Long-term scenarios for the number of new hospitalisations during subsequent waves in the Belgian COVID-19 epidemic

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Aim

This report provides predictions from different models describing the spread of SARS-CoV-2 (COVID-19) in Belgium. The presented scenarios coming from these models reflect structural (model) uncertainty on top of uncertainty in factors influencing the spread of the disease. However, the added value of combining different models is validation of their projections over the course of time.

UHasselt stochastic compartmental model

Model structure and limitations

We use a stochastic discrete age-structured compartmental model (Abrams et al., 2020) calibrated on high-level hospitalisation data (Sciensano), serial serological survey data (Herzog et al., 2020) and Belgian mortality data (Sciensano). More specifically, the stochastic model predicts (stochastic realisations of) the daily number of new hospitalisations per age group (i.e., 10 year age groups). The modeling approach depends on assumptions with regard to the transmission process which inevitably implies an underestimation of the level of uncertainty. As the model-based long-term predictions rely on changes in social contact behaviour following the exit strategy initiated May 4, 2020, we present such predictions under various scenarios which aim at giving some insights in the future course of the epidemic without being able to assign a probability to each scenario related to the likelihood of a given scenario to become reality. We do account for the current resurgence of COVID-19 in the selection and presentation of plausible scenarios. As more data will become available in the next weeks, further model validation and updated prediction results are needed. Model results should be interpreted with great caution.

Some limitations of the model are listed below:

- The different scenarios are expressed in terms of changes in social contact behaviour, as a proxy for changes in transmissibility as a result of social distancing and hygienic measures taken at different locations, e.g., at work and school
- In the stochastic model we are not explicitly accounting for re-importation of the pathogen in the population
- All scenarios are hypothetical and we are not able to discern the more plausible scenario given the unpredictive nature of adjusted social behavior and future measures.
- We did not include seasonality in the model
- Contact tracing, testing and self-isolation are not incorporated in the exit strategies nor subsequent waves outlined in this report
- Although a gradual re-opening of society and relaxing of the lockdown measures is done in different phases, we assume a specified change in social contact behaviour from May 4 onwards

Schematic diagram (UHasselt)

