# Model Predictive Pandemic Control: A Data-Driven Framework for Infectious Diseases Identification and Control

D. Herceg, M. Dell'Oro, R. Bertollo, D. Krishnamoorthy, M. Salazar

## Introduction

As consequence of the recent COVID-19 pandemic, the scientific community has retaken interest in epidemiological models of various nature, the majority of these being **compartmental models**.

**Challenges presented by compartmental models**

- Simpler models lack in capturing **Hospitalised/ICU dynamics**
- Complex models are **harder to identify** due to lack of **data quality**
- No guarantees in **parameter uniqueness** (poor predictive ability)

We propose a **data-driven** architecture that leverages **moving horizon estimation (MHE)** to estimate the dynamics of slowly time-varying parameters, while providing guarantees for identifiability and observability striking the balance between model expressiveness and usability.

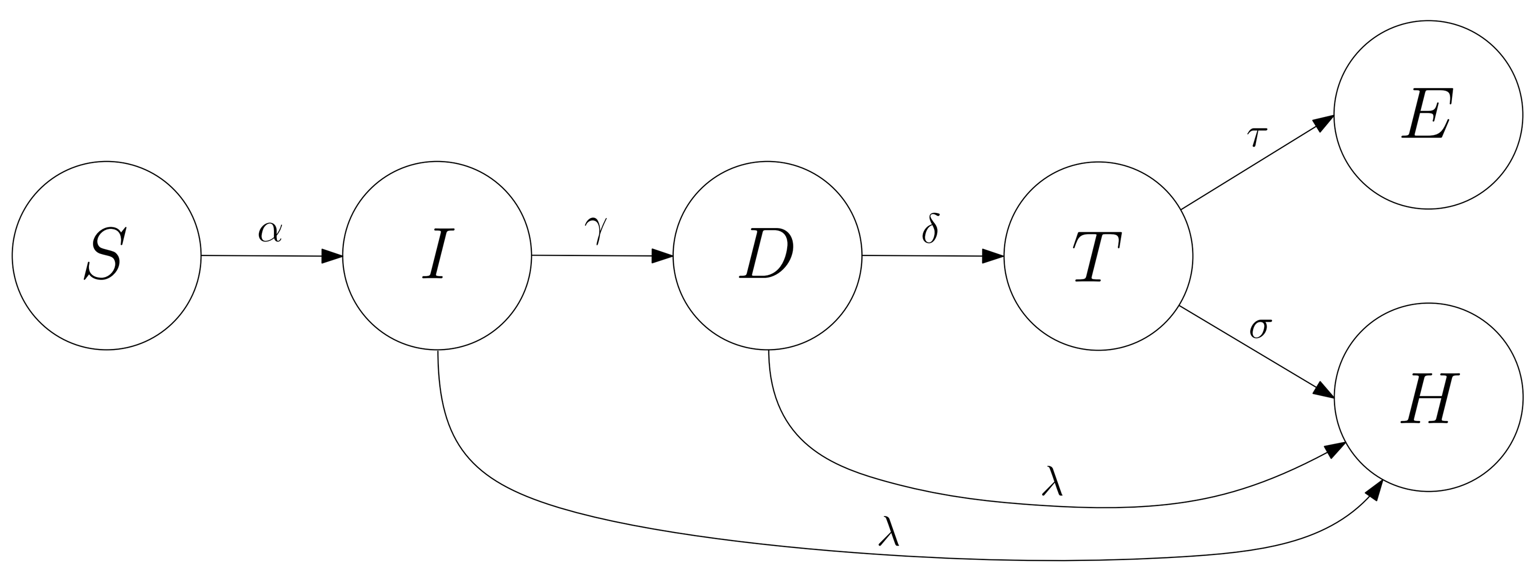


**Fig.1** *Proposed SIDTHE compartmental model.*

## Methods

MHE algorithm solves the least square error problem over a moving time window, accounting for the compartmental model dynamics constraints.

