **(iv)** The onset of changes and periods that the system stays after the changes until the next change (e.g., the region can't be quarantined until two months after the onset of the pandemic and must return to no-quarantine status after one month).

4.4 Strategy Exploration

When the relationship between inputs in the *Description Space* and outputs in the *Performance Space* is specified (either formulated or estimated), this step would be the final step in the POD process. The last step of the POD process is dedicated to exploring all possible movements in the *Description Space* through experiment analysis to find the most desirable ones to be as close as possible to the optimum outputs. This is necessarily dependent on clear information about the following elements presented in the previous steps. **(i)** Inputs (what are they, which type they have, and which type of consequences might they have in terms of movement in the *Description Space*), **(ii)** Outputs (which ones are considered to study and which one is more important to optimize), and **(iii)** The constraints (the limits of movements, their preferences, onset and period of the movements).

Table 1 presents the POD process (the first and second steps) for the presented model in subsections 3.2 and 3.3. Table 1 presents an overview of the system and possible potentialities for system management. **The managers of the system identify the *"Managed"* consequences and adopt strategies that are related to the inputs that their movement in the *Description Space* lead to this group of consequences.** The highlighted rows in Table 1 refer to such inputs with such properties for the pandemic model. The third and fourth steps of the POD process for the presented pandemic model is more investigated in section 5. In the POD approach, the key point is to locate the system (region) and the faced potential (pandemic) within the *Description Space* in order to parametrize and initialize the Decision Support System. The approach addresses the identified system with all of its constraints and the possible strategies to explore when it comes to automated functioning. Finally, following the strategy exploration (4.4), the best-fit strategies to execute will be offered automatically.

5 Experiments and Results

The main experiments are centered on strategy exploration to find the most desirable outcomes to the objectives of the system. The exploration in this context is to study the possible movements in the *Description Space* and finally propose the best ones at any time t that divert the passive trajectory toward the objective of the system in the *Performance Space*.

The input vector for the presented well-known SEIR model in subsection 3.2 includes the "Attribute", the parameters of the system, and "Characteristics", the parameters of the system's potential. The "Attributes" and "Characteristics" refer to region and pandemic respectively.

The ***Description Space*** $\mathcal{U}$ for the presented SEIR model includes the inputs of the pandemic and the region with vectors $P(t)$ and $S(t)$ respectively.

$$u(t) = [\underbrace{P_1(t), P_2(t), \cdots, P_r(t)}_{\text{Potential}}, \underbrace{S(t)}_{\text{System}}]^T,$$
$$u(t) = [\underbrace{u_1, u_2, u_3, u_4}_{\text{Pandemic}}, \underbrace{u_5, u_6}_{\text{Region}}]^T. \tag{19}$$

The given vector $u(t)$ illustrates the state $x(t)$ of the system and its potentials in the specific time t through function Φ.

The ***Performance Space*** $\mathcal{Y}$ for the presented SEIR model indicates by vector $y(t)$ in a given $x(t)$ through function Ψ. This vector includes some notable KPIs.

$$y(t) = [s(t), e(t), i(t), h(t), r(t), d(t)]^T \tag{20}$$

The vector $y(t)$ presents the current position of the system at time t in its multi-dimensional KPI space (*Performance Space*). Different perspectives might be considered for the strategy exploration step of a specific system. Which KPIs are considered to study (it could be all of them at the same time) and which one between selected ones is prior to another one to optimize (they may not have priority): These are two essential questions that must be answered before strategy exploration.

Sensitivity analysis of the inputs and outputs depicted in Fig. 4, (e.g., through simulation campaign) presents the correlation between them. This analysis proposes the priority for the movements in the *Description Space*. The inputs with "Managed" consequences (See Table. 1) are highlighted in blue frame in Fig. 4. The correlation between inputs ($u(t)$) and the outputs (KPIs presented with $y(t)$ vector) are as follows: on average 0.035, 0.012, and 0.0036 for the contact rate (cr), infectious rate (ir), and fraction hospitalized (fh) respectively.

