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AN OPTIMIZATION MODEL TO REDUCE THE HUMAN FATALITIES IN SRI LANKA DUE TO COVID-19 CONSIDERING DIFFERENT NON-PHARMACEUTICAL INTERVENTION PLANS

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By considering Sri Lanka's limited healthcare resources and economic productivity in the absence of a vaccine, this study aims to control an epidemic outbreak while balancing its sanitary and economic repercussions to reduce the effects of COVID-19 and investigate its dynamics. The World Health Organization (WHO) recommended implementing a number of non-pharmaceutical interventions (NPIs). As a result, certain combinations of NPIs together with lockdowns were used to control the outbreak in Sri Lanka. These control measures are not only economically expensive but also have the potential to cause political instability, societal exhaustion, and annoyance. NPIs' stringency has reduced the number of deaths due to COVID-19, but it has also had negative consequences for the public and commercial sectors, hindering economic growth and significantly affecting people's mental health. In order to assist policymakers in assessing the level of funding that the nation can afford to reduce the spread of disease and, as a result, the number of fatalities, we propose an optimization model after carefully analyzing the Sri Lankan epidemic context. By empowering policymakers to execute a series of NPIs in the relevant district using the available but constrained health care resources, we aim to identify a method to reduce the number of deaths within the various budget options. The first step is to apply a Mixed Integer Non-Linear Programming epidemic model to determine the optimal NPI sequence for each of the 25 districts over various planning horizons. Non-linear terms in the model are linearized to transform this Mixed Integer Non-Linear Programming model to a Mixed Integer Linear Programming model. This Mixed Integer Linear Programming model is thus transformed into an Integer Linear Programming model using the decreasing severity property of the NPI sequence. For each district, three plans, namely P_1, P_2, and P_3, are taken into consideration. There are no limitations on lockdowns in the plan P_1, but plans P_2 and P_3 included relaxations on the implementation of lockdowns. By altering the budget, the fatality is estimated over the three plans. The IBM ILOG Optimization Studio is used to solve the Mixed Integer Linear Programming model. This study shows that the NPI sequence, which has stringent lockdown conditions, is a better implementation plan to minimize the infection and, consequently, minimize the fatality in the country.

Keywords: COVID-19, Integer Linear Programming model, non-pharmaceutical interventions, NPI sequence, severity property

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Introduction

COVID-19 (coronavirus disease 2019) is a disease that originated in the People's Republic of China in late 2019 (WHO COVID-19 Dashboard, 2020). It is the only viral disease declared as a global pandemic by the World Health Organization (WHO). Non-Pharmaceutical Intervention (NPI) is one of the positive mitigation measures to control an epidemic like COVID-19. Globally, the confirmed cases emerge periodically, and by September 17, 2021, the virus had affected 218 countries, with the number of confirmed cases surpassing 226.8 million and total deaths being 4.67 million. (www.covid19.who.int). According to the available statistics, Sri Lanka has recorded a cumulative of 672,746 cases, with the total deaths is 16,897 and the total recovery cases is 655,848. The Government of Sri Lanka and other severely affected countries responded to the outbreak by implementing possible NPI sequences to control the transmission of the disease and hence minimize the fatality.

In order to identify the optimal NPI sequence that lowers infections and deaths while manipulating the healthcare resources and financial limitations, this study presents a mathematical optimization approach specifically designed for Sri Lanka. We examine the efficacy of different NPI tactics across three national plans using a modified SICRD epidemiological model combined with resource limitations and a national severity budget. The findings show that, implementation of strict lockdowns, despite financial costs, greatly reduces infections and deaths.

Materials and Methods

SICRD Compartmental Framework

In this section, we recall the classical compartment model proposed in (Kermack, W.O. & McKendrick, A. G., 1932) and the extension of this model proposed in (Biswas, D., Alfandari, L., 2022) to study the dynamics of the spread of COVID-19 in Sri Lanka. Accordingly, the Sri Lankan population was divided into five compartments, namely Susceptible (S), Infected (I), Critical/Hospitalized (C), Recovered (R), and Dead (D). Further, considered NPSs and the five NPI levels as shown in Table 1. We adopt the same notations for the parameters, but the values are replaced according to the Sri Lankan context.

