Plasma-Assisted Air Cleaning Decreases COVID-19 Infections in a Primary School

Modelling and Experimental Data

van Bennekum, Tika; Colin, Marie; Krzhizhanovskaya, Valeria; Bonn, Daniel

DOI
10.1007/978-3-031-63772-8_19

Publication date
2024

Document Version
Final published version

Published in
Computational Science – ICCS 2024

Plasma-Assisted Air Cleaning Decreases COVID-19 Infections in a Primary School: Modelling and Experimental Data

Tika van Bennekum[1](✉), Marie Colin[2](✉), Valeria Krzhizhanovskaya[1](✉), and Daniel Bonn[2](✉)

[1] Institute of Informatics, University of Amsterdam, Amsterdam, The Netherlands
tika.v.bennekum@gmail.com, V.Krzhizhanovskaya@uva.nl
[2] Institute of Physics, University of Amsterdam, Amsterdam, The Netherlands
mariecolin103@gmail.com, D.Bonn@uva.nl

Abstract. We present experimental data and modelling results investigating the effects of plasma-assisted air cleaning systems on reducing transmission of SARS-CoV-2 virus among pupils in a primary school in Amsterdam, the Netherlands. We equipped 4 classrooms (120 pupils) with the Novaerus NV800 ICU air cleaning system, and 8 classrooms (240 pupils) had standard ventilation systems. We found a significantly lower number of infections in classrooms with air cleaning systems in the first two weeks after instalment, suggesting that air cleaning decreases aerosol transmission. In the subsequent weeks, however, infection numbers increased in the Netherlands, and the difference between classrooms with and without air cleaning ceased to be significant. We analyzed the experimental results, performed a Kaplan-Meier survival estimation and developed a SIR-based computational model that simulates the results of this experiment. We performed sensitivity analysis, optimised model parameters, and tested several hypotheses. This research gives the potential for implementing improved air quality measures in public spaces, which could result in better air quality regulations in spaces such as schools.

Keywords: SARS-CoV-2 · COVID-19 · aerosol · air cleaning · transmission · prevention · public healthcare · SIR model · sensitivity analysis · Kaplan-Meier survival estimation

1 Introduction

The World Health Organization (WHO) emphasizes the role of aerosols in the transmission of SARS-CoV-2 [9] and states that 'much more research is needed given the possible implications of such route of transmission'. This is particularly relevant for crowded public spaces such as schools, where distancing is not possible and the risk of aerosol transmission of SARS-CoV-2 is high. According to Lu et al., air conditioning allows for the movement of infected droplets, which can

L. Franco et al. (Eds.): ICCS 2024, LNCS 14835, pp. 196–209, 2024.
https://doi.org/10.1007/978-3-031-63772-8_19

infect people if they inhale these droplets [8]. One of WHO's recommendations to decrease aerosol transmission of the Coronavirus is to improve ventilation and use air cleaning, for example by installing air purification systems. Such purification can remove virus particles by means of filtration [7] or inactivate them by non-thermal atmospheric plasma discharge [6,10]. We investigated the effect of a combined HEPA filter and plasma air cleaning on aerosol concentration and persistence time in a primary school in Amsterdam, the Netherlands. This research can help determine whether a serious investment in such air filters is justified and whether advanced air cleaning systems should be incorporated into the policies of public spaces.

To investigate the reduced risk of infection transmission, a computational model can be developed. Various types of Susceptible-Infected-Removed (SIR) disease dynamics models have been used for Covid-19 pandemic modelling [20, 21]. SIR-based models proved to be well-suited for this purpose, and will thus also be employed in this paper. The SIR model classifies the population into three groups: Susceptible, Infected, and Removed. The model predicts the dynamics of these three groups based on the infection and recovery rates characterising the disease.

Our model simulates an experiment conducted in a primary school in Amsterdam, the Netherlands, where the numbers of pupils with Covid infection were recorded daily in 4 classes with air cleaning systems and in 8 classes without these systems (as control group). The model is designed to reflect two distinct situations: school environment during the day (6 h) and outside the school environment the rest of the day.

Model parameters are derived from the existing research on Covid-19 epidemic. Parameter values outside the school environment are obtained from relevant studies on the spread of Covid-19 [12–15]. However, determining appropriate parameter values within the classrooms with air cleaning required extra investigation, as we did not find published data on such experiments. Our results of sensitivity analysis show how much influence each parameter has on the model.