According to these values, the impact of "contact rate" is more than the impact of "infectious rate", which is greater than the impact of "hospitalized fraction". In other words, potentialities are equally important as following commands, according to the **"Considered Potentiality"** column in Table. 1; Lockdown/Curfew comes first, followed by Mask/Social Distance, and then Partial Lockdown.

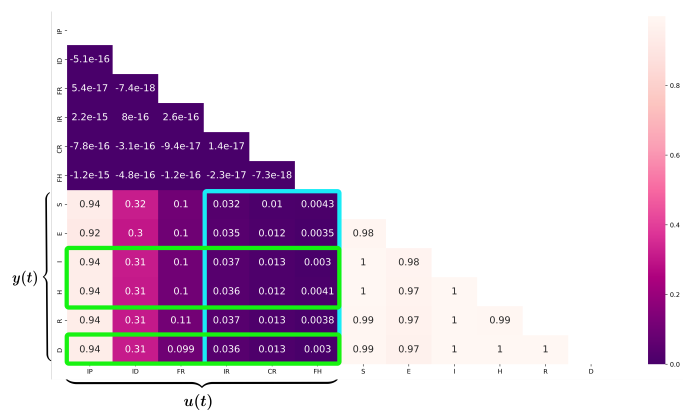

Fig. 4. Input-Output correlations of the presented SEIR model in section 3.2

To examine the POD framework, the three most dominant KPIs in terms of management, including I, H, and D compartments (**I**nfected, **H**ospitalized, and **D**ead) are selected to study the possible movements (strategies) through potentialities, considering the onset and period of the strategies in the 3D *performance space*. **The POD perspective for the selected KPIs is to minimize them as much as possible without any preferences between them. The rest of this section is centered on this objective.** According to this objective, the foremost objective is the minimum value for each KPI at any time t. In the 3D *Performance Space*, the reference to study different possible movements (strategies) would be the origin of the space, the $(0, 0, 0)$ coordinates for each axis.