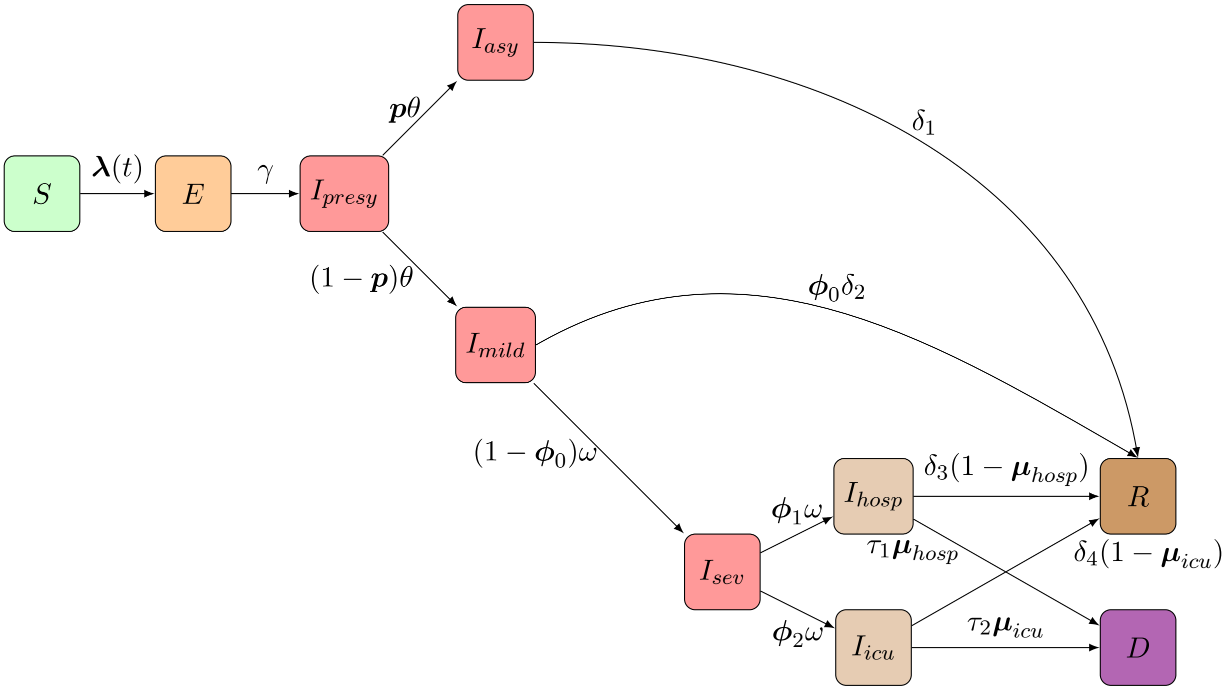

Figure 1: Schematic overview of the flows of individuals in the compartmental model: Following SARS-CoV-2/COVID-19 infection susceptible individuals (S) move to an exposed state (E) and after a latent period individuals further progress to a pre-symptomatic state (I_{presym}) in which they can infect others. Consequently, individuals stay either completely symptom-free (I_{asym}) or develop mild symptoms (I_{mild}). Asymptomatic individuals will recover over time. Upon having mild symptoms, persons either recover (R) or require hospitalization (going from I_{sev} to I_{hosp} or I_{icu}) prior to recovery (R) or death (D).

Long-term predictions under different scenarios

In Figure 2, we graphically depict the predicted daily number of new hospitalizations accounting for a reduction in school-related contacts upon the Christmas Holiday and spring half-term. More specifically, scenario S1 (blue lines) represents the scenario under the current social contact behaviour. It is observed that this implies a substantial incidence of new hospitalizations. Scenario S2 (purple lines) assumes a 10% reduction in work- and transport-related contacts and a similar reduction in leisure contacts until the Christmas holidays. Finally, scenario S3 (orange lines) implies a 20% reduction in the aforementioned contacts. Note that in all scenarios, contact behaviour following the Christmas period is presumed to be similar to the current social contact behaviour, thereby implying a small to moderate resurgence in scenarios S2 and S3, respectively.

In order to show the complete extent of the number of hospitalisations as of October 1, 2020, we present the cumulative number of hospitalisations for scenarios S1-3 and accommodating a closure of schools during the Christmas and spring holidays (see Figure 3). The cumulative number of hospitalisations by the end of the March are very different across the different scenarios due to the difference in rate of increase of the number of daily hospitalizations over time.

The hospital load is graphically depicted in Figure 4, assuming a Weibull distribution for the time spent in the hospital (scale = 10.46, shape = 1.34) (Faes et al., 2020), which implies an average duration of hospitalisation of about 9.6 days. Furthermore, the ICU load is displayed therein as

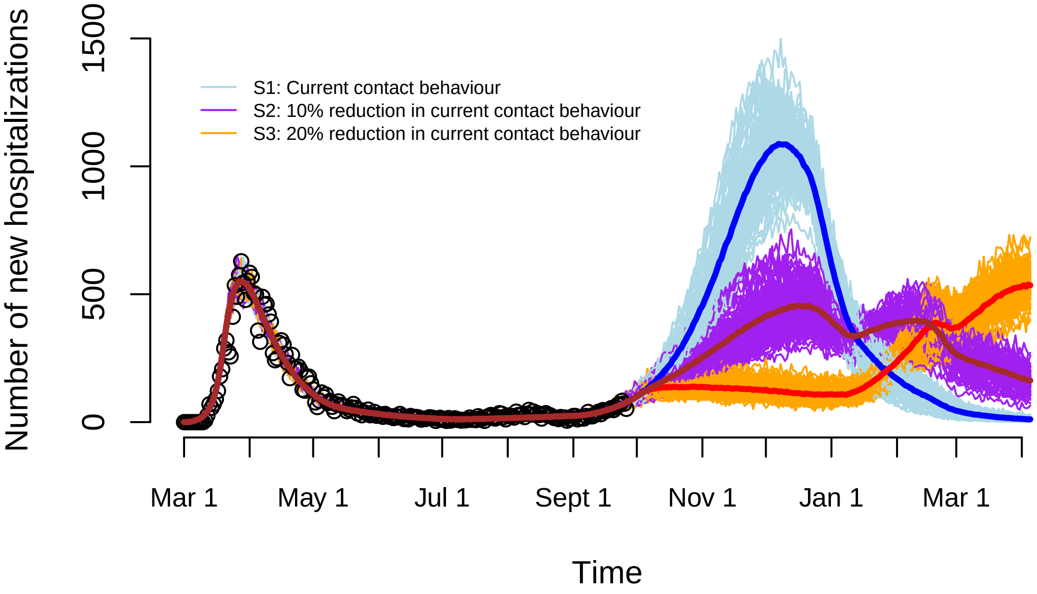

Figure 2: Long-term prediction of the number of new hospitalisations.