The main research question of this study is: How can the SIR model be modified to simulate the reduced risk of infection in classrooms with a plasma-assisted air filter? The main hypothesis is that the time-varying infection rate can be calibrated to adequately simulate real data. We will show that by adjusting the parameters of the model over time, simulating a low infection rate in the classrooms with a filter during school hours, and adjusting the infection rate outside the school hours depending on the situation in the country the model can be fitted to the data.

2 Methods

2.1 Experiment Description and Experimental Results

The experiment began after the Covid lock-downs on January 10, 2022 and ended on February 16, 2022, after which there was a two-week school holiday. The study population was a group of 360 pupils aged 9 to 12 years old, in a school in Amsterdam, the Netherlands. These pupils were divided into two groups: The first group of 240 individuals was the control group, taking classes in 8 classrooms without plasma-assisted air cleaning system. The second group of 120 individuals studied in 4 classrooms equipped with the plasma air cleaning systems, which reduce the concentration of potentially infectious aerosol particles [5]. The plasma air cleaning system was a Novaerus NV-800 [5], in one classroom a similar air cleaning system was used that was also equipped with a HEPA filter, a Novaerus Defend 400. The graph shows the results of this experiment.

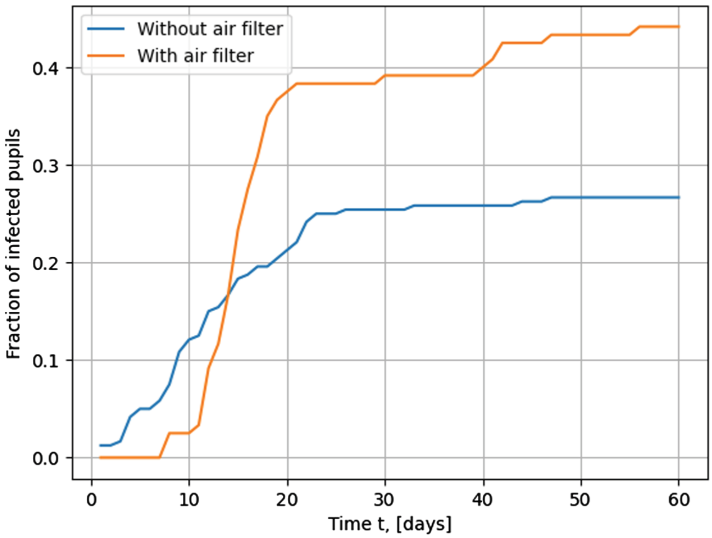


Fig. 1. The number of infected pupils over time in the experiment.

We observe significant differences in the rate with which pupils are infected: after 10 days already more than 8% of all the pupils in the control group have caught Covid-19 (Fig. 3), whereas from the group with the plasma air cleaning system this value is less than 3%. The data also suggest that air cleaning measures only help when the disease pressure is not too high; if too many pupils are infected, the school as a source of new infections is less substantial, and the 'delay' in getting Covid-19 due to the air cleaning rapidly disappears.

Plasma discharge breaks down the aerosols and reduces the concentration of fine dust particles in the air [5]. There were some initial worries at the school that the plasma air cleaning might create ultra-fine dust particles by breaking down the fine dust. We therefore measured the effect of the air cleaning system in a separate test by counting the total number of ultra-fine dust particles (diameters 6–600 nm) in the air of a typical classroom, using a TSI Model 3091 ultra-fine Particle Counter [4]. As shown in Fig. 2, the particle count as a function of time is stable prior to switching on the air cleaning system (green dotted line) and decreases after switching it on (orange dotted line). The graph displays the total number of particles summed over all channels.

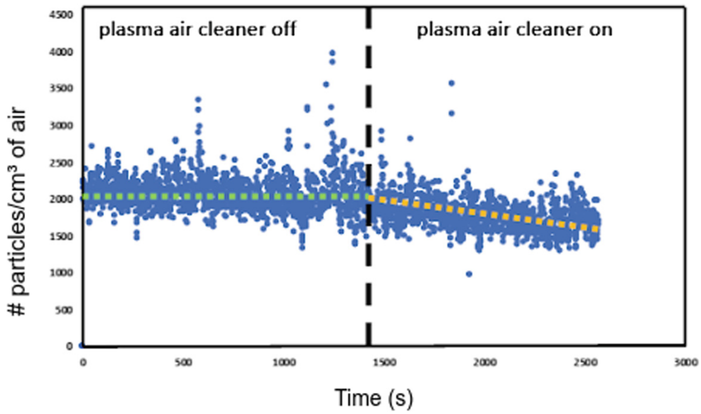


Fig. 2. Concentration of ultra-fine dust particles per cm^3 of air. Plasma air cleaner was switched on at 1400 s. Particles with diameters between 6 nm and 600 nm were counted. Dotted lines show linear fits of the two periods (before and after switching the system) as guides to the eye. (Color figure online)