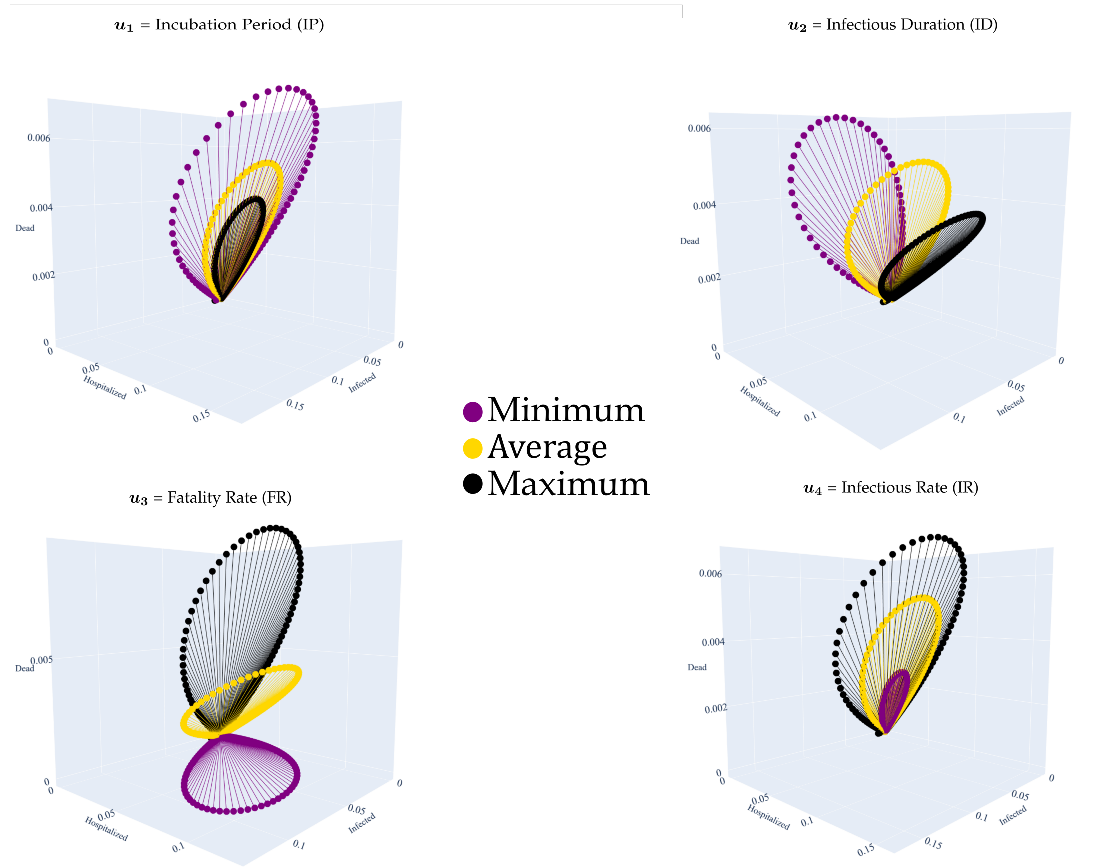

Fig. 5. Pandemic positioning results for its inputs and their distances from the system objective, (0,0,0) coordinates

According to Table. 1, on the one hand, the linked potentiality to vector $\boldsymbol{P}$'s inputs (pandemic), involves **wearing masks** or keeping a safe distance from other people in the community (**social distance**), both of which might lower the *infectious rate* **(ir)**. **Lockdown** and/or **Curfew** to minimize *contact rate* **(cr)** or **Partial lockdown** of the fragile group to receive the virus, to lower the *fraction hospitalized* **(fh)**, on the other hand, are associated potentialities to the inputs of vector $\boldsymbol{S}$ (region). These strategies are applied to the ODEs of the presented SEIR model which is equivalent to changing the system states in the *Description Space* through the movements (See subsection 5.2).

The POD will be ready to investigate strategies once the possible potentialities and their implementation limits, such as their start time and duration, have been defined.

5.1 Potential positioning

Understanding the possible effects of potential on the system trajectory in the *Performance Space* is the first step in the experiment analysis. Various viruses may have different parameters as inputs in vector $\boldsymbol{u}$ [2], [20]. According to column **"Variation"** in Table. 1, considering that 1% of the total population is infected at first ($\boldsymbol{\alpha = 0.01}$ in equation 15), the Fig. 5 presents the different trajectories of **Minimum**, **Average**, and **Maximum** values for the $\boldsymbol{u_1(t)}$, $\boldsymbol{u_2(t)}$, $\boldsymbol{u_3(t)}$, and $\boldsymbol{u_4(t)}$ in **purple**, **yellow**, and **black** colors respectively. The values for non-varying inputs of "Potential" (e.g., in the case of $\boldsymbol{u_1}$ trajectories in Fig. 5, the $\boldsymbol{u_2}$, $\boldsymbol{u_3}$, and $\boldsymbol{u_4}$) as well as the "System" inputs are considered on "Average" in Table. 1.

The inverse impact of $\boldsymbol{u_1}$ and proportionate impact of $\boldsymbol{u_2}$, $\boldsymbol{u_3}$, and $\boldsymbol{u_4}$ on the selected KPIs (**I**, **H**, and **D**) are shown in Fig. 5 (In the proportional impact, the distance between the points and the origin (0,0,0) grows as the value of input grows, and vise versa for the inverse impact). In addition, Table 2 shows that $\boldsymbol{u_2}$ and $\boldsymbol{u_4}$ have bigger fluctuations on the KPIs than $\boldsymbol{u_1}$ and $\boldsymbol{u_3}$.

TABLE 2
Pandemic positioning results for its inputs and the sum of distance from the system objective, (0,0,0) coordinates

Input	u	Min	Avg	Max
Latent Period	$\boldsymbol{u_1}$	8.82	8.62	8.50
Infectious Duration	$\boldsymbol{u_2}$	5.34	8.62	11.48
Fatality Rate	$\boldsymbol{u_3}$	8.62	8.62	8.63
Infectious Rate	$\boldsymbol{u_4}$	6.99	8.62	9.17

Table. 2 presents an overview of the potential impacts on the selected KPIs (**I**, **H**, and **D**). Except the "infectious rate" row, the value of other rows would be on average for the system positioning (subsection 5.2). Because this parameter is the only potential parameter that could have **"Managed"** consequence in terms of movement in the *Description Space* (*i.e.*, between the "Elusive" inputs, there is only "feasible potentiality" for infectious rate which could be wearing mask and social distance potentialities).

