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RESEARCH ARTICLE

Scheduling Lockdowns Under Conditions of Pandemic Uncertainty

RADOSŁAW KAPŁAN, ROGER KSIĄŻEK, KATARZYNA GDOWSKA, AND PIOTR ŁEBKOWSKI

Faculty of Management, AGH University of Krakow, 30-059 Kraków, Poland

Corresponding author: Katarzyna Gdowska (kgdowska@agh.edu.pl)

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ABSTRACT The objective of our work was to develop a tool to support the process of making strategic decisions about the COVID-19 pandemic by optimizing suppression intervention schedules. We focus mainly on hard lockdowns that have the effect of containing the spread of the virus and, consequently, minimizing the number of infections and keeping the incidence of COVID-19 at low levels. Properly implemented restrictions can reduce the likelihood of infection and thus push the pandemic back. On the contrary, lifting restrictions results in a sharp increase in likelihood of infection and the development of a pandemic. The model proposed in this paper indicates the optimal moments to implement full lockdown, accounting for both the costs of lockdown and the costs of not applying lockdown.

INDEX TERMS COVID-19, decision making, lockdown scheduling, mixed integer programming, strategic management.

I. INTRODUCTION

December 2019, in Wuhan, China, the first cases of unusual pneumonia were confirmed. The spread of the SARS-CoV-2 virus has soon become a global problem that has not yet been effectively contained [1], [2], [3], [4], [5]. The Coronavirus Disease 2019 (COVID-19) is a pulmonary disease produced by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). According to the official report [6], by February 22, 2022, the number of confirmed cases of Coronavirus infection was 424.51 million, and the number of deaths related to COVID-19 reached 5.89 million. The SARS-CoV-2 coronavirus pandemic is the largest pandemic since influenza in 1918 and the largest global crisis since World War II [7], [8].

Research indicates that the environmental effects of COVID-19 are complex and multifaceted. While some studies have shown a decline in air quality, there is also evidence of positive impacts on the natural world. Additionally, various factors play a role in the transmission of the virus and its impact on public health [9], [10], [11], [12], [13], [14], [15], [16], [17]. Recent studies have revealed that COVID-19 has had significant impacts on multiple aspects of society, including biological and behavioral factors, economic benefits, and psychological well-being. These effects have the potential to be both negative and positive, with long-term consequences that are still being analyzed [18], [19], [20], [21], [22], [23], [24], [25], [26], [27].

The scope and gravity of the challenge posed to the healthcare system by the disease, which often requires hospitalization and specialized care, has quickly brought the capacity of the system to a critical level. Therefore, the use of nonpharmaceutical interventions (NPIs) has become crucial. NPIs range from the lightest, such as social distance, increased hygiene, and use of personal protective equipment (masks, gloves, visors), to measures that restrict social freedom, including the recommendation to work and study remotely and lockdown.

There are two predominant approaches to dealing with the pandemic: (1) mitigation, which seeks to slow the proliferation of the virus through non-pharmaceutical interventions (social distancing, isolation, etc.) implemented to flatten the incidence curve over time and reduce the exposure of the most susceptible individuals, and (2) suppression, which involves taking decisive actions (mainly lockdowns) that have the effect of suppressing the spread of the virus and consequently minimizing the number of infections and keeping them low [7], [28], [29], [30], [31]. The effectiveness of NPIs depends

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not only on the discipline of the society but also on how they are implemented by local and state administrations. It is the responsibility of policy makers to develop strategies to manage pandemic prevention and implement measures that affect the economy and functioning of the country. Each of these strategies and measures entails economic and social costs that burden countries and regions to varying degrees [32], [33], [34], [35], [36], [37].

To evaluate the effectiveness of these NPIs, most scientists use the basic reproductive number $\mathcal{R}_0$ defined in Lau et al. [38] as the "number indicating disease transmission, which reflects the average number of secondary infections produced by a typical infection case in a population where everyone is susceptible". The value of $\mathcal{R}_0$ determines whether the infection will spread exponentially ($\mathcal{R}_0 \geq 1$), die ($\mathcal{R}_0 \leq 1$), or remain constant ($\mathcal{R}_0 = 1$) [39], [40]. As the research presented in Xiang et al. [41], shows, there are significant differences in the effects of various interventions at the time of the pandemic. For example, according to Hellewell et al. [42] contact tracking allows outbreak control even with $\mathcal{R}_0 = 3.5$. Such a high level of $\mathcal{R}_0$ requires the tracking and isolation of more than 90% of contacts which, as the authors point out, is a considerable problem. However, tracking and isolation are effective in the early stages of an outbreak. In Koo et al. [43] is presented the impact analysis of NPIs on $\mathcal{R}_0$: combined NPIs that involve quarantining the infected as well as their families, keeping distance on the job, and closing schools can significantly reduce $\mathcal{R}_0$. It should be noted that the impact of these measures depends on the initial level of $\mathcal{R}_0$. According to the authors of this article, using all interventions simultaneously as soon as possible is the most effective. Namely, with $\mathcal{R}_0 = 1.5$, the median of the infected can decrease by 99.3%, and for $\mathcal{R}_0 = 2.5$ it is only 78.2%.