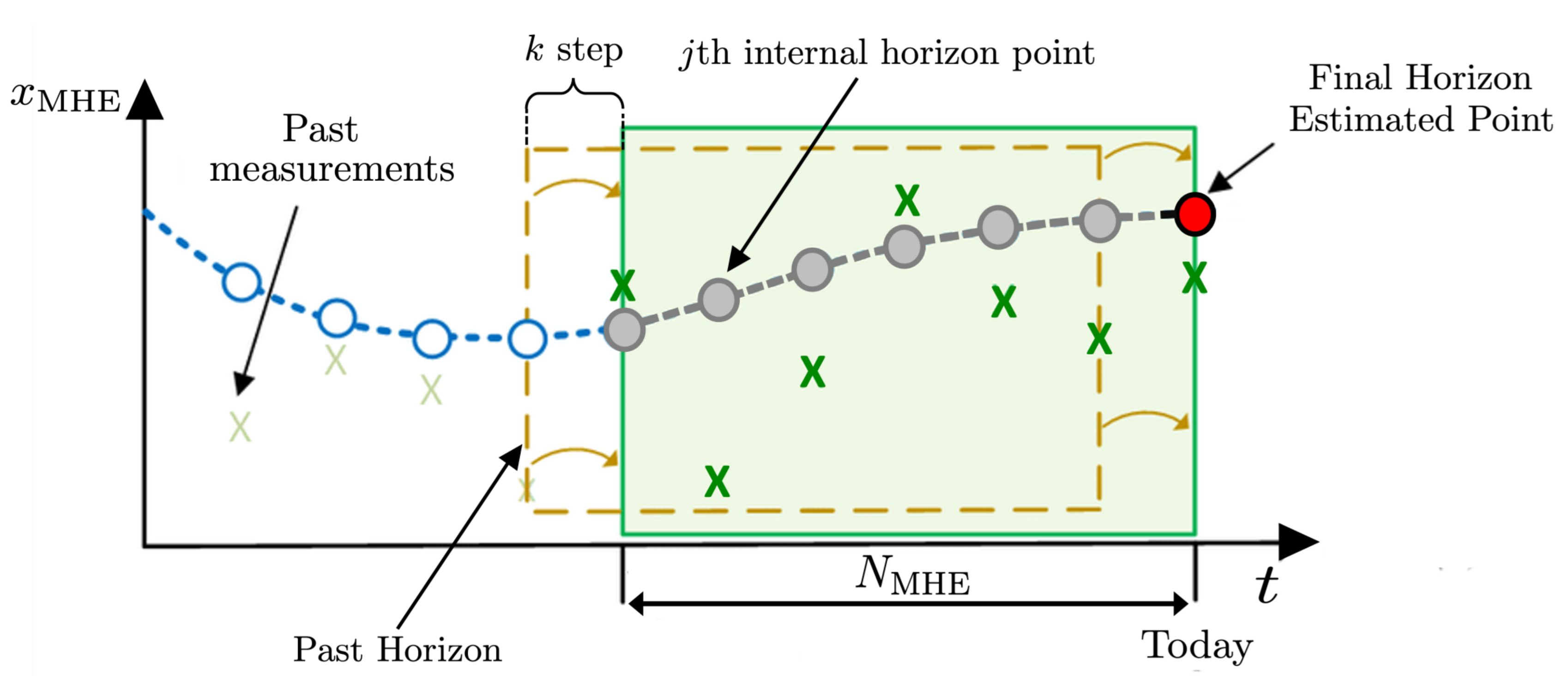


**Fig.2** *Basic idea behind MHE algorithm.*

In our framework, the previous **three weeks** are used to update the pandemic model.

## Model Predictive Control

**Model Predictive Control** (MPC) uses a mathematical model of the pandemic to predict possible future pandemic evolution and optimizes non-pharmaceutical interventions (NPIs) in order to minimize societal burden while keeping pandemic in check.

**MPC algorithm**

1. Estimate **current state**
2. Minimize a **cost function** over *N* future NPI actions
3. Apply the first predicted NPI
4. Go to step **1**

Repeated online optimization introduces **feedback!**

## Model uncertainty and recourse

Parameters of the model are rarely known with complete confidence and can result in unexpected behavior if not accounted for properly. We consider a finite number of discrete parameter values (**scenarios**) with accompanying probability values to account for possible pandemics trajectories. Furthermore, for each scenario we compute a dedicated NPI trajectory, called **recourse action.** These different NPI actions need to agree on the first control actions to be causal and implementable in practice. This approach enables us to have a backup action for every scenario, i.e uncertainty realization.