All classes functioned normally without any supplementary measures being taken. The classes consist of generally healthy children with an approximately equal number of males and females. The experiments were done in a period when the Netherlands had an abundance of Covid-tests, and people usually tested at the first symptoms. Parents kept their children at home with either some Covid symptoms or a positive SARS-CoV-2 test, and the school was informed by the parents. The number of reported infections per class was used as the data set for this study.

2.2 Statistical Model for Data Interpretation

The Kaplan-Meier (K-M) survival curve and the log-rank test were used to analyse the experimental results. The Kaplan-Meier analysis [2] estimates the proportion of survivors as a function of time (here, a "survivor" means not infected by Covid-19), describing the conditional probability that the individuals who survived at the beginning of the period, will survive till the end of the period. K-M estimator can be interpreted as (and derived from) non-parametric maximum likelihood estimator. An advantage of the K-M model is that it takes into account the notion of censoring. Indeed, at the end of the study, if the event (here, infection by Covid-19) did not occur, we speak of censorship of the information. For the analysis, the censorship is exact and of type II, i.e. the event declared occurs at the time indicated, and each individual is followed until an event is observed.

We then apply the log-rank test to determine whether the differences between two survival distributions are significant [1]. For each period, the expected number of cases without the difference between the groups (O) and the total number of observed cases (E) is calculated. The statistic is obtained by summing for each group $\frac{(O-E)^2}{E}$. This statistic is then studied according to a chi-square distribution. If a p-value lower than 5%, then the difference is said to be significant.

2.3 SIR Model Assumptions and Equations

Characteristics of Covid-19. For the SIR model, several assumptions need to be taken into account. *Assumption 1* is about the duration of the infectious period, which refers to the time during which an infected individual can transmit the disease to others. For Covid-19, the infectious period ranges from 2.3 to 10 days [12,13]. *Assumption 2* concerns the latent period, which is the time between an individual's infection and when they become infectious to others. For Covid-19, the latent period ranges from 2.2 to 6 days [14,15], which appears to be about the same time period as when symptoms start showing up [11]. *Assumption 3* is about what happens after an individual is recovered from the disease. While it is possible for some individuals to experience severe outcomes, in the case of children, such occurrences are negligible. Children are assumed to develop immunity after recovery. Although the exact duration of this immunity remains uncertain, it is estimated to be between a few months and a few years [16]. Since this experiment runs for a duration of 60 days, it will be assumed that no child contracts the disease more than once. *Assumption 4* is that new individuals are not introduced into the system, because the experiment covers only 2 months and involves a fixed group of school children.

SIR Equations and Modifications. For the group without an air filter, there were no adjustments needed from the basic SIR model described by the following equations for the susceptible group s (1), the infected group i (2) group r (3):

$$\frac{\delta s}{\delta t} = -\beta\, s(t)\, i(t) \tag{1}$$

$$\frac{\delta i}{\delta t} = \beta\, s(t)\, i(t) \;-\; \gamma\, i(t) \tag{2}$$

$$\frac{\delta r}{\delta t} = \gamma\, i(t) \tag{3}$$

Where beta is the infection rate and gamma is the recovery rate of the disease. For the group with air cleaning in classrooms, the disease transmission rate coefficient (β) during the 6 h in school is $\beta = \beta_{classroom}$, and during the rest of the day outside of school and on weekends $\beta = \beta_{world}$.

Model Implementation. This SIR system of ordinary differential equations was solved by using the Python package ODEINT. The ODEINT function uses the LSODA algorithm, which is part of the FORTRAN library ODEPACK [17]. The LSODA algorithm dynamically adjusts the step size array to strike a balance between accuracy and efficiency. It achieves this by considering the local error estimate and attempting to maintain it within an acceptable range. If the error estimate falls outside this range, the step size is reduced, and the calculation is recalibrated until the error falls below a user-defined threshold. Once the error estimate is within the acceptable range, the algorithm proceeds to the next time step.