The objective of our work was to develop a tool to support the process of making strategic decisions about the COVID-19 pandemic by optimizing suppression intervention schedules. Suppression requires decisive actions (in this article, we focus mainly on hard lockdown) that have the effect of containing the spread of the virus and, consequently, minimizing the number of infections and keeping the incidence of COVID-19 at low levels. As already stated, properly implemented restrictions can reduce $\mathcal{R}_0$ to less than 1 and thus push the pandemic back. On the contrary, lifting restrictions results in a marked increase in $\mathcal{R}_0$ and the development of a pandemic. The model proposed in this paper indicates the optimal moments to implement full lockdown, accounting for both the cost of lockdown and the cost of not applying lockdown.

Since its inception, the development of the COVID-19 pandemic has been the subject of scientific research in epidemiology, statistics, data science, and mathematical modeling with the aim of predicting the rate of virus spread, as well as the consequences of individual decisions in the short and long term [44], [45], [46], [47], [48], [49], [50]. Models used to predict the course of a pandemic and plan the actions to be taken to defeat it. It enables us to distinguish two main groups of models supporting decisions during a pandemic: (1) predictive, which aim to forecast the selected characteristics that determine the development of a pandemic, and (2) decisional, which aim to support decision makers in NPI planning. Most research is focused on developing predictive models. However, only the appropriate use of these predictions in the decision-making process can allow for an effective fight against the pandemic and its implications. Therefore, decision-making issues have become the focus of the research described in this article. The proposed NPI scheduling model is decisional in nature and can be based on the information provided by any predictive model. Presenting the essence of the proposed decision support model requires knowledge about the values of parameters over time, e.g., the basic reproduction number ($\mathcal{R}_0$), Susceptible (S), Insusceptible (P), Exposed (E), Infective (I), Quarantined (Q), Recovered (R) and Death (D), contact number (σ) and replacement number ($\mathcal{R}''$), referred to as the characteristics in this paper. The source of knowledge about these characteristics is the predictive models described above [46], [50], [51], [52]. The values of these parameters are estimated on the basis of real data measured for the observed phenomenon. A particularly important problem in the application of predictive models to make short- and long-term forecasts is the proper estimation of the value of the parameter $\mathcal{R}_0$ [54], [55], [56], [57].

As shown in Li et al. [53], a hard lockdown can contribute to reducing the parameter $\mathcal{R}_0$ below the critical value $\mathcal{R}_0 < 1$: $\mathcal{R}_0$ for South Korea before the implementation of restrictions was almost 4.2, while extensive NPIs caused $\mathcal{R}_0$ to drop to 0.1. Similar results were obtained in Hubei Province, China and Iran. Conterminous findings are presented in Kucharski et al. [51]: the reproduction number $\mathcal{R}_0$ in Wuhan decreased from 2.35 a week before the implementation of the restrictions to 1.05 in the first week after the implementation. However, the results of the study for the Wuhan region presented in Li et al. [58] show that due to the implementation of NPIs, the value of the parameter $\mathcal{R}_0$ decreased from 2.38 to 0.98–1.34 depending on the period analyzed. The examples mentioned above show a strong link between the level of introduced NPIs and the reduction of $\mathcal{R}_0$, thus stopping the development of the pandemic. Needless to say, the interventions mentioned above have profound socioeconomic consequences [33], [35], [36], [37], so it is crucial to choose the right set of interventions, the timing of implementation and the duration. Furthermore, introducing interventions too late or insufficiently can lead to pandemic overexpansion and ultimately reduce the effectiveness of these restrictions [30], [43], [59], [60].