well relying on 25% of the hospitalisations becoming Intensive Care Unit (ICU) admissions. Limits on the number of available ICU beds for COVID-19 patients are indicated with red dashed lines. In general, scenarios S2 and S3 do not exceed the upper limit on COVID-19 beds (i.e., 2000 ICU beds), whereas scenario S1 does.

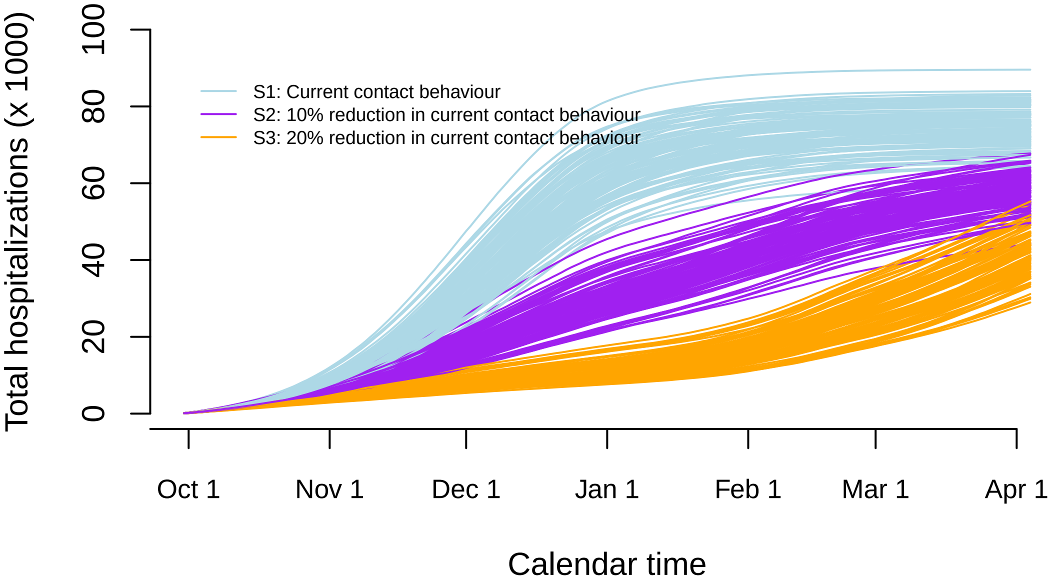

Figure 3: The cumulative number of hospitalisations.