Calibration of Infection Rate and Recovery Rate Parameters. In order to reproduce the observed real data, model parameters are calibrated by minimising the root mean squared error (RMSE) defined as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - D_i)^2}, \tag{4}$$

where D_i is the observed data point, S_i is the simulation result, and n is the number of observations.

To overcome the problem of a slight mismatch of the varying time steps in simulations (which leads to the simulation results output at different moments not matching exactly the experimental time stamps of 1 day), we used linear interpolation for simulated results [18].

For model parameter calibration, Grid Search technique is employed in this study, systematically testing possible combinations of parameter values to identify the optimal combination. This is used to optimise the infection rate and recovery rate parameters.

2.4 Sensitivity Analysis on SIR Model

Sensitivity Analysis is a valuable method for investigating the influence of parameter variations on a model. It examines how the outputs of a system are connected to and impacted by its inputs [19]. It is a way to understand how changes in independent variables affect the model while considering specific assumptions. It does so by exploring the different sources of uncertainty within a mathematical model and quantifying their impact. For this paper, SALib (Sensitivity Analysis Library) is used. This is a Python library that provides tools for conducting sensitivity analysis. One of the methods it supports is the computation of first-order Sobol indices. The computed Sobol indices provide a measure of the relative importance of each input parameter. Higher indices indicate that a parameter has a larger influence on the output variability, while lower indices suggest a lesser impact.

3 Results

3.1 Statistical Modelling Results

Figure 3 shows the estimated 'survival probability', i.e. the probability of remaining in the uninfected group without Covid-19 during the period of the test. We can see that during the first 15 days, the survival probability in Group 1 (with the air cleaning system) is significantly higher than in Group 2 (without the air cleaning). We can therefore make a preliminary conclusion that the plasma air cleaning system reduces the risk of infection of Covid-19. However, we see that after Day 15, the difference between the groups becomes insignificant (falls within the 95% confidence interval).

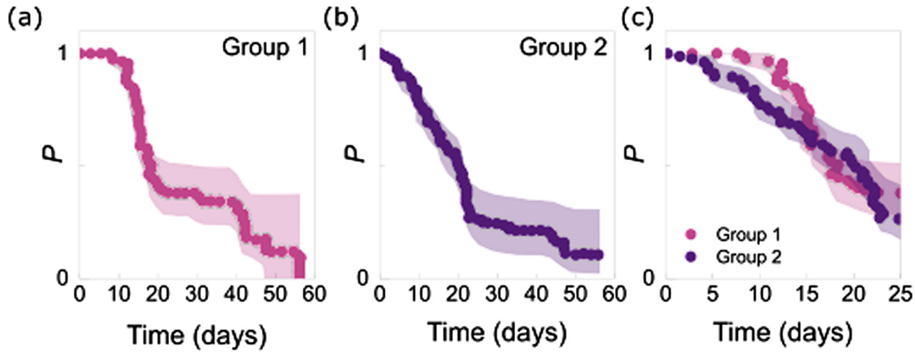


Fig. 3. Kaplan-Meier plot of the probability of not catching Covid-19 as a function of time. (a) in classrooms with plasma air cleaning system (Group 1); (b) in classrooms without the air cleaning (Group 2). The shaded area shows the 95% confidence interval; (c) both groups during the first 25 days.

To explain the slightly lower survival probability in Group 1 after Day 15, we looked at the total number of daily registered Covid cases in the Netherlands [3] and found an exponential growth during that period, with the number of cases sky-rocketing from 31,321 cases in Day 9 to 104,549 in Day 22 (see Fig. 6). This means that after the first 2 weeks of the experiment, the disease pressure in the country becomes so large that the probability of getting Covid-19 outside the school completely dominates, and air cleaning during the 6 h in school can no longer reduce the infection spread in the population.

For further analysis of the statistical results we used the log-rank test to see whether the observed difference between the classrooms with and without air cleaners is significant. The calculated p-value is smaller than 5%, therefore we conclude that the difference is significant.

3.2 SIR Modelling Results

We experimented with several SIR model modifications to simulate the reduced risk of infection in classrooms with an air filter and to reproduce the observed dynamics. Below we present the simulation results.