Reduction Factor (α_i) and Severity Cost (c_i)

The measures to reduce social activities, in particular, physical contact between people, negatively impact the economic activities of the country. Therefore, the implementation of NPI, while ensuring a reduction in transmission rate by reducing the physical contacts between people, leads to a reduction in productivity and hence has a cost impact. Severity budget is an indicator of the maximum economic loss that the policy makers are willing to offer to safeguard public health. In some literature, this metric is also interpreted as a loss of labor hours due to containment measures. To compute severity cost (c_i), which is a convex, quadratic function of the reduction factor α_i, we follow the social contact matrix calculation proposed by (Prem, K., Cook, A., R., & Jit, M. , 2017) and simplified by (Biswas, D., Alfandari, L., 2022) and use the relation $c_i = \alpha_i^2$ (Charpentier, A., Elie, R., Lauriere, M., & Tran, V., C. , 2020).

National Severity Budget (B)

The national severity budget is a measure of the greatest financial sacrifice that the decision-maker is prepared to pay to protect the health of the public. Table 1, given below, shows the notation of different NPIs that we considered in this study and their description:

Notation	**Description**
I	Isolation/Quarantine of vulnerable/symptomatic people for 7 days
T	Travel restrictions
S	Closure of schools/ universities
G	Public gathering ban >50 people
L	Complete lockdown

Table 1

NPI Level (i)	**NPI Combination**	**c_i**	$\alpha_i = \sqrt{c_i}$
1	I	0.03	0.17
2	I+T, I+G, I+S	0.11	0.33
3	I+T+S, I+T+G, I+S+G	0.17	0.41
4	I+T+S+G	0.35	0.59
5	L	0.68	0.82

Table 2

Table 2 shows the five NPI levels and their combinations, severity cost, and reduction factor.

The decision variables, objective function, and constraints have the following mathematical definitions, given in Table 3:

β_k : weekly transmission rate of infection per infected person in district k	β_k^H : weekly transmission rate at which doctors are infected in the district k
ρ: proportion of infected people who need hospitalization	θ: proportion of hospitalized people who require ICU care

λ_1: proportion of ICU cared people who recovered	λ_2: proportion of non-ICU cared people who recovered
γ_1: weekly rate at which ICU-cared person leaves the hospital	γ_2: weekly rate at which non-ICU cared patients leave the hospital
μ: weekly rate at which a non-severe infected person recovers	ϕ: weekly rate at which infected patients enter the critical compartment
r^H: percentage of infected doctors who become re-infected	i: index for the NPI level, $i \in N = \{1,2,3,4,5\}$
t: index for time period (weeks), $t \in \{1,2,\dots T\}$	r: index for medical resources, $r \in \{1,2,3\}, 1 = Doctors, 2 = ICU, 3 = Regular\ beds$
k: index for the district, $k \in \{1,2, \dots, 25\}$	$b_{3,k}$: number of regular beds in district k
n: number of patients attended by one doctor	
$b_{2,k}$: number of ICU beds in district k	B: upper bound on the average severity of NPIs per individual, per period (budget)
$\eta_{r,k,t}$: proportion of resource r allocated for non-COVID cases in period t, district k	P: total human population in Sri Lanka
ε: percentage of critical patients who self-isolate	$I_{k,t}, C_{k,t}, H_{k,t}$: epidemic state variables, when $k = 1$these are epidemic state values
P_k: Human population in district k	$Q_{r,k,t}$: Minimum between the number of patients needing (demand) and actually availing (capacity) resource r at week t in district k
$S_{r,k,t}$: Number of units of resource r in shortage at week t in district k	$Z_{r,k,t} = 1$, if demand for the resource r exceeds supply, 0 otherwise
$Z_{0,k,t} = 1$ if the number of untreated patients due to shortage of doctors is less than the number of untreated	$W_{k,i,t} = 1$ if NPI level i is not selected for the week $t-1$ and selected for the week t, 0 otherwise

patients due to shortage of regular beds , 0 otherwise, at week t in district k	

Table 3

Decision variables for MINLP

$$x_{k,i,t} = \begin{cases} 1, \text{if NPI level } i \text{ is selected for week } t \text{ of district } k \\ 0, otherwise \end{cases}.$$