II. MATERIALS AND METHODS

The model presented in this paper works for each of the characteristics. More importantly, it also works for the simultaneous testing of several characteristics. The waveforms tested must be described using probability functions, for example, the probability of death, the probability of survival or the probability of infection. The Weibull distribution was chosen for this work. It plays a central role in reliability analysis as one of the most important generalizations of the exponential distribution [61]. The continuous probability distribution introduced by Weibull [62] is distinguished by the following distribution function:

$$F(x) = 1 - e^{-(\frac{x}{T})^b} \tag{1}$$

where:

x – non-negative variable, e.g. time

T – scale parameter

b – shape parameter

The scale parameter T is related to the spread rate of the phenomenon analyzed. It represents the value of x, for which the probability of, e.g. infection, death, etc., is about 63.2% [63]. The parameter b can be used to describe various shapes of the distribution function and the probability distribution function over time. The Weibull function has been extensively used for the analysis of COVID-19 pandemics in recent studies [41], [63], [64], [65], [66], [67], [68].

The total number of deaths – Death (D) was chosen as the characteristic analyzed. Data on this and other characteristics used in this work were obtained from the *Our World in Data* [6] website.

The function (1) presented above was used to describe the relationship between the number of confirmed deaths whose main cause was COVID-19 and the duration of the first wave of the pandemic. The first 100 deaths that occurred as a result of SARS-Cov-2 virus infection were assumed to mark the beginning of the pandemic in a given country. The end of the first wave was defined as a decrease in the daily number of deaths to 10. Four European countries – France, Germany, Italy, and Spain – were included in the analysis, and the entire set of historical data was used to create a set of sample empirical distribution functions that served as the basis for determining the parameters of the Weibull distribution. The distributions and actual data for each country are presented in Figure 1. The Weibull function for the parameters $T = 36.496$ and $b = 1.669$ is colored purple.

It should be noted that the selected characteristics, the function built on its basis, and the adopted methodology are illustrative and are the starting point for the construction of a decision support tool.

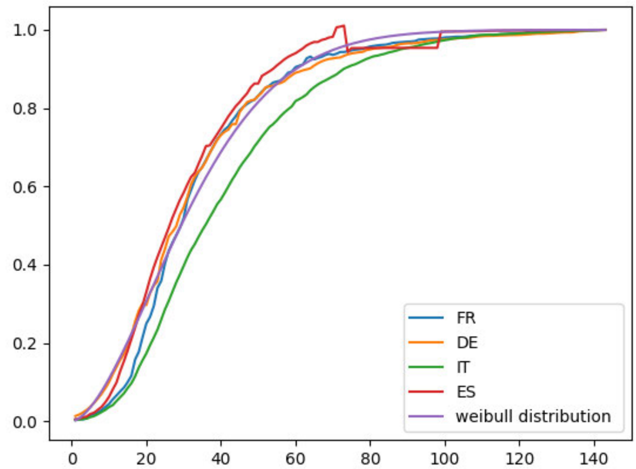

FIGURE 1. Empirical distributions for the number of deaths during the first wave of the pandemic in the analyzed countries compared with the Weibull function for parameters $T = 36.496$ and $b = 1.669$.

A. MATHEMATICAL MODEL OF THE LOSS MINIMIZATION PROBLEM

This section presents a proposed new mixed integer programming model (MIP) that seeks to minimize the total losses for a certain analyzed process that can be described by a set of its characteristics $\mathcal{E}$. Each characteristic $e \in \mathcal{E}$ is described by its maximum attainable value Ω_e in the studied period (e.g., the total number of deaths in the first wave of the pandemic) and by a certain probability function of reaching the maximum value of Ω_e. We write a discrete function for successive periods p of the planning horizon and a given characteristic e and denote it by A_{pe}.

We can define the behavior of a given characteristic e over time as the emergence of the lost value, which in subsequent p periods is expressed by decreasing the expected value determined as $\Omega_e \cdot A_{pe}$. The defined lost value for a given characteristic is greater if the number of consecutive periods in the planning horizon is high (in each consecutive period, the probability of achieving the Ω_e value decreases). To break the loss of value, it is possible to implement a certain action at any time (e.g., hard lockdown) that will have the effect of restoring a given characteristic e to its initial probability value A_{0e}. The period for which the restoration action is in effect is called the reset of a given characteristic e, and its length n_e must be specified in advance.

Let $\mathcal{T}$ denote the set of consecutive identical periods on some fixed time horizon, starting from period 0 to period m. Therefore, $\mathcal{T} = [0, \ldots, m-1]$ is a set of m consecutive identical planning periods.

Let $\mathcal{E}$ be the set of certain process characteristics for which the probability of value loss over time is expressed by an arbitrary decreasing function. Hence, $\mathcal{E} = [0, \ldots, l-1]$ is the set of l characteristics.

Let $\mathcal{P}_e$ be the set of successive values of the probability function that will be assigned appropriately to a given period t, starting from element 0 to element k_e. Hence, $\mathcal{P}_e = [0, \ldots, k-1]$ is the set of k consecutive decreasing values of the probability function for the characteristic e.