For the Grid Search algorithm, we defined the bounds for the parameter values based on experimental studies. For instance, in a study on the spread of Covid-19 in Canada [22], a time period of 320 days was divided into three time periods and assigned respective disease transmission rates of 0.18, 0.30 and 0.13. We therefore set the range of the disease transmission rate β values from 0.1 to 0.7.

Our experimental data (Fig. 1) showed that the group with an air filter had a higher percentage of the Covid-19 infections at the end of the experiment. This is counter-intuitive and can only be explained by a different disease transmission rate β_{world} outside the classroom, higher than in the group without air filter. The unexpectedly high number of Covid-19 cases in the group with the air filter could be caused by a birthday party in the group or by some pupils visiting regions with a very high prevalence of Covid-19 cases.

There is no research available yet to get an estimate for the disease transmission rate β specifically for the air-filtered classrooms. Thus, this was first estimated and further adjusted in numerical experiments. For the disease transmission rate inside the classrooms β_{class} we use the range from 0 to 0.7.

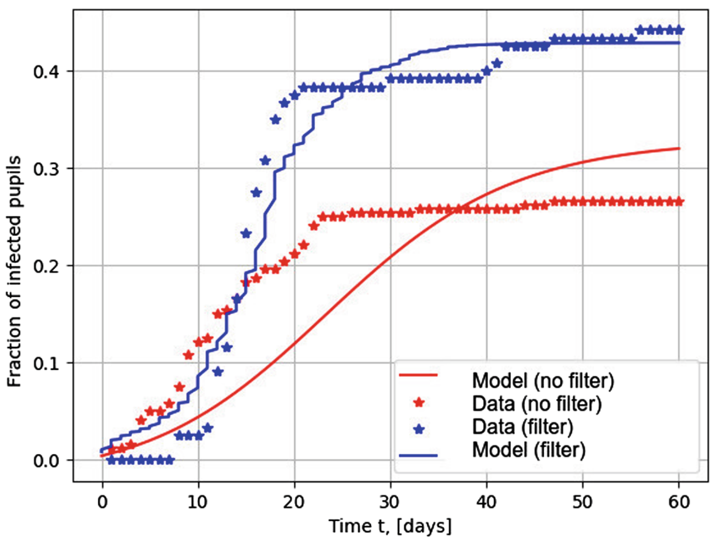


Fig. 4. SIR modelling results compared to experimental data. Calibrated $\beta_{world\ filter} = 0.4$, $\beta_{class} = 0.66$ and $\gamma_{filter} = 0.129$ for the model with the filter. The model without the filter the values are $\beta_{no\ filter} = 0.6$ and $\gamma_{no\ filter} = 0.5$. (Color figure online)

The model with the air filter (blue curve) produces significantly similar results to the data, having a quick rise in infected pupils after which the infections slow down. The main difference being that the rise starts earlier then is shown by the data. As we see, the modelled number of infected pupils with no filter (red curve) grows slower than in the observed data. Further analysis of experimental data shows that the initial fraction of infected people in this group is higher than in the group with air filter, we should therefore adjust the I_0 parameter. With more initially infected pupils, the number of infected people will grow faster. The bounds for I_0 will be from 1 to 10 infected people (Table 1).

Table 1. Optimal model parameters.

Parameter	Minimum	Maximum	Optimum filter	optimum no filter
β_{class}	0.1	0.7	0.56	–
β_{world}	0.1	0.7	0.4	0.5
γ	0.083	1	0.129	0.5
I_0	1	10	1	4

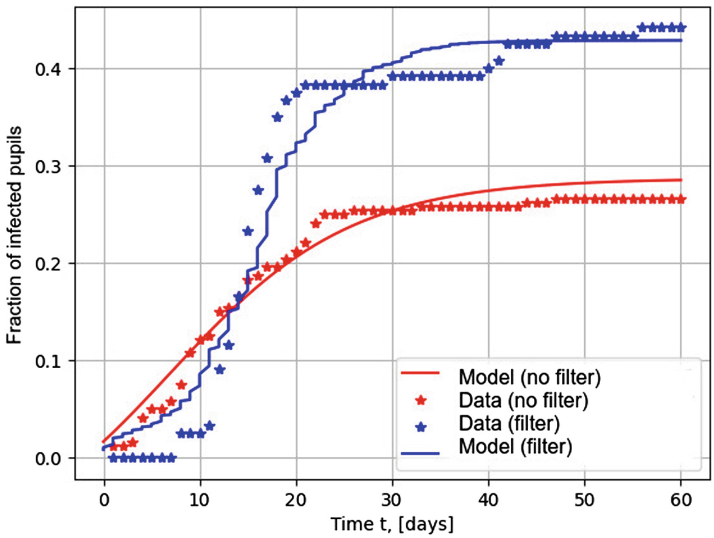


Fig. 5. SIR modelling results compared to experimental data. An extra parameter I_0 is calibrated indicating the initial number of pupils infected. All other parameters are fixed as in Fig. 4.