The objective function, to minimize the number of infections, of the MINLP model is $\sum_{k=1}^{25} \sum_{i\in N} \sum_{t=1}^{T} \beta_k (1-\alpha_i)(1-\rho\varepsilon) I_{k,t} x_{k,i,t}$. In this model, shortages in healthcare resources are captured, and their impacts on the epidemiological state variables are given in the last three constraints. Proposed MINLP model converted to MINP model by linearizing the quadratic terms involved. Consequently, when we apply the descending severity property of the sequence of NPI, which will be discussed in the next section, all the state and shortage variables can be calculated from the data related to COVID-19 in Sri Lanka.

Additional constraints on NPI sequences

In this section, three plans $P_1, P_{2,}$ and P_3 are introduced, where plan P_1, is considered as a default model as no restrictions are imposed on lockdowns, while plans P_2 and P_3 have.

Plan P_1: The time horizon considered is T weeks with no more than l_0 number of changeovers:

i. $x_{k,i,t} + \sum_{j\in N\backslash\{i\}} x_{k,i,t-1} \geq 2W_{k,i,t}, \;\; \forall\, i \in N, \;\; \forall\, t \in \{1,2,\dots,T\}, \;\; \forall\, k \in \{1,2,\dots,25\}$

ii. $x_{k,i,t} + + \sum_{j\in N\backslash\{i\}} x_{k,i,t-1} - W_{k,i,t} \leq 1, \;\; \forall\, i \in N, \;\; \forall\, t \in \{1,2,\dots,T\}, \;\; \forall\, k \in \{1,2,\dots,25\}$

iii. $\sum_{t=1}^{25} \sum_{i\in N} W_{k,i,t} \leq l_0 \; \forall\, k \in \{1,2,\dots,25\}$

If an NPI is selected, it should be for at least two consecutive weeks:

i. $x_{k,i,t+1} \geq W_{k,i,t}, \quad \forall\, i \in N, \;\; \forall\, t \in T-1, \;\; \forall\, k \in \{1,2,\dots,25\}$

ii. $x_{k,i,t+1} \geq x_{k,i,t}, \quad \forall\, i \in N, \;\; \forall\, t \in \{1,2,\dots,T-1\}, \;\; \forall\, k \in \{1,2,\dots,25\}$

Plan P_2: No more than $l_1$weeks of lockdown during the planning horizon

iii. $\sum_{t=1}^{T} x_{k,5,t} \quad \leq l_1, \quad \forall\, k \in \{1,2,\dots,25\}$

Plan P_3: Maximum l_2 weeks of consecutive lockdowns with a minimum gap of l_2' weeks during the planning horizon

iv. $\sum_{t=t'}^{t'+l_2} x_{k,5,t} \leq l_2, \quad \forall\, t' \in \{1,2,\dots,T-l_2\},\ \forall\, k \in \{1,2,\dots,25\}$

v. $\sum_{t=t'}^{t'+l_2'-2} x_{k,5,t} \leq (l_2' - 1)\left(2 - x_{k,5,t'-2} - \sum_{i=1}^{4} x_{k,i,t'-1}\right),\ \forall\, t' \in \{3,4,\dots,T+2-l_2'\}, k \in \{1,2,\dots,25\}$

The Sequence-based optimization model

Lemma 1: For a given feasible solution, if for some district the NPIs at two periods t_1 and t_2,

where $t_1 < t_2$, are swapped, then the number of deaths in the period $t_2 + 1$ remains equal. Note that this lemma does not say that the cumulative number of deaths until the week $t_2 + 1$ is equal.