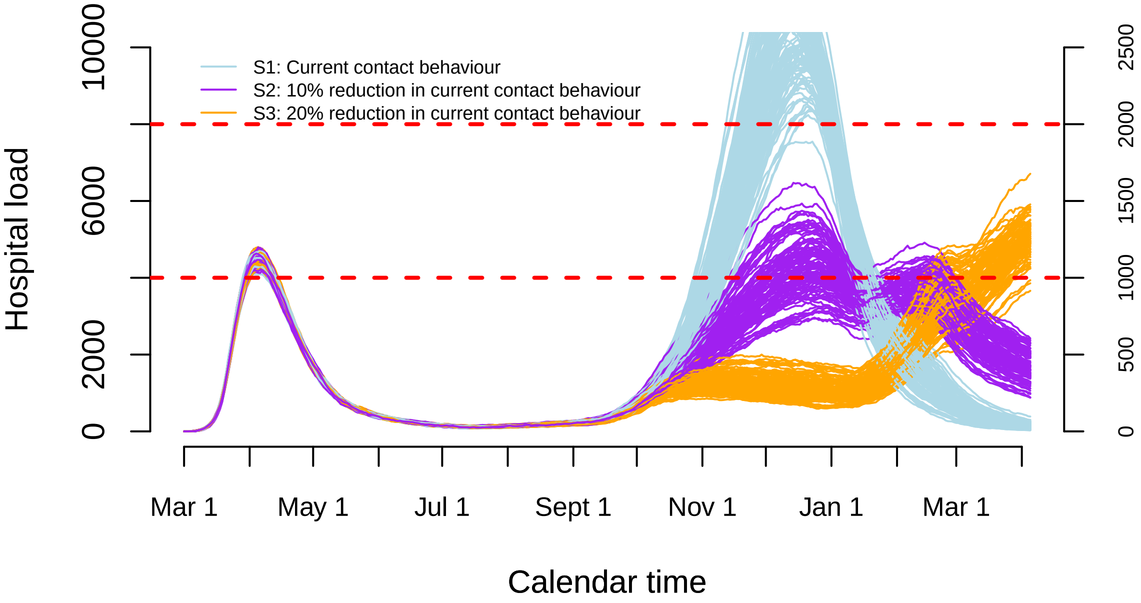

Figure 4: The time-dependent number of hospitalisations in the three scenarios under the assumption of a Weibull distribution for the time spent in the hospital (scale = 10.46, shape = 1.34). Red dashed lines indicate limits on the number of available ICU beds for COVID-19 patients (1000: normal COVID ICU capacity, and 2000 ICU beds: increased COVID ICU capacity).

UNamur deterministic compartmental model

Model structure and limitations

The model initially developed at UNamur is a continuous age-structured compartmental model based on differential equations calibrated on public Sciensano data on hospitalisation, mortality and serology from blood donors. Transmission between age classes is computed using social contact data at different places (home, work and transport, school, leisure and others). The model has 65 estimated parameters with probability distribution given by an MCMC method. Nursing homes are considered in a specific way as 2000 isolated entities with random infection and variable hospitalisation policy depending on hospital load. Continuous care improvement from the first wave is taken in consideration. The model specifically accounts for the under-reporting in new hospitalisations due to transfers of patients from a non-COVID unit, hence, **all figures and data concerning this model already include an additional incidence estimated at 15.7% with 90% confidence interval** [**9.6%,24.1%**]. The recent update of the model takes also potential re-importations during the holidays season into account. Technical details can be found in Franco (2020).

The model does not take into account the spatial structure on the population as well as gradual compliance, seasonality or cross-immunity effects. Contact tracing, testing and self-isolation are not specifically incorporated in the model, except for the aggregated effect on reducing the number of high-risk contacts.

Schematic diagram (Unamur model)