National Infection Cases. The infection rates observed in the experiment are undoubtedly affected by the situation in the Netherlands. Therefore, the effect of the national infection statistics (Fig. 6) on the model is tested. The hypothesis is that incorporating the daily count of new infections in the Netherlands will improve the model accuracy.

The data on the daily infection cases in the Netherlands is used to calculate the daily infection rate β_{world}. The pre-calibrated infection rate parameter is multiplied by the number of cases at the current day divided by the mean of the daily new infections. This ensures that days with a relatively high number of infections in the Netherlands will have a higher infection rate in the simulation. This modification only applies to the infection rates outside the classroom.

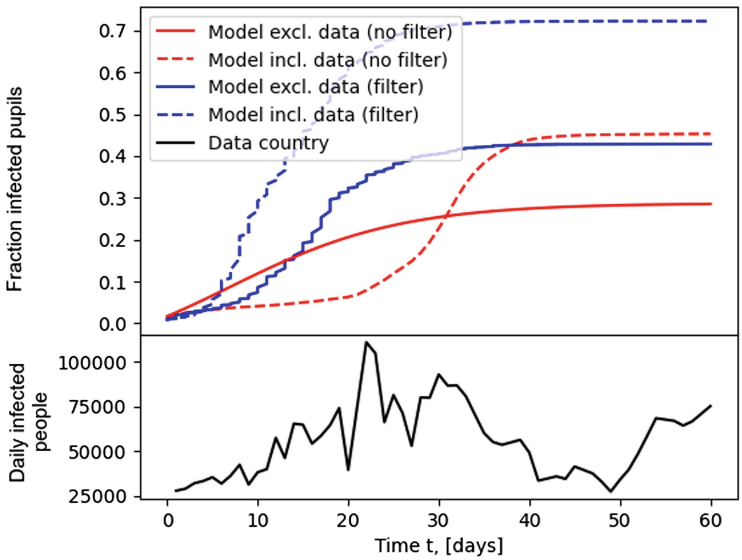


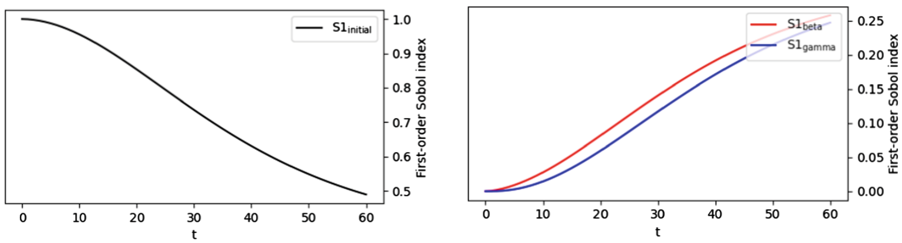
Fig. 6. SIR modelling results including and excluding the national data. For visual clarity, the number of daily infections in The Netherlands is plotted below.

Simulation results of this adjusted model are plotted against the model without the national data input in Fig. 6. We can see that the models including the national infection data yield very different results. For the model with air filter, incorporating the data results in a substantial increase in the number of infected pupils. Conversely, in the model without an air filter, the total number of infected pupils remains unchanged, but the increase in infections is delayed in the simulation. The model without an air filter was already closely aligned with the experimental data, and the inclusion of national infection statistics only reduced its accuracy. Similarly, the model without an air filter was already quite accurate, but required a slight delay in the number of infections. This delay is evident in the model with the incorporated national data, but the overall outcome significantly deviates from the observed data.

Incorporating the national infection numbers did not improve the accuracy of the models, perhaps because the data is generalised over the whole country, while the local numbers where the pupils resided could vary significantly. To investigate that, further analysis and advanced model adjustments should be performed in the future.

