SCENARIO-DRIVEN FORECASTING: LESSONS LEARNED FROM MODELING THE COVID-19 PANDEMIC




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SUMMARY: The Forecasting patterns and their implied end states remains cumbersome when few (stochastic) data points are available during the early stage of diffusion processes. Extrapolations based on compounded growth rates do not account for inflection points nor end-states. In order to remedy this situation, we advance a set of heuristics that blend forecasting and scenario thinking. Combined they provide an actionable decision space as short term predictions are accurate, while a portfolio of different end states informs the long view.

The creation of such a decision space requires temporal distance; only to the extent that one refrains from incorporating more recent data, more plausible end states become visible. As such, our contribution implies a plea for dynamically blending forecasting algorithms and scenario oriented thinking, rather than conceiving them as substitutes or complements.

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INTRODUCTION: MODELING DIFFUSION PATTERNS OF COVID-19 PANDEMIC

The current COVID-19 pandemic spurred efforts to model and forecast its diffusion patterns, either in terms of infections, people in need of medical assistance (hospitalization, ICU occupation) or casualties.

Forecasting the evolution of COVID-19 and related dynamics (e.g. ICU occupation) remains cumbersome when only few stochastic data points are available during the early stage of the outbreak. Extrapolation based on compounded growth rates could result in unstable predictions as they do not include inflection points (i.e. the peak of the net ICU increase) nor end states (i.e. the maximum ICU capacity). Several forecasting models suggest that the implied growth patterns follow sigmoid growth curves, like the logistic equation (Verhulst, 1838) or the Bass (1969) model. Predicting the evolution of these S-shaped curves involves an estimation of at least three parameters, related to the takeoff and the steepness of the curve as well as its saturation level. However, delineating robust parameter estimations – and consequently portraying the end-state – based on a limited time series results in quite rudimentary predictions. Recently, Decock, Debackere & Van Looy (2020) adapted the initial Bass (1969) model in order to quantitatively model different diffusion scenarios for Electrical Vehicles. The heuristics advanced start from the premise of multi-finality (Buckley, 1967): "similar initial conditions may lead to dis-similar end-states". The proposed heuristics revolve around the development of a three-dimensional search space, reflecting the presence of three model parameters to be estimated.

In the context of the COVID-19 pandemic, it remains unclear at this stage which end states will occur with respect to e.g. casualties, capacity of ICU beds needed at its highest burden (in different regions/countries) as the available numbers for a wide range of countries suggest high spreads (both in terms of contamination and potential end states). This complicates the quest for accurate predictions, unless one considers the potential presence of multiple end states and different growth dynamics (reflected in the three parameters to gauge) simultaneously.

As such, the COVID-19 diffusion patterns for Belgium have been modeled by means of the heuristics proposed by Decock, Debackere and Van Looy to see whether they allow to arrive at a better informed decision space, both in the short (daily/weekly) and in the medium term (end states). Models have been developed both for deceased and for ICU occupation rates. In this contribution, we focus on the ICU models, due to space constraints (the insights are similar across indicators).

The considered search grid consists of 250,000 different parameter combinations (consisting of 10 different end-states scenarios multiplied with 250 values for the relevant infection parameter and 100 values for the relevant contamination parameter). By means of a loss function, all 250,000 pathways are assessed in terms of how well they explain the already available observations. In this exercise, the diffusion paths with a goodness-of-fit exceeding 99 percent have been considered as more likely scenarios and have been further analyzed in terms of growth dynamics and end states.

ICU OCCUPATION IN BELGIUM

In Belgium, a first COVID-19 deceased was registered on March 10. With an initial overall capacity around 1,900 ICU beds in the Belgian hospitals, policy makers decided to increase ICU capacity and allocated approximately 2,300 ICU beds exclusively for COVID-19 patients. The question that then becomes crucial: will this be enough for the coming weeks and months?

Table 1 depicts the number of patients in ICU (related to COVID-19) in Belgium, between March 12 and March 24:

Table 1 *COVID-19 ICU occupation in Belgium between 12/03/2020 and 24/03/2020 (Source: Sciensano)*

DATE	ICU OCCUPATION	DATE	ICU OCCUPATION	DATE	ICU OCCUPATION
12/03/20	5	17/03/20	100	22/03/20	322
13/03/20	24	18/03/20	130	23/03/20	381
14/03/20	33	19/03/20	164	24/03/20	474
15/03/20	53	20/03/20	238		
16/03/20	79	21/03/20	290		

Table 2 *COVID-19 ICU occupation in Belgium between 25/03/2020 and 04/04/2020 (Source: Sciensano)*

DATE	ICU OCCUPATION	DATE	ICU OCCUPATION	DATE	ICU OCCUPATION
25/03/20	605	29/03/20	927	02/04/20	1,205
26/03/20	690	30/03/20	1,021	03/04/20	1,245
27/03/20	789	31/03/20	1,088	04/04/20	1.261
28/03/20	867	01/04/20	1,144		