Lemma 2: If a solution satisfies $x_{k,i_1,t_1} = 1$ and $x_{k,i_2,t_2} = 1$ with $t_1 < t_2$ and $\alpha_{i_1} < \alpha_{i_2}$, then the swap $x_{k,i_2,t_1} = 1$ and $x_{k,i_1,t_2} = 1$ will strictly improve the objective value.

Proposition 1: For the plans P_1 and P_2, the optimal NPI sequence is always ordered in descending order of severity.

Proposition 2: For the plan P_3, the optimal NPI sequence always follows an ordered sequence from higher to lower severity for every subsequence containing a lockdown, and for non-lockdown NPIs across subsequences.

Using the above propositions 1 and 2, it can be generated a set called ***sequence-set*** satisfying the property of descending severity, together with the budget constraint, and satisfying the constraints associated with plans P_1, P_2 and P_3. Therefore, the cost of each sequence $S \in sequence-set$ can be calculated as $c_s = \sum_{i \in N} \sum_{t=1}^{T} q_{s,i,t}\, c_i$, where $q_{s,i,t} = 1$, if NPI level i is assigned for the week t in sequence S, 0 otherwise. By doing so, the state variables and shortage variables become constants and can be calculated for the model, and let $\bar{I}_{k,s,t}, \bar{C}_{k,s,t}$ and $\bar{H}_{k,s,t}$ represent the state values corresponding to the sequence S at week t at district k, let $\bar{Q}_{r,k,t}, \bar{Q}_{0,k,t}$ and $\bar{S}_{r,k,t}$ represent the same parameter values.

In the Sri Lankan context, according to the Department of Census and Statistics, there are 47,717 registered government doctors and 90,240 hospital beds. Statistics in the Health Departments reveal that the number of doctors: population ratio is 2.153:1000, and the number of beds: population ratio is 407:100,000 (in main cities like Colombo 600:100,000), while the ICU beds: population ratio is 2.5:100,000. But according to the WHO guidelines, the ICU: non-ICU beds ratio must be at least 13:1000, but at present it is 6.143:1000 (Rashan, H., Silva, A ., D., et al., 2014). From these data, district-wise shortages in doctors, ICU-beds, and non-ICU beds can be determined to feed into the model.

For this developed ILP model, the new decision variables and the model are as follows:

$$y_{k,s} = \begin{cases} 1, \text{if sequence } s \in \text{Sequence} - \text{set is selected for district } k \\ 0, \text{otherwise} \end{cases}$$

$$Minimize \sum_{k=1}^{25} \sum_{S \in \text{Sequence}-\text{set}} \sum_{t=1}^{T+2} [\gamma(1-\lambda)\bar{C}_{k,s,t} + \bar{S}_{2,k,s,t}]y_{k,s}$$

subject to

- $\sum_{S \in \text{Sequence}-\text{set}} y_{k,s} = 1, \ \ \forall\, k \in \{1,2,\ldots,25\}$
- $\frac{1}{P\,T}\sum_{k=1}^{25}\sum_{S \in \text{Sequence}-\text{set}} p_k c_S y_{k,s} \le B$
- $y_{k,s} \in \{0,1\}, \ \forall\, S \in \text{Sequence} - \text{set}, k \in \{1,2,\ldots 25\}$

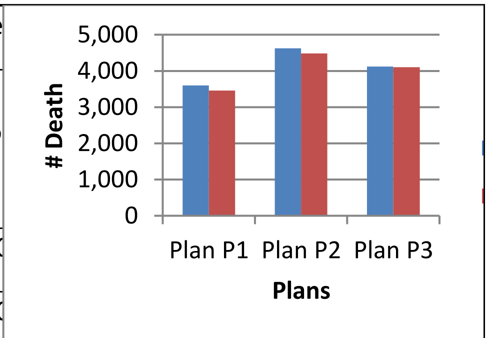
In the objective function, the time horizon is extended to $T+2$, as the impact of the NPI in the week T affects the infection level of the week $T+1$, and the critical infection in $T+2$, which influenced the death, together with the factor $\bar{S}_{2,k,s,t}$.