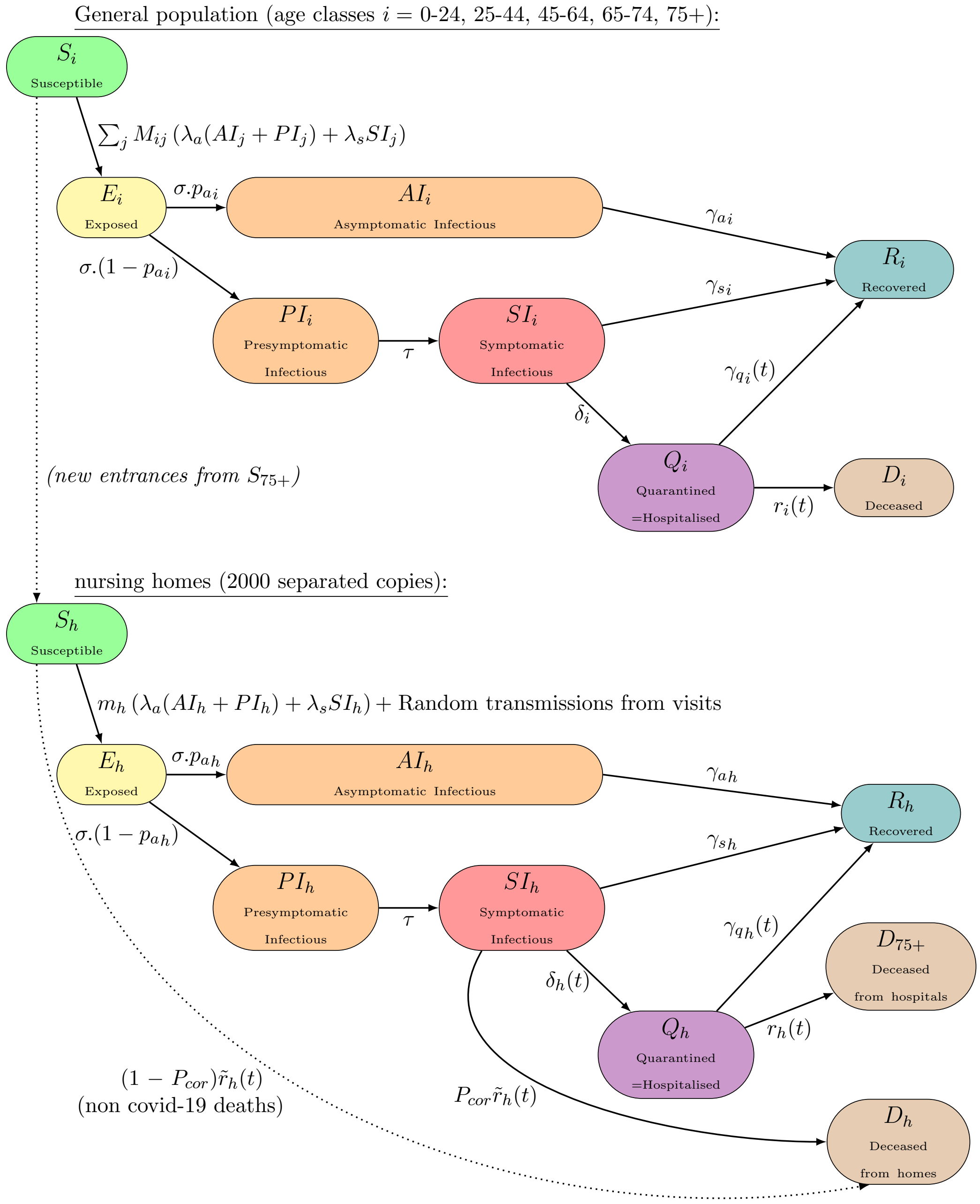

Figure 5: Schematic view of the UNamur compartmental model

Long-term predictions under different scenarios

The different scenarios are expressed in terms of changes in social contact behaviour, as proxy for changes in transmissibility as a result of social distancing and hygienic measures taken at different locations. The current estimations by the model for the month of September are (% of pre-pandemic contacts):

- Home/family contacts: 50.5% [46.5%,54.1%]
- Work contacts (+ transport): 9.2% [5.8,12.9%]
- Leisure contacts (+ others): 30.6% [21.9%,38.2%]
- School contacts: 69.7% [44.2%,88.6%]

Note that those percentages are applied to both asymptomatic and symptomatic classes, without considering any self-isolation from symptomatic people. Hence their estimated absolute values might differ from the UHasselt stochastic model but proportional variations over the different periods and scenarios are similar.

Due to the recent introduction of school contacts and the particularly long delay before the impact on hospitalisations data coming from infectious inside a young class, school contacts are still currently estimated by the model with a large confidence interval, which is one of the main source of uncertainties for the different scenario-based forecasts.

We present two different scenarios which are explained below, in terms of hospital admissions per day (Figure 6), cumulative numbers (Figure 7) and hospital load (Figure 8). Figures are represented by the median and all 5% percentiles. Those scenarios are assumed without upcoming major change in governmental measures, hence, these scenarios only represent projections from a constant situation and any major change in measures, behaviour or additional effect would result in a deviation from the forecast.

Scenarios with current behaviour

The red line scenario is under the assumption that the current social contact behaviour from people remains constant over time, hence with the previously described percentages. The calibration takes account of an estimated amount of re-importation coming from travellers during the period July-September from the following countries: France, Spain, Italy and The Netherlands and according to the 2019 Belgian travel trends given by ABTO and the evolution of the epidemic in those countries given by ECDC. The estimation of 30.6% of leisure contacts is an average over the period September 1-27, which is assumed different from the previous period (August) due to a clear change in the evolution of the epidemic which cannot be completely explained by schools opening and re-importations.

Due to the combined effect of re-importations and social contacts in September, the forecast is a bit more optimistic than the ones in the stochastic model since re-importations from holiday travellers are assumed nonexistent starting from October. Nevertheless, the projection still implies a full load or overload of Belgian hospital capacities.