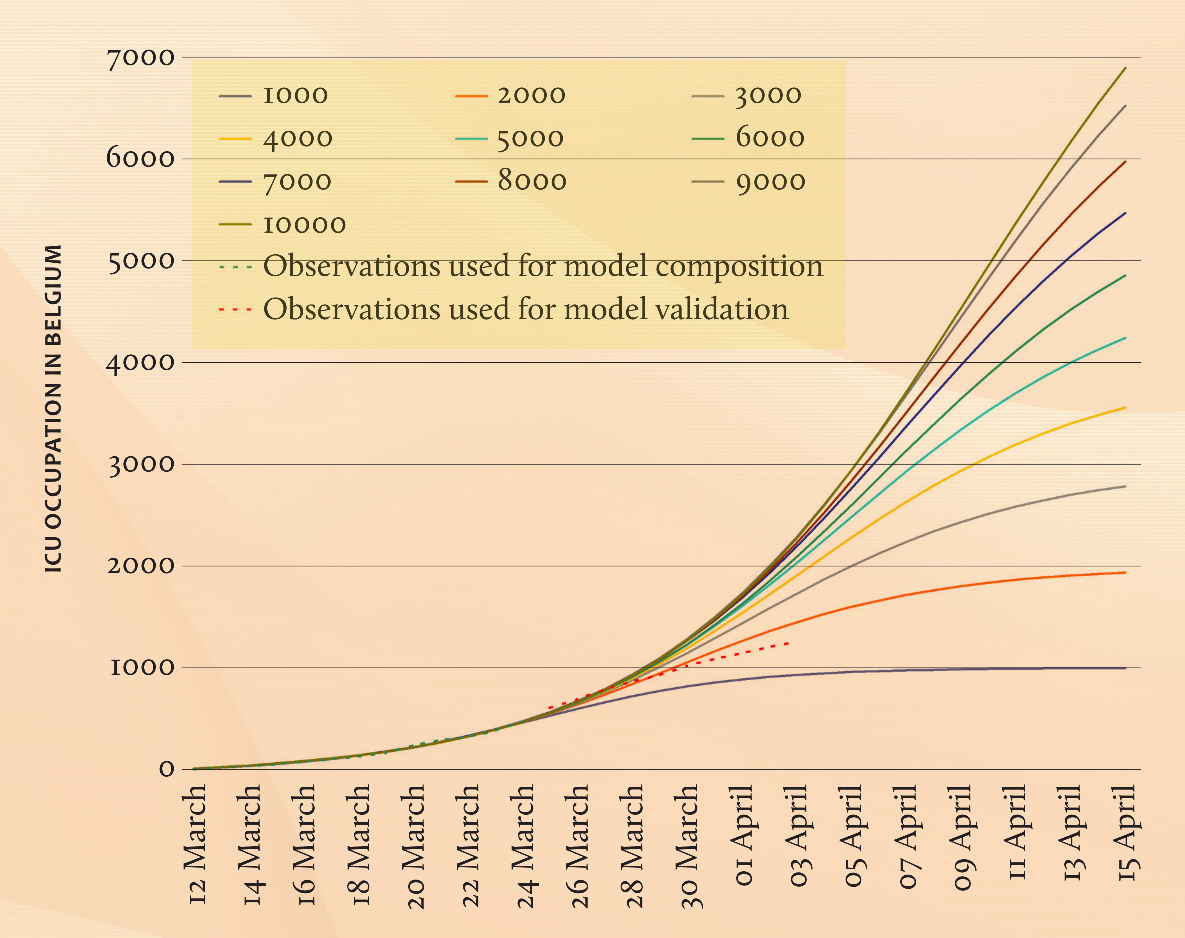

Fig 1 *Overview of stylized pathways reflecting more likely scenarios, including the observations used for model composition (i.e. green dotted line) and the unfolding observations afterwards (i.e. red dotted line). Belgium, R^2 > .99; n = 806.*

Building on the observations until March 24 (i.e. time series of 13 data points), a multi-dimensional search space was assessed implying a potentially required ICU-capacity ranging from 1,000 to 10,000 beds. Figure 1 visualizes the initial observations (i.e., the green dotted line) combined with the stylized more likely scenarios (averaged by end-state).