4 Uncertainty Quantification

A sensitivity analysis has been conducted on the SIR model presented in this paper to assess the influence of each parameter on the model's outcomes. The sensitivity analysis is performed on the model whose results are presented in Fig. 5. The results for the case without air filter are presented in (Fig. 7). The initial number of infected pupils (Fig. 7a) has the largest impact during the starting days. In agreement with this idea, the disease transmission rate β parameter (Fig. 7b) has a low impact at the beginning, but gradually becomes more influential over time. The recovery rate γ parameter (Fig. 7b) follows a similar trend to the disease transmission rate, having a low impact at the start and growing influence as time advances. The initial number of infections thus has the strongest impact on the model outcomes, with a first-order Sobol index S_i between 0.5 and 1. The beta and gamma parameters have a lower but still significant impact, with the first-order Sobol indices ranging from 0 to 0.25.



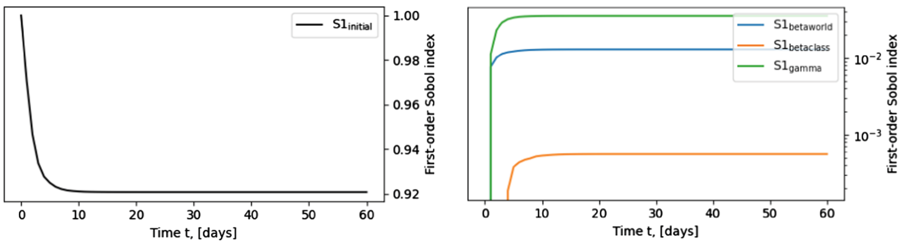
(a) initial infected pupils (b) beta and gamma

Fig. 7. The firs-order Sobol indexes of the model parameters for the model without air filter over 60 days.

The results for the case with air filter are presented in Fig. 8. The initial number of infected pupils (Fig. 8a) again has the highest influence in the beginning of the model, then quickly decreases, but stays relatively high (first-order Sobol index $S_i = 0.92$ for the rest of the period. This indicates that the initial number of infected pupils has a greater impact on the model with an air filter compared to the model without one.

The disease transmission rate of the world β_{world} parameter (Fig. 8b) starts with S_i zero at the beginning of the simulation, but rapidly climbs to an index of 0.0125. Compared to the model without an air filter, the overall impact of β_{world} is lower. The disease transmission rate in the classroom β_{class} follows a similar trend as β_{world} but with a delay. The overall impact of the classroom parameter is very low, with a first-order Sobol index ranging between 0 and 0.0005. Although the disease transmission rate in the classroom has a low direct influence on the model, it plays a crucial role in influencing the impacts of other parameters. This is because the influences of other parameters are significantly different in the model with an air filter compared to the model without one.

The recovery rate γ (Fig. 7b) follows a similar trend as the disease transmission rates. It initially has a low impact on the model, but its influence gradually increases over time. The first-order Sobol index for the recovery rate ranges from zero to 0.03, this means it has a higher impact on the model with an air filter than the model without one.



(a) initial infected pupils (b) beta and gamma

Fig. 8. The first-order Sobol indexes of the model parameters for the model with air filter over 60 days.

5 Conclusion

Adding the plasma air cleaning system on top of the normal ventilation significantly reduces the aerosol concentration and persistence during (school) activity [5]. This has important implications: In addition to preventive measures as wearing facemasks and space ventilation, active air-clearing of aerosols by a dedicated system such as the plasma system tested here, further reduces the SARS-CoV-2 transmission risk. In this study we found that a significant reduction in Covid-19 infections can be realized by adding a plasma air cleaning system to the existing ventilation in a primary school in at least the first two weeks of installment.

The Kaplan-Meier results reveal a significant reduction in Covid-19 infection risk in classrooms equipped with a plasma air cleaning system during the initial 15 days of the experiment. After this period, this difference becomes statistically insignificant, falling within the 95% confidence interval.

We showed that a SIR model with some adjustments and model calibration is capable of reproducing the experimental data. The most optimal model was found by using a time-varying infection rate. This means that the pupils with air filters in their classrooms had different infection rate values based on the time of day and the day in the week. The sensitivity analysis showed that the number of initially infected pupils had the highest impact on the model, decreasing its influence over time. The infection rate and recovery rate parameters have a lower influence in the first days of the simulation, increasing as the simulation progressed. This analysis confirmed the conclusions of the healthcare authorities that it is critically important to monitor the early onset of the highly contagious deceases like the SARS-CoV-2.