Furthermore, let $\mathcal{T}'_e$ be the set of consecutive periods that must be assigned to the reset of characteristic e. Since n_e denotes the required number of these periods. Therefore, $\mathcal{T}'_e = [0, \ldots, n_e - 1]$ is the set of n_e consecutive reset periods for the characteristic e.

Let the values of successively decreasing probabilities for each characteristic be represented by the parameter A_{pe}. In other words, A_{pe} is the value of the probability function for the characteristic $e \in \mathcal{E}$ for the element $p \in \mathcal{P}_e$.

Let Δ denote the smallest decrease in probability between successive A_{pe} values for all functions that describe each characteristic. This means that Δ is the minimum probability loss between consecutive values of the function for particular characteristics. Analogously, Ω_e is the maximum probability value that describes the characteristic e.

The parameter Γ represents the periodic cost of performing a reset, that is, the cost of introducing lockdowns.

Let the binary variable y_{pet} be equal to 1 if a given A_{pe} value of probability p for a given characteristic e is assigned to period t, otherwise $y_{pet} = 0$.

Let the binary variable $z_{t',t,e}$ sequentially take values equal to 1, that is, $z_{n_e-1,t-n_e,e} = 1$ if the reset of a given characteristic e begins in period $n_e - 1$ (lockdown starts) and $z_{0,t,e} = 1$ if the reset finishes in period t(lockdown ends), otherwise $z_{t',t,e} = 0$.

Let the binary variable x_t, respectively, take a value equal to 1, if a reset of at least one characteristic is in progress in a given period t, otherwise $x_t = 0$. The variable x_t is used to aggregate the periods mentioned for the set of characteristics.

The MIP model for the loss minimization problem in a process where the probability of a lost value for its individual characteristics is described by a time-dependent probability function, which can be formulated as follows:

$$\text{maximize} \sum_{e\in\mathcal{E}} \sum_{p\in\mathcal{P}_e} \sum_{t\in\mathcal{T}} \Omega_e A_{pe} y_{pet} - \Gamma \sum_{t\in\mathcal{T}} x_t \tag{2}$$

$$\sum_{p\in\mathcal{P}_e} y_{pet} \leq 1 - \sum_{t'\in\mathcal{T}'} z_{t't};\ t \in \mathcal{T}, e \in \mathcal{E}; \tag{3}$$

$$\sum_{p\in\mathcal{P}_e} (A_{pe} y_{p,e,t-1} - A_{pe} y_{pet}) \geq \Delta - M \sum_{t'\in\mathcal{T}} z_{t',t-1,e};$$
$$t \in \mathcal{T}, e \in \mathcal{E} : t > 0; \tag{4}$$

$$z_{t'te} = z_{t'+1,t-1,e};\ e \in \mathcal{E}, t' \in \mathcal{T}'_e, t \in \mathcal{T} : t' < n_e, t \geq n_e; \tag{5}$$

$$\sum_{t'\in\mathcal{T}'_e} z_{t'te} \leq 1;\ e \in \mathcal{E}, t \in \mathcal{T}; \tag{6}$$

$$M \cdot x_t \geq \sum_{e\in\mathcal{E}} \sum_{t'\in\mathcal{T}'_e} z_{t'te};\ t \in \mathcal{T}; \tag{7}$$

$$y_{tet} = 1;\ t \in \mathcal{T}, e \in \mathcal{E} : t < n_e; \tag{8}$$

$$z_{0te} = 0;\ t \in \mathcal{T}, e \in \mathcal{E} : t < n_e; \tag{9}$$

$$y_{pet} \in [0, 1];\ p \in \mathcal{P}, e \in \mathcal{E}, t \in \mathcal{T}; \tag{10}$$

$$z_{t'te} \in [0, 1];\ e \in \mathcal{E}, t \in \mathcal{T}, t' \in \mathcal{T}'_e. \tag{11}$$

The objective function (2) minimizes the total lost value, the loss of the characteristics under study, over the assumed planning horizon. The expected value $\Omega_e \cdot A_{pe}$ for a given characteristic e in subsequent periods decreases until a reset is performed. Furthermore, the objective function takes into account the periodic cost of performing the reset Γ common to all the characteristics studied. Constraints (3) ensure that for a given period t, only one indicated value of the probability function can be assigned to each characteristic e, but only if there is no scheduled reset in the given period t. The constraint (4) allows, in a consecutive period t, to assign successively decreasing values of the probability function of a given characteristic e, provided that in the previous period $t-1$, the assigned probability was higher at least by the value Δ, or any value thereof if the reset ended in the previous period $t-1$. Note that M is a large constant that is commonly used in sequencing constraints. Constraints (5) and (6) ensure that the reset of the characteristic e lasts for the required number of consecutive planning periods. The constraint (7) ensures the binarity of the variable x_t. Constraints (8) and (9) set the initial values of the variables, respectively.