Scenarios with less leisure and other contacts

The blue line scenario is under the assumption that leisure social contacts are 20.6% [11.9%,28.2%] of the pre-pandemic observations starting on October, 1. This is absolute reduction of -10% in comparison to September. Such a reduction is a realistic scenario since it can come either (or both) from the effect of new measures locally taken (as e.g. the recent new measures in Brussels) and/or from a self-evolution in the population behaviour. This scenario still implies a large load of hospital capacities which might be similar to the first wave but over a longer period. We must note that the decrease of this potential second wave is due to the natural increase of immunity rather than from lockdown measures.

In order to reach a scenario without any real second wave, we should have leisure contacts at a similar level than June's situation, which is estimated at 13.5% from this model. We can also remark that the variation in leisure contacts is the most important factor in the evolution of the epidemic, since according to those scenarios a -10% change in leisure contacts as an effect almost similar to a -25% change in school contacts.

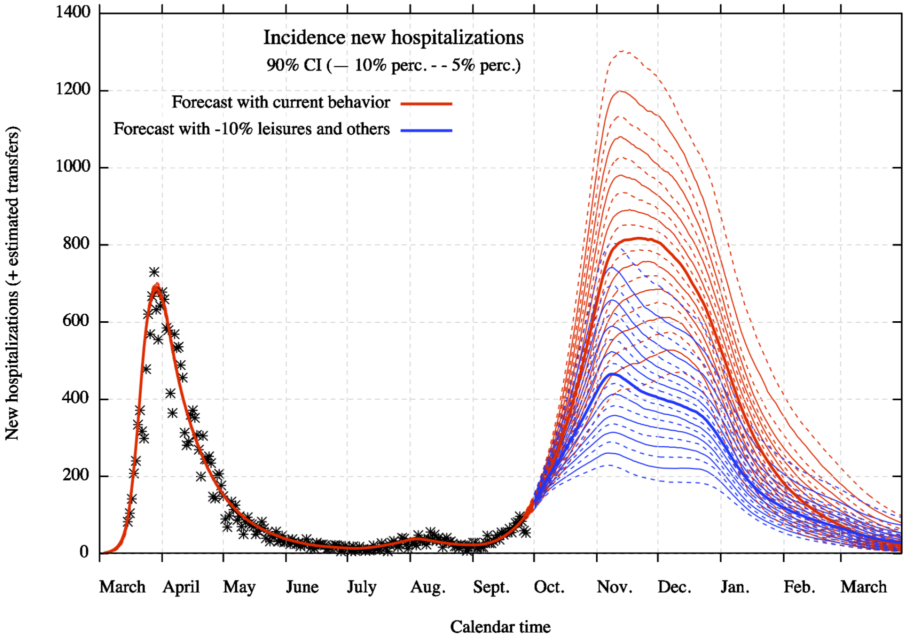

Figure 6: UNamur model: Incidence in new hospitalizations. The model estimates an amount of transfers from other pathologies as an additional 15.7% [9.6%,24.1%] which are included in the forecasts and real data. An estimation of re-importations from travellers is taken into consideration. Data are considered up to September, 27.