Results and Discussion

The Python programming language is used to generate the NPI sequences associated with each plan. The first column in Table 4 shows the total number of sequences corresponding to the values T=8 and T=10, respectively, and the subsequent columns show the number of sequences satisfied descending severity property together with conditions stipulated in the respective plans P_1, P_2 and P_3:

` Total # sequences (5^T)		# feasible sequence		
		Plan P_1	Plan P_2	Plan P_3
8	300,625	115	106	10[illegible]
10	9,765,625	225	206	18[illegible]

Table 4



Graph 1

For initiating the progression of the epidemic, it is assumed that 0.004% of the population of each district is infected at the beginning of the planning horizon. Further, it is assumed that $l_0 = 0.2\text{T}$, $l_1 = 0.5\text{T}$, $l_2 = l_2' = 3, \eta_{r,k,t} = 0.1, \lambda =$

0.971, $\gamma = 0.6501$, $\rho = 0.1$, $\varepsilon = 0.18$, $\mu = 0.24$, $\phi = 1$, (Wickramaarachchi, W . P. T. M., Perera, S. S. N., & Jayasinghe, S. , 2020).

The above ILP model was executed by using the optimization tool CPLEX Studio IDE 22.11 on an Intel(R) Core (TM) i5-5300U CPU @ 2.30 GHz, 8 GB RAM system. Graph 1, given above, shows the optimal number of deaths in plans $P_1, P_{2,}$ and P_3 for the time horizon, T=8. From Graph 1, it can be confirmed that if the policymaker reduces the National Severity Budget, the number of deaths will increase. Further, in comparison with the three plans, with a planning horizon of 8 weeks, the infection level is low in the Plan P_1 as it does not impose any restrictions on the lockdown, while in the Plan P_2 , the number of weeks of lockdown and, in Plan P_3 length of the lockdown, as well as gaps between blocks of consecutive lockdowns are restricted. In Plan P_1, when B=5, we obtained the optimum number of deaths as 3,456; when B=4, it increased to 3,600. In Plan $P_{2,}$ these values are 4,620 and 4,478, while in Plan P_3, 4,123 and 4,099, respectively. On one hand, these calculations show that the Plan P_1 is the best choice to minimize the number of deaths in Sri Lanka. On the other hand, the country is severely impacted economically when Plan P_1 is strictly imposed. According to the Sri Lankan government's official website (Ministry of Health, 2021), the number of deaths in the third wave, which spans an eight-and-a-half-month duration (15.04.2021 to 31.12.2021), the number of deaths was 14,375, which is a compatible result that we obtained in Plan P_1 with a planning time horizon of 8 weeks.

CONCLUSION

This work presents a MINLP optimization model for reducing the number of deaths due to COVID-19 in a given population, taking into account financial limitations on the policymaker's chosen set of NPIs as well as healthcare resource shortages. The traditional SIR epidemic compartmental model of Kermack (1932) is used with certain modifications to represent the dynamics of COVID-19. We account for healthcare resource limitations in terms of doctors, ICU beds, and normal beds. The original MINLP model was linearized and then leveraged the property that NPI severity decreases over time to transform it into a solvable ILP model. We applied social contact matrices from empirical research, as well as recorded data with respect to the epidemic from Sri Lankan government official websites and Sri Lankan COVID-19-related articles for the study. Despite the dynamic nature of the epidemic and the uncertainty surrounding data, these findings provide policymakers with some guidance for adopting NPIs optimally while considering both the sanitary and economic consequences of their actions. We derived a compatible number of deaths in Plan P_1 with the most devastating third wave of COVID-19 in Sri Lanka. Therefore, it can be concluded that this study has proven that the proposed mathematical model is capable of making decisions to minimize death due to the outbreak of COVID-19, and also with necessary modifications to the model in managing future outbreaks of this nature.

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