The experiments cover the period from the initial observation of infected cases to 180 days (six months) afterwards. In other words, each point of the given curves in Fig. 5 represents the values for one day of the selected KPIs (daily cases), and the results in Table. 2 are the total sum of the distance between the point (0,0,0) and the 180 points of the curves.

The results presented in Fig. 5 show the system passive trajectories of daily KPIs. In this case, the initial position of the system (region, on the average value) and potential (pandemic) remain constant for the period of study (180 days).

$$x(t_1) = x(t_2) = \cdots = x(t_{180}) \tag{21}$$

5.2 System positioning

The impact of potential inputs on KPIs is discussed in the preceding section in the absence of any strategy (no movement on the axis related to the system in the *Description Space* has been taken). This section investigates the active trajectory by examining the results of several possible movements in the *Description Space* of the COVID-19 (potential) for the state of Georgia (region) as alternative strategies that the system manager could take to control the system's trajectory in the *Performance Space* based on the selected system objectives.

The average considered value of the "latent period" and "infectious duration" for the COVID-19 are 6 days and 12 days respectively [19] (these values could vary, for example, the infectious duration is shorter when children or less severe cases are involved [32]). The study uses real data from the COVID-19 virus in the state of Georgia between July 2020 and April 2021 to obtain the values of "fatality rate" and "fraction hospitalized" experimentally [35], [36].

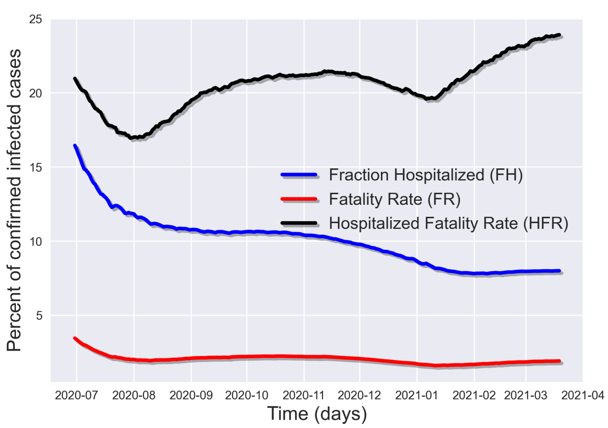

Fig. 6. Fraction Hospitalized and Fatality Rate of the COVID-19 in the State of Georgia

The average value for the *fatality rate* (fr) indicated in the red plot in Fig. 6, is 2%. Also indicated in blue is the *fraction hospitalized* (fh), which is 10% on average. In equation 7, the "hospitalized fatality rate" (hfr) is calculated by dividing the (fr) by (fh), as illustrated in the black plot. Based on what has been mentioned so far, the input vector of the Covid-19 potential in the state of Georgia is as follows (see Table. 1 for the units of input vector).

$$\boldsymbol{u} = [u_1, u_2, u_3, u_4, u_5, u_6]^T = [6, 12, 2, u_4, u_5, 10]^T \tag{22}$$

The three highlighted inputs with *"Managed"* consequences of vector $\boldsymbol{u}$ are presented in Table. 1. The wearing mask potentiality, to reduce "infectious rate" (u_4) and the lockdown potentiality, to reduce "contact rate" (u_5) are considered to study the active trajectories through these two potentialities.

The three related alternatives to these potentialities are being investigated to determine the ideal timing for movements equivalent to the considered potentialities in the *Description Space* of the COVID-19 (Potential) in the state of Georgia (System).

(i) The two-week lockdown potentiality from week i-th to two weeks after (6 months contains 24 weeks starting at the first day after week-first),
(ii) The wearing mask obligation starting from week i-th until the end of the study (6 months),
(iii) The two potentialities **(i)** and **(ii)** simultaneously.