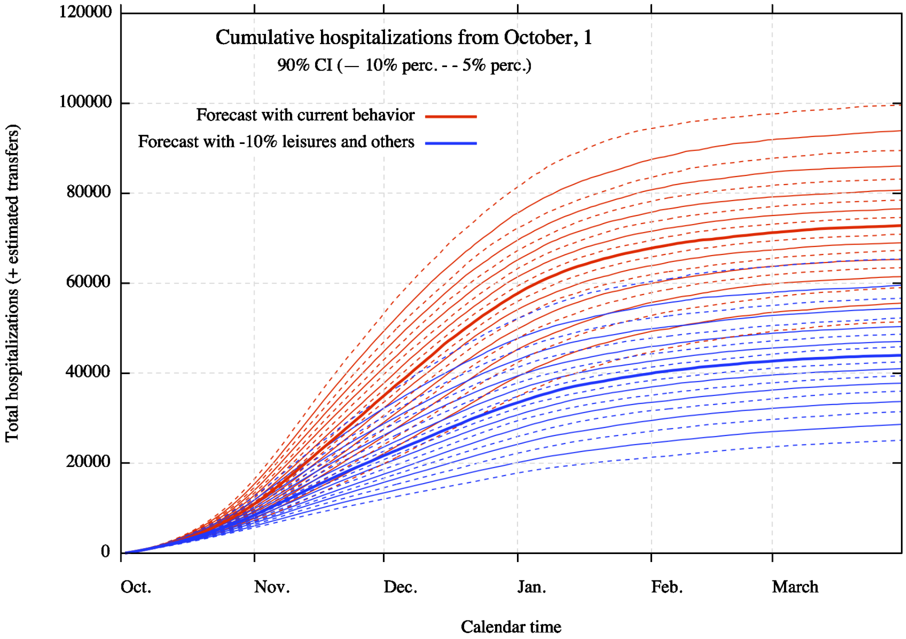

Figure 7: UNamur model: Cumulative numbers of new hospitalizations since October 1st. The model estimates an amount of transfers from other pathologies as an additional 15.7% [9.6%,24.1%] (within hospital referrals) which are included in the forecasts and observed data. An estimation of re-importations from travellers is taken into consideration. Data are considered up to September, 27.

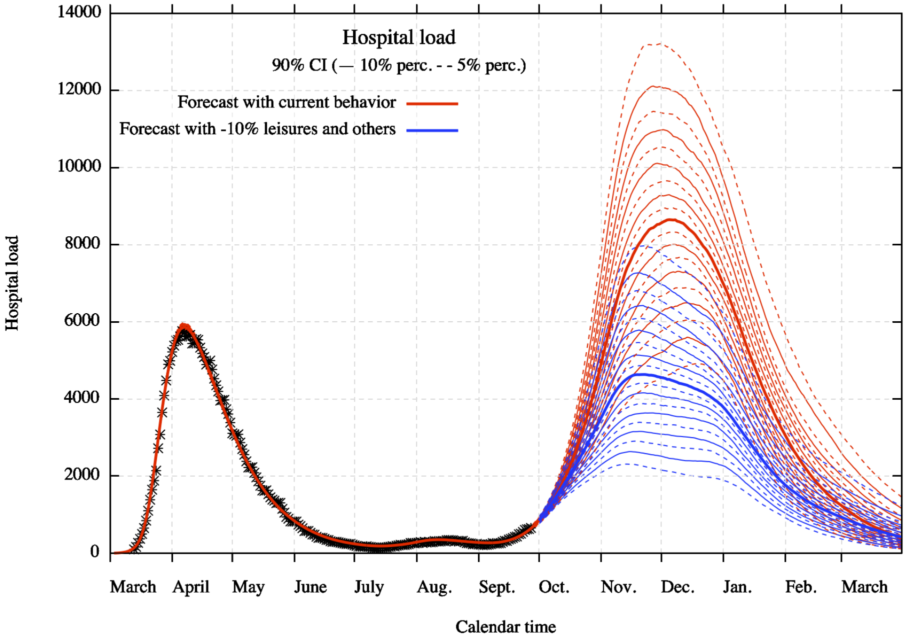

Figure 8: UNamur model: Hospital load (prevalence). The model is calibrated both on hospitalizations and deaths, with an estimation of care improvement over time. An estimation of re-importations from travellers is taken into consideration. Data are considered up to September, 27.

VUB time-series model

This analysis applies a time series approach wherein the log-number of events $\log(X_t)$ (with X_t the number of events of interest) is assumed to follow a first order auto-regressive process with a piecewise linear drift driven by a Gaussian cyclo-stationary process. The cyclo-stationarity is a priori set to a weekly periodicity to account for the weekend effect. The model choice is derived from a linearisation of the standard SEIR-model equations. The analysis uses the publicly available national data daily distributed by Sciensano. Forecasts are obtained by transforming the time series parameters to the parameters of the SEIR model equations proceeded by solving the SEIR differential equations numerically through a standard Runge-Kutta 4/5 numerical scheme.

The model is data-driven which serves as a prediction model with limited possibility of scenario simulations. The uncertainty analysis relies on the assumed Gaussian cyclo-stationary noise process. The weekend-effect is modelled non-parametrically by analysis of the periodogram of the model residuals w.r.t $\log(X_t)$. The Fourier coefficient corresponding to a weekly periodicity is used in the residual's spectral density.