TABLE 1. Survival function used for computational experiments (A_{pe}).

Weeks	Mortality	Survival	Weeks	Mortality	Survival
1	0.0025	0.9975	11	0.9520	0.0480
2	0.0763	0.9237	12	0.9713	0.0287
3	0.2028	0.7972	13	0.9834	0.0166
4	0.3492	0.6508	14	0.9907	0.0093
5	0.4940	0.5060	15	0.9950	0.0050
6	0.6237	0.3763	16	0.9973	0.0027
7	0.7315	0.2685	17	0.9986	0.0014
8	0.8157	0.1843	18	0.9993	0.0007
9	0.8781	0.1219	19	0.9997	0.0003
10	0.9222	0.0778	20	0.9998	0.0002

III. RESULTS

Figure 1 shows the determined Weibull function transformed to the form $1 - F(x)$ that was used in the calculations. While in its original form we can interpret it as an increased probability of death, after the transformation we will talk about a decreasing probability of survival, which will be the chosen characteristic of the process under study (the duration of the pandemic will be treated as the examined process). The planning horizon will be one year divided into 52 discrete identical planning periods of one week. The values of the "survival" function used in the calculations are provided in Table 1.

Let Ω_e be equal to 1, which, together with the probability function indicated earlier, we will interpret as the expected survival value for a certain individual positive for COVID-19 and belonging to the group D (that is, Deaths in the sense of interval deterministic prediction models), and let Γ be equal to 0.

The periodic loss minimization cost Γ can be interpreted as the cost of implementing lockdown in a given period. This parameter, together with the appropriately adopted values of Ω_e – both Ω_e and Γ must have equivalent units – will allow minimizing the total cost of the pandemic. This approach increases the functionality of the model, but at the same time imposes the need to estimate Ω_e in the given units (e.g. monetary). It is obvious that in many situations such quotation is problematic not only for technical but also ethical reasons. As presented above, the correct operation of the model does not require the use of this functionality. It can be used when decision makers have the knowledge necessary to describe the maximum value of the characteristic and lockdown costs in a unified unit. The approach proposed in this example – Ω_e equal to 1 and Γ equal to 0 – can be interpreted as assuming an infinitely large value for human life. The common parameters assumed for all calculations are summarized in Table 2.

The calculations were performed for scenarios that differed in lockdown duration. The duration of a lockdown was assumed to be between 1 and 10 weeks; however, as the

TABLE 2. A summary of the parameters used in the calculations.

Parameter	Value
M	10.0000
Δ	0.0001
A_{pe}	see Table 1
Ω_{e}	1.0000
Γ	0.0000

studies presented in the introduction of this article suggest, a restrictive lockdown lasting 1-2 weeks can reduce $\mathcal{R}_0$ of the COVID-19 pandemic to about 1 – the level at which standard preventive measures (for example, contact tracking, quarantine) are sufficient.

The resulting weekly distribution of the maximum expected value for one person's "survival" function (or, conversely, the minimization of "mortality") and lockdown duration is shown in Figure 2. Solutions for different lockdown periods are presented there. The gray bars represent the expected value of survival, while the gaps reflect the lockdown periods. The model aims to increase the gray bars' "area", i.e., the cumulative "probability of survival". Thus, the first chart from the top – lockdown lasting 1 week – suggests that according to the model, the lockdown should be implemented in week 3 and then in week 8. Conversely, in the fourth chart from the top – lockdown lasting 4 weeks – the lockdown is planned for week 5. It can also be observed that in the case of a lockdown longer than 7 weeks, the model allows for a much greater decrease in the probability of survival. This may be due to the short planning horizon. The optimal solution of this model for the mentioned lockdown periods would probably change in a longer time perspective. However, such a perspective is not needed in the case analyzed.

Another conclusion that can be drawn from the model sensitivity analysis presented in Figure 2 is that the shorter the lockdown, the more often it can be applied, especially since the total lockdown period may be shorter – of course, this applies only to strict and fully enforced lockdown. In other words, for the analyzed case, due to the adopted objective function, the most effective solution involves frequent, yet short, lockdowns.

The optimal values obtained for the objective function in particular solutions are presented in Figure 3. The total expected value of survival determined by the first segment of the objective function (2) is represented by the gray line in Figure 3.