These results show the possibility to implement better air quality regulation in public spaces such as elementary schools, by incorporating advanced air cleaning systems. In future research it would be interesting to determine the number of such systems needed for different spaces and different number of people.

Disclosure of Interests. The authors have no competing interests to declare.

References

1. Bland, J., Altman, D.: The Logrank test. BMJ **328**, 1073 (2004)
2. Bland, J., Altman, D.: Survival probabilities (the Kaplan-Meier method). BMJ **317**, 1572–1580 (1998)
3. RIVM, I&V & EPI: Covid-19 besmettelijke personen per dag. *Rivmdata* (2021). https://data.rivm.nl/meta/srv/dut/catalog.search#/metadata/097155aa-75eb-4caa-8ed3-4c6edb80467e
4. Wensing, M., Schripp, T., Uhde, E., Salthammer, T.: Ultra-fine particles release from hardcopy devices: sources, real-room measurements and efficiency of filter accessories. Sci. Total Environ. **407**, 418–427 (2008)
5. Somsen, G., Bonn, D.: Infection control unit suppresses airborne aerosols during cardiac stress testing in an outpatient cardiology clinic. J. Clin. Exp. Cardiolog. **12**, 692 (2021)
6. Smith, S., et al.: Probability of aerosol transmission of SARS-CoV-2. *MedRxiv*, pp. 2020-07 (2020)
7. Elias, B., Bar-Yam, Y.: Could air filtration reduce COVID-19 severity and spread. New Engl. Compl. Syst. Inst. **9**, 1–2 (2020)
8. Lu, J., et al.: COVID-19 outbreak associated with air conditioning in restaurant, Guangzhou, China, 2020. Emerg. Infect. Dis. **26**, 1628 (2020)
9. Organization, W.: Transmission of SARS-CoV-2: implications for infection prevention precautions: scientific Brief, 09 July 2020
10. Fennelly, M., et al.: Effectiveness of a plasma treatment device on microbial air quality in a hospital ward, monitored by culture. J. Hosp. Infect. **108**, 109–112 (2021)
11. Xiang, Y., Jia, Y., Chen, L., Guo, L., Shu, B., Long, E.: COVID-19 epidemic prediction and the impact of public health interventions: a review of COVID-19 epidemic models. Infect. Dis. Model. **6**, 324–342 (2021)

12. Wang, C., et al.: Evolving Epidemiology and Impact of Non-pharmaceutical Interventions on the Outbreak of Coronavirus Disease 2019 in Wuhan, China, MedRxiv (2020)
13. Zhao, S., et al.: Imitation dynamics in the mitigation of the novel coronavirus disease (COVID-19) outbreak in Wuhan, China from 2019 to 2020. Ann. Transl. Med. **8** (2020)
14. Chinazzi, M., et al.: The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. Science **368**, 395–400 (2020)
15. Kucharski, A., et al.: Early dynamics of transmission and control of COVID-19: a mathematical modelling study. Lancet. Infect. Dis **20**, 553–558 (2020)
16. Baraniuk, C.: How long does Covid-19 immunity last? BMJ **373** (2021)
17. Petzold, L.: Automatic selection of methods for solving stiff and nonstiff systems of ordinary differential equations. SIAM J. Sci. Stat. Comput. **4**, 136–148 (1983)
18. Bayen, A., Siauw, T.: Chapter 14 - interpolation. In: An Introduction to MATLAB®Programming and Numerical Methods For Engineers, pp. 211–223 (2015)
19. Razavi, S., et al.: The Future of Sensitivity Analysis: an essential discipline for systems modeling and policy support. Environ. Modell. Softw. **137**, 104954 (2021). https://www.sciencedirect.com/science/article/pii/S1364815220310112
20. Davidsson, R.: Modelling Covid-19 Interventions with Machine Learning and SIR Models (2021). https://scripties.uba.uva.nl/search?id=record_28773
21. Carcione, J., Santos, J., Bagaini, C., Ba, J.: A simulation of a COVID-19 epidemic based on a deterministic SEIR model. Front. Public Health. **8**, 230 (2020)
22. Jayatilaka, R., et al.: A mathematical model of COVID-19 transmission. Mater. Today Proc. **54**, 101–112 (2022). International Conferences & Exhibition on Nanotechnologies, Organic Electronics & Nanomedicine - NANOTEXNOLOGY 2020