Forecasts are based on two estimators: maximum likelihood estimator and the prediction error estimator (see Figure 9. In the first estimator the residual error is minimized between model output and observed data which is denoted as the maximum likelihood estimator. The second estimator minimizes the multi-step ahead prediction error based on a time window since 18/9 denoted by the prediction error estimator. The peak moment is expected around November 13th which is based on the ML-estimate estimated on 4333 occupied beds while this is 2552 beds accordingly to the PE-estimate. The uncertainty interval on the peak-value is large as given by $[2424, 6656]$ due to the prediction uncertainty. The prediction error estimate is identified as the current solution path that the pandemic is following based on the past validation window since 18/9. This gives an assessment w.r.t. the confidence interval where the projection is currently positioned compared to the maximum likelihood estimator estimated on 18/9 which is approximately centered in the confidence interval. Thus, the prediction error estimated considers the current situation slightly more optimistic than what was anticipated on 18/9.

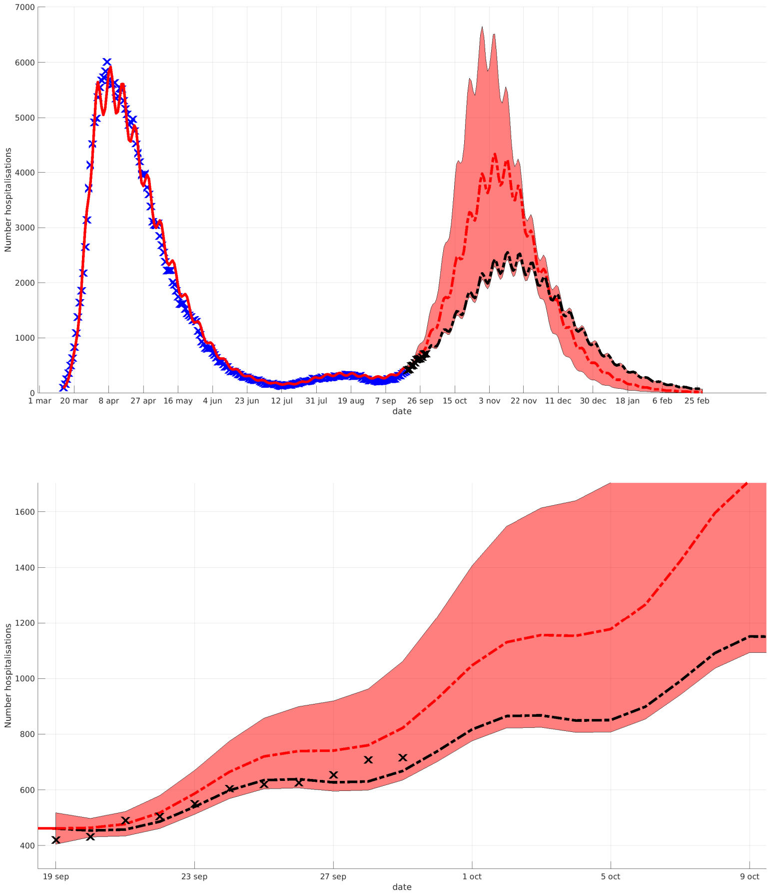

Figure 9: Projection VUB model based on the time series up to 18/9 (red) and validated on the time series since 18/9 up to 29/9 (black): Observations up to 18/9 (blue crosses), Observations since 18/9 (black crosses), maximum likelihood estimation (dashed red), Prediction error estimate (dashed black), confidence area (shaded red), model fit up to 18/9 (full red).

Conclusions

On October 1st, the observed daily number of hospitalizations comply with the most pessimistic scenarios, with a hospital load peak around the end of the year. The information regarding the increasing number of confirmed cases could imply a change in contact behaviour in the Belgian population, thereby lowering the incidence of new hospitalizations in the near future. We present scenarios that account for a reduction in social contacts (as proxy for transmission) (S2 and S3, UHasselt model) and (S2, UNamur model). Given the unpredictive nature of adaptive social contact patterns in pandemic times and measures taken, we can only report ranges through scenario analysis without identifying a most-likely situation. The evolution of the number of hospitalizations in the next days and weeks will show which of these scenarios will unfold.

The combination of individual decision making and appropriate measures are still key in the reduction of COVID-19 hospital admissions to realise one of the more optimistic scenarios.

Acknowledgements

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