Interpreting the relationship between the duration of the lockdown and the change in the objective function presented in Figure 3 may lead to the misconception that the longer the lockdown, the smaller the survival chance. This is not a valid conclusion, as the objective function does not take into account the chance of survival during the lockdown period. The solution to this problem may be to include the probability of survival during the lockdown period in the model, which is the authors' goal in their future work. However, in the studied case, the main parameter supporting the decision on the duration of the lockdown is the blue line in Figure 3 that represents the average expected μ value of survival

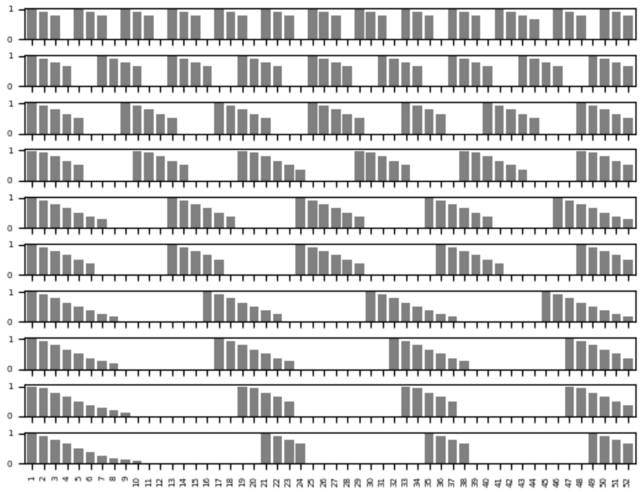

FIGURE 2. Optimal schedules for implementing lockdowns lasting 1,..., 10 weeks over a planning horizon of 52 weeks.

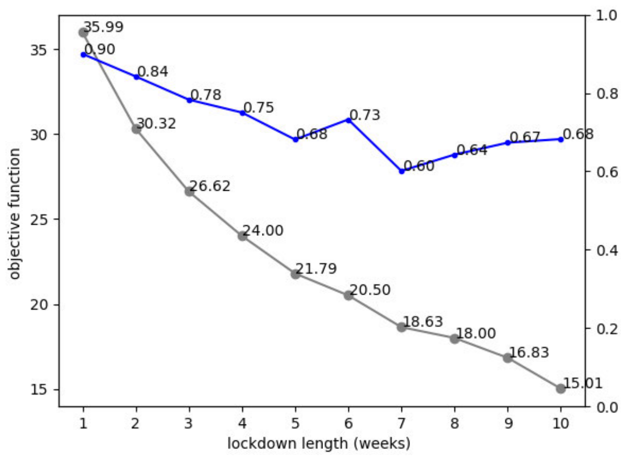

FIGURE 3. Values of the objective function for the assumed lockdown durations and mean value of the objective function for days without lockdowns.

calculated only for periods without lockdown, according to Equation (12).

$$\mu = \frac{\sum_{e\in\mathcal{E}} \sum_{p\in\mathcal{P}_e} \sum_{t\in\mathcal{T}} \Omega_e A_{pe} y_{pet}}{\sum_{t\in\mathcal{T}} x_t} \tag{12}$$

As the duration of a single lockdown increases, the average chance of survival decreases. In the fifth week of lockdown, the chance of survival fluctuates and then increases. This situation may also be influenced by the already mentioned problem of the limited period of analysis (1 year).

The above considerations lead the authors to conclude that the most effective solution would be to implement the shortest possible hard lockdown that would have the strongest impact on a given pandemic. As mentioned in the introduction, in the case of the COVID-19 pandemic, the hard lockdown period that allows us to reduce the $\mathcal{R}_0$ parameter to about 1 is from 1 to 3 weeks [33], [69], [70], [71], [72], [73]. Of course, the period also depends on social factors in a given region, which should be considered when making the decision about lockdown [46], [74], [75], [76], [77].

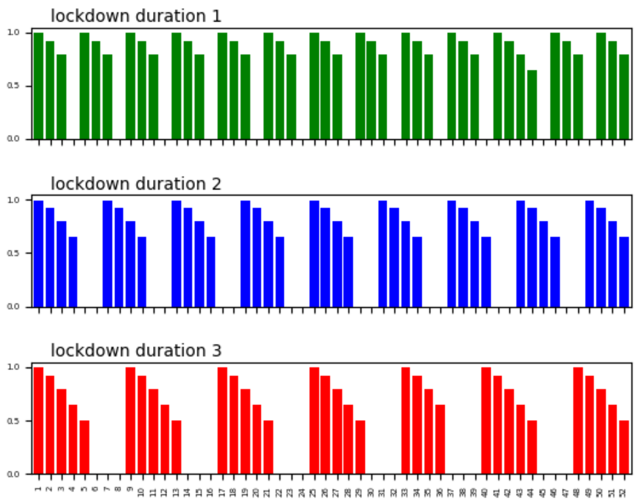

FIGURE 4. A detailed schedule of 1, 2, and 3-week lockdowns.