The results are presented assuming that the managers can only carry out the potentialities (changing the colored point(s) in the *Description Space*) on the first day of the week for the pandemic-affected region. In other words, the state of the system is altered at the following set.

$$x(t_{7i}) | i \in \{1, 2, \cdots, 24\} \tag{23}$$

The passive trajectory of the COVID-19 in the state of Georgia is shown in blue in Fig. 7. This trajectory is the result of the "potential positioning" presented in subsection 5.1 and the reference to examine specified alternatives. The active trajectories in Fig. 7 are related to alternatives **(i)**, **(ii)**, and **(iii)** of daily KPIs depicted in brown, yellow, and red respectively. It's important to note that these alternatives may have an influence on potential (virus) and system inputs, which isn't reflected in the results (e.g., lockdown and wearing mask potentialities may reduce the fatality rate and fraction hospitalized).

The system positioning related to alternatives of week 2, week 3, week 5, and week 10 after week-first of outset (t_1 to t_7) is presented in Fig. 7. The following are some related observations.

(i) The active trajectories correspond to the passive trajectory (blue) until the moment of activation, t_{21}, t_{28}, t_{42}, and t_{77} linked to the specified weeks,
(ii) The deviations of the active trajectories related to the "wearing mask" potentiality from the moment of execution to the end of the path are smooth,
(iii) In the early weeks, the deviations of the active trajectories associated with the "lockdown" potentiality are

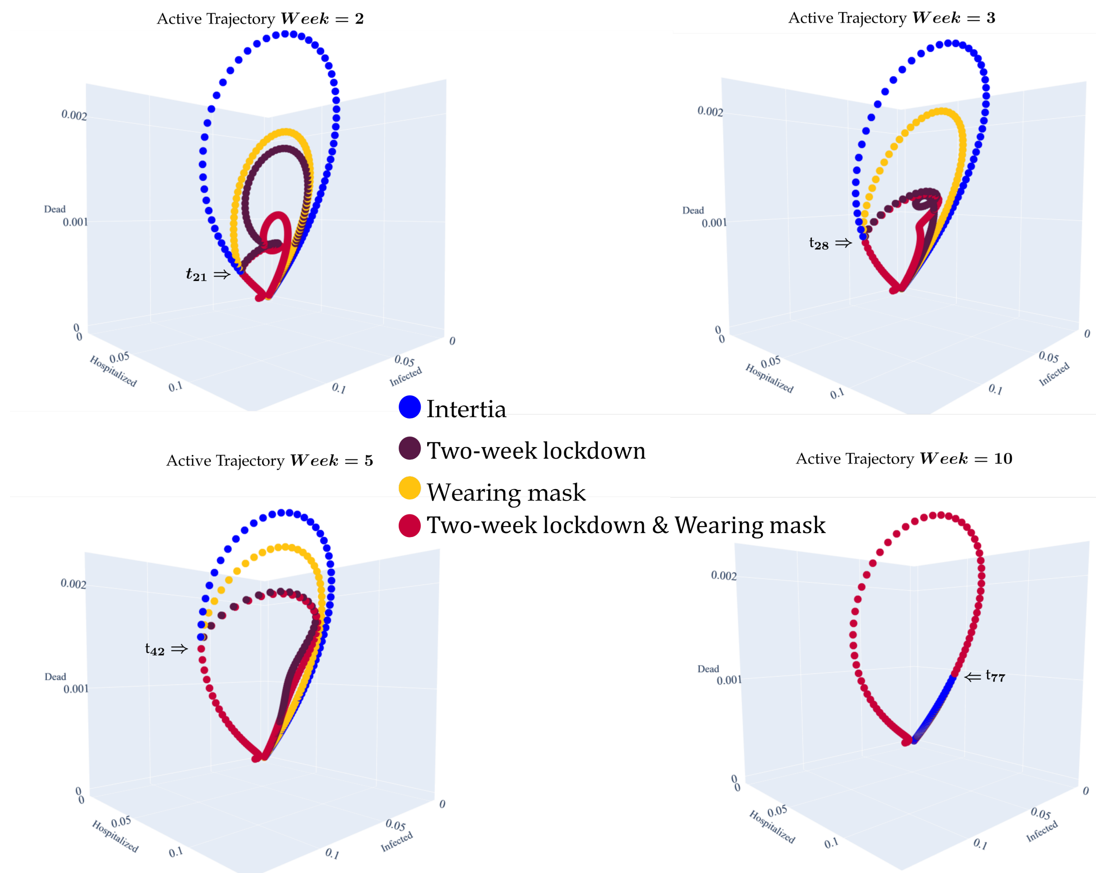

Fig. 7. Region positioning results for its inputs and their distances from the system objective, (0,0,0) coordinates