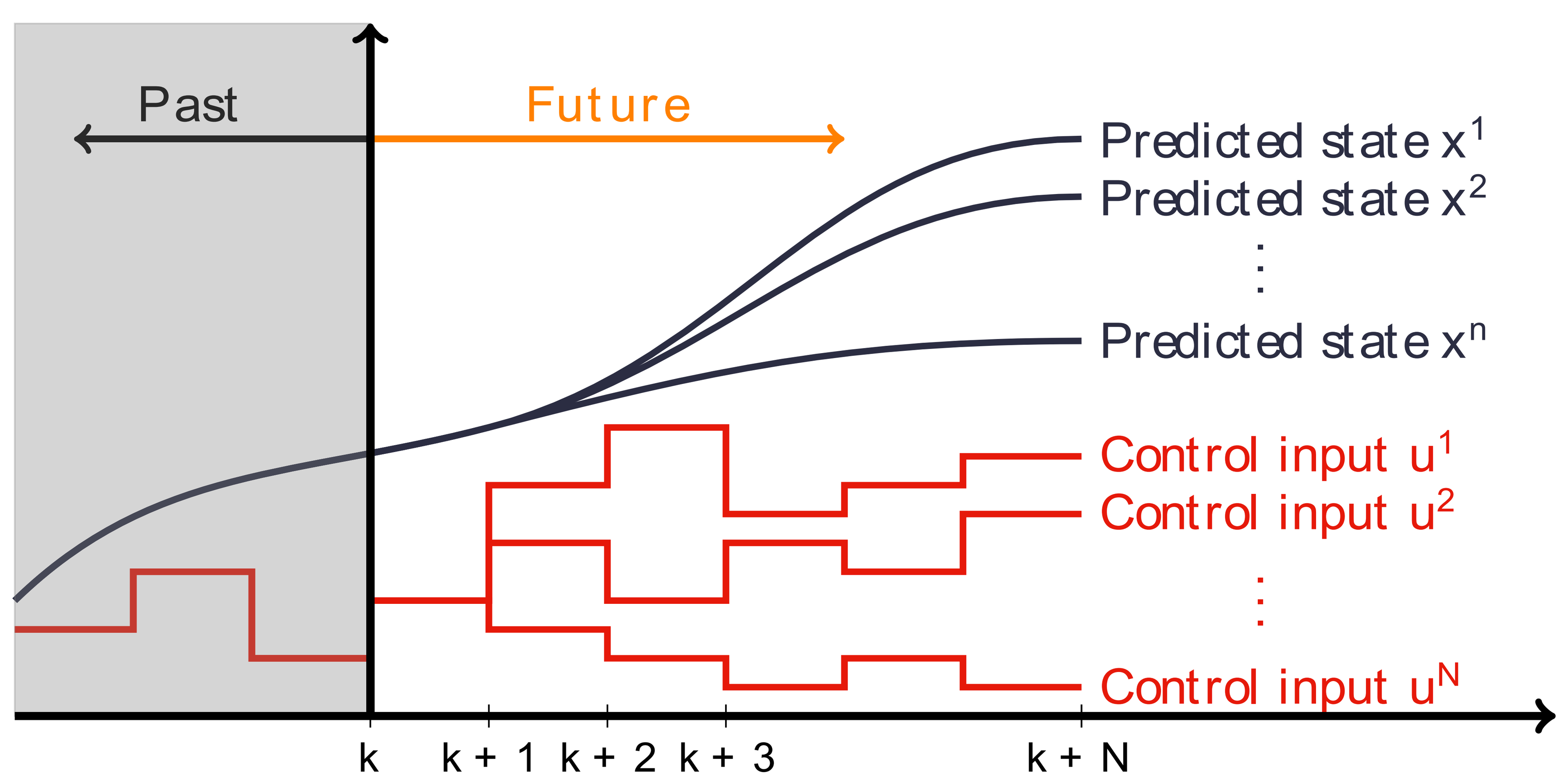


**Fig.3** *Basic idea behind scenario-based MPC.*

**Department of Mechanical Engineering, Control Systems Technology**