It is important to remember that the main goal of the proposed tool is not the optimal choice of the duration of the shutdown, but the development of an optimal schedule for the implementation of the shutdown given: (1) the evolution of key characteristics of the studied pandemic is expressed in the probability function – in the analyzed case, it is the Weibull function that represents the probability of survival; (2) the duration of the shutdown 1, 2 or 3 weeks for the COVID-19 pandemic.

Figure 4 presents a detailed schedule for the above assumptions. As shown in Figure 4, in the case of a one-week lockdown, the total lockdown duration over the year is 12 weeks. The society functions normally for a total of 40 weeks divided into 3-week periods. This approach maintains the chance of survival above 80%. In the case of a 2-week lockdown, the analyzed parameters are as follows: (1) the total period of all lockdowns is 16 weeks; (2) the total period of normal functioning of the population is 36 weeks, divided into approximately 4-week periods; (3) the chance of survival remains above 65%;

In the case of a 3-week lockdown, the situation is as follows: (1) the total period of all lockdowns is 18 weeks; (2) the total period of normal functioning of the society is 34 weeks, divided into approximately 4-week periods; (3) the chance of survival remains above 50%.

IV. DISCUSSION

The wavelike spread of the SARS-CoV-2 virus [82] requires the development of adequate and effective tools to support the making of strategic decisions regarding the COVID-19 pandemic by optimizing the schedules for the implementation of subsequent preventive and non-pharmaceutical countermeasures. According to the authors of this paper, such a tools should have the following functionalities:

- Possibility to include at least one characteristic that describes the development of the pandemic: The proposed model can be based on any number of characteristics. As shown in the example (see Section III), in the case of one characteristic, the model indicates the moment of lockdown implementation that is optimal in terms of minimizing the cumulative probability of that characteristic. It is possible to add different characteristics to the model, and the proposed schedule will be optimal in terms of all these characteristics.
- Possibility to include lockdown costs in the analysis – as discussed in Section II-A, the proposed model can independently include lockdown implementation costs and lost value. According to the authors of this and many similar studies (e.g. [70]), such a feature is necessary, for example, to compare the cost of restrictions with the costs of hospitalization. However, such a valuation may be difficult or even impossible. Therefore, this functionality is included in the model as an option.
- Possibility of considering other types of restriction: the proposed model can take into account any type of restriction, as long as its influence on the analyzed characteristics is known and it is possible to predict the course of these characteristics after restrictions are lifted.
- The possibility of simulated different lockdown durations: as presented in the exemplary calculations, the model allows one to conduct a kind of sensitivity analysis in terms of lockdown duration, which facilitates the choice of the optimal period.

It is important to remember that the WHO developed several recommendations to limit the spread of the SARS-CoV-2 virus, but the decisions to implement the actions are the responsibility of local and state authorities. The factor that is always considered when choosing a pandemic management strategy is the capacity of the health care system, as its overload can deprive those severely affected by COVID-19 of professional help. The primary goal of these activities is to spread the peak of the epidemic over time in particular countries and to limit the impact on the economy. Recent studies that predict the occurrence of similar events in the future [64] suggest that the development of tools for the management of pandemic crisis and health management during a pandemic is essential. The presented findings are intended to support decision-makers in a given country or region in making strategic decisions about the implementation of interventions. Final decisions should also take into account social factors in the region analyzed. The implementation of hard lockdowns in European countries differs completely from lockdowns in Asia, which is reflected in the length of a single cycle. It should be emphasized that knowing the lockdown implementation schedule offers many benefits (not only economic, but also social) and reduces the uncertainty associated with planning actions during the pandemic crisis.

The conclusions that can be drawn from the presented analyses, in the context of the overall costs of a pandemic, including not only health costs, but also far-reaching consequences of the freezing economy, are as follows: The period of hard lockdown should be as short as possible (taking into account the nature of the pandemic and social factors in the analyzed region), but it should be implemented periodically.

Such an approach provides a clear and structured schedule of lockdown activation, which ultimately allows minimizing its impact on the functioning of the economy and society as a whole. In summary, a lockdown should be restrictive, periodic, and as short as possible.