like a forth and back break (deviation), and as we move away from the early weeks, these deviations become smoother,

(iv) The later the movement of colored points in the *Description Space* (taking the strategies), the closer the active trajectories are to the passive trajectory.

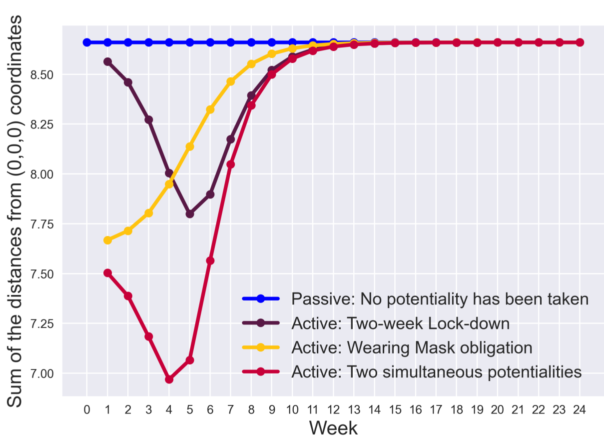

Fig. 8. The considered potentialities for the COVID-19 in the State of Georgia and the sum of the distances from system objective for given potentiality in the 3D framework during 6 months (week 1 to week 24).

Fig. 8 shows the final results of the study for the considered potential strategies for the state of Georgia to containment the COVID-19 in this region. Since the less the sum of the distances from the origin, the better the movement in the *Description Space*, the following results can be deduced from Fig. 8.

(i) Week **5th** is the ideal time for movement on the **"cr"** axis, which is the lockdown strategy (starting lockdown after two months),

(ii) The sooner the "wearing mask obligation" strategy (movement on the **"ir"** axis) is implemented, the better. Over the weeks, the total distance from the target, (0,0,0) has increased,

(iii) The best time to implement two strategies simultaneously is the **4th** week,

(iv) From about the **11th** week onwards, the implementation of strategies has very little influence on pandemic control (the sum of the distances is approximately equal to the passive mode).

6 Conclusion and Perspectives

In this paper, a simplified version of the SEIR model for pandemic spread through Ordinary Differential Equation (ODEs) has been introduced to support a wide range of instances of viruses and populations. The considered parameters allow covering a wide range of scenarios by assessing the consequence of an observed pandemic on the KPIs of a given population. The POD vision has been established to examine the influence of mitigation measures on the evaluation of these KPIs to control COVID-19 in the state of Georgia (USA) and a potential future pandemic.

Within the system KPIs framework, this prediction may be visually displayed as a performance trajectory. Furthermore, decisions may be represented as "what if" scenarios, and their influence, as well as the deviation of the performance trajectory, can be predicted. The next stage in this research is first, to look at the addition vector of the impacts of several simultaneous actions on the performance trajectory in the performance space, and second, to employ this pandemic model as a data supplier for neural network systems. The primary idea is to perform large-scale combinatory simulation campaigns to collect big datasets concerning the general situation of a pandemic-affected social system. Using this data to train neural network systems will allow us to create a formal system capable of simulating any social system affected by a pandemic and implementing any mitigation actions. Optimization algorithms may be used with these tools to determine the best set of actions to do in each given situation (whatever social system is hit by any virus). Finally, the ultimate goal is to develop a modeling system that can characterize the population affected by a specific virus and suggest a combination of timed measures, which can be viewed as physical forces pushing or pulling the observed system's performance trajectory within the performance framework, to optimize its response to the looming pandemic.

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