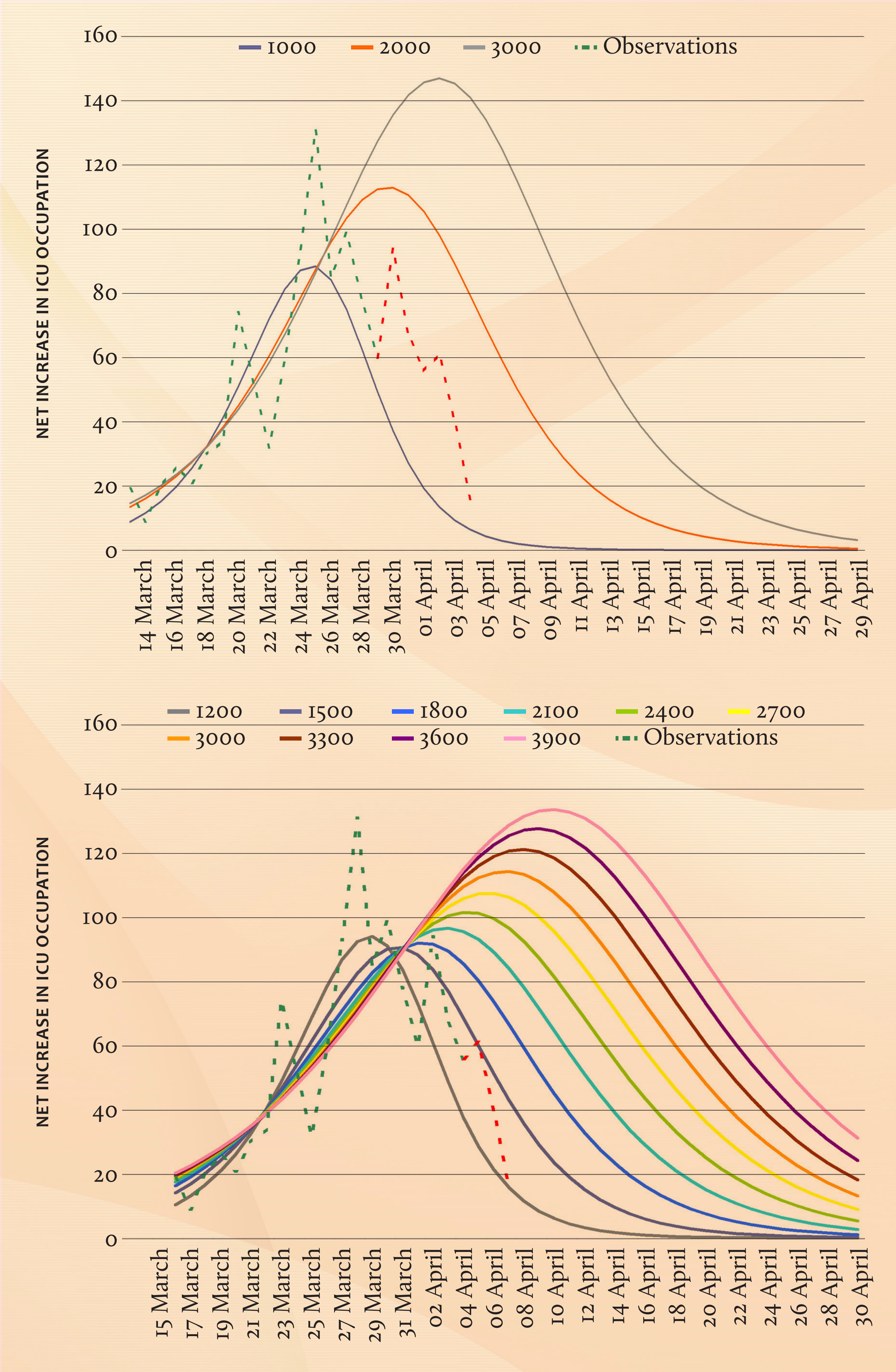

Fig 2 Comparing the daily net increase in ICU occupation (i.e., dotted line) with the "more likely" scenarios ($R2 > .99$) in Belgium.

As the data of the 11 days between March 25 and April 4 became available (see table 2 and visualized as red dots in figure 1 below), it becomes feasible to further qualify the likelihood of different pathways and their corresponding end-states.

As from March 28 onwards, it became clear that the end state of ICU occupation in Belgium was more likely to become situated in a range between 1,000 and 3,000. Consecutive updates and refinements in terms of feasible end states allowed us to predict the growth pattern and the peaks even more precisely, as depicted in figure 2. On April 2nd we informed the Belgian authorities that the growth peak has been reached and that the coming days, the growth rate for ICU capacity would decline markedly. This prediction materialized as shown by the red dots in figure 2.

DISCUSSION AND CONCLUSION

In this contribution we illustrate how blending forecasting models with scenario-oriented thinking yields novel insights, which inform decision makers in a number of distinctive ways. The heuristics implied, combine a broad range of end states with an assessment of more likely pathways. Not only do these models provide accurate predictions in the short term; when additional observations become available, they also signal plausible end-states in the scenario portfolio. The creation of such a decision space requires temporal distance: only to the extent that one refrains from incorporating immediately more recent data, more plausible end states become visible. At the same time, updating and re-calibrating the pathways seem to offer potential to start qualifying Knightian uncertainty (Knight, 1921).

As such, our contribution implies a plea for combining forecasting algorithms with a foresight-oriented methodology and vice versa. This dynamic blending of forecast and foresight has the potential to inform policy makers in situations of urgent decision needs conditioned by profound uncertainty. At such critical moments during an unfolding crisis, the use of large amounts of data cannot inform decision-making, as those data are largely absent in such instances. Though, it is the judicious use of the limited data available combined with various scenarios that may unfold. Our combination of forecast and foresight hence does not signal yet another case in evidence-based policy, but it rather illustrates the good governance of evidence as advocated by Parkhurst (2016).

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