V. LIMITATIONS AND FUTURE RECOMMENDATIONS

The limitations of the model described in this paper include the lack of possibility of adjusting for changes in the characteristics studied during the restriction period. In the proposed approach, once the restriction is implemented, the tested characteristic is reset. As a result, the model does not take into account the costs generated by the analyzed characteristics during the restriction period. The authors believe that this simplification does not affect the objective function in the analyzed case of hard lockdown. However, when analyzing other restrictions on simultaneous valuation, for example, in monetary units, the model may not adequately reflect the actual dependencies between the analyzed factors.

Another problem is the lack of the possibility to change the functions describing the analyzed characteristics in subsequent cycles of the schedule. Namely, in the case of an accurate forecasting model for a given characteristic, it is possible to take into account the change of this characteristic in subsequent cycles of the schedule, e.g., the function of infection growth in the case of a new pandemic in the first cycle may drastically differ from the function in the second cycle (this may result from the unavailability of the tests).

Additional limitation of the presented solution is the period and resolution of the analysis. The resolution and computation time depend on the computational power, which is not a significant problem at the moment, and on the precise long-term prediction of changes in the analyzed characteristics. As the literature review demonstrates, this problem has already been extensively described, and the available models are increasingly accurate, for instance, due to the change from deterministic static models to data-driven dynamic models, e.g. using machine learning [41], [78], [79], [80], [81]. Of course, the mentioned problems are the basis for the development of the described model, which is the objective of the authors' further work.

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RADOSŁAW KAPŁAN received the M.S. degree in mechanical engineering and robotics and in management and the Ph.D. degree in industrial engineering from the AGH University of Science and Technology, Cracow, Poland, in 2008, 2010, and 2015, respectively.

Since 2010, he has been a Research Assistant with the Institute of Management, AGH University of Science and Technology. His research interests include evaluation of multi-criteria effectiveness of decision and risk management. He deals also with the broadly understood concept of quality, with a particular emphasis on statistical process control.

ROGER KSIĄŻEK received the M.Sc. degree in management science from the AGH University of Science and Technology, Krakow, Poland, and the Ph.D. degree in industrial engineering. He is currently an expert in the field of operations research and management science. He is also a Researcher and an Assistant Professor with the Faculty of Management, AGH-UST. He specializes in scheduling and planning problems, including project planning and managing problems. He develops optimization models for lot sizing and scheduling, delivery synchronization, bus timetabling, and other problems of industrial logistics. He has authored or coauthored two books, 16 chapters, 11 journal articles, and 22 conference papers.

He is a Co-Organizer of conferences: "International Conference on Industrial Logistics ICIL" (2016) and "International Conference on Decision Making in Manufacturing and Services DMMS," in 2017 and 2019.

KATARZYNA GDOWSKA received the M.Sc. degree in management science from the AGH University of Science and Technology (AGH-UST), Krakow, Poland, the M.A. degree in philosophy from Jagiellonian University, and the Ph.D. degree in industrial engineering.

She is currently an expert in the field of operations research and management science. She specializes in scheduling and planning problems, including project planning and managing problems. She develops optimization models for resource planning, transport, and logistics. She is also a Researcher and an Assistant Professor with the Faculty of Management, AGH-UST. She collaborates with the Industrial Engineering and Management Centre (CEGI), INESC TEC, Porto, Portugal. She is also a certified academic tutor; teaches classes on operations research, computer-aided tools for project planning, and project management. She was a principal investigator in small grants aimed at innovations for SMEs. She was the Team Leader of Erasmus+ CBHE projects: "GameHub University-Enterprises Cooperation in Game Industry in Ukraine" and "MoPED—Modernization of Pedagogical Higher Education by Innovative Teaching Instruments." She is also a Managing Editor of *Decision Making in Manufacturing and Services*.

PIOTR ŁEBKOWSKI received the Ph.D. degree in automatic control and robotics from the AGH University of Science and Technology, Cracow, Poland, in 1986, the Postdoctoral degree, in 2001, and the Doctor (Honoris Causa) degree from the Lviv University of Technology, Lviv, Ukraine.

Since 2003, he has been a Professor with the Faculty of Management, AGH University of Science and Technology. From 2005 to 2012, he was the Deputy Dean of Science and from 2012 to 2020, he was the Dean of the Faculty of Management, AGH-UST. From 2010 to 2016, he was the Secretary of the Production Engineering Committee of the Polish Academy of Sciences and from 2016 to 2017, he was the Vice-President of the Committee. Since 2020, he has been the Head of the Department of Strategic Management, Faculty of Management, AGH. He is the author of 15 books, the scientific editor of 12 books, and more than 230 articles. His research interests include flexible production systems, control of production processes, control in integrated production systems, and operational research.