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Nowcasting the COVID-19 epidemic in the Maldives

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ABSTRACT *The novelty of COVID-19 prompted reliance on mathematical modelling to guide decision making and planning pandemic response. The compartment model using suspected, infected recovered and death (SIRD) as used in the Maldives to forecast the epidemic which was nowcasted (adjusted in real-time) to produce parameters on epidemic progression in the Male' area to allow for quick decision making. Deriving the model input parameters were challenging and introduced a greater level of uncertainty in model output parameters. Recognition of the data limitation in presenting model outputs allowed for quick decision making in the COVID-19 early phase towards control of the epidemic.*

KEYWORDS *COVID-19, Mathmetical Modeling, Maldives, epidemic progression, SIRD*

Introduction

The COVID-19 pandemic continues to spread across the globe at an unprecedented rate. The novelty of the disease dynamics and unknown virus characteristics propelled the reliance on compartment modelling to understand the transmission scenarios, particularly to determine the epidemic parameters and the effects of interventions. As such, forecasting the epidemic has become an essential tool to inform policies on public health response and containment measures, that is required to make frequent adjustments. Modelling approaches are being used to predict pandemic dynamics, to forecast the spread and to estimate mortality (Anastassopoulou et al., 2020; Hauser et al., 2020; Wu et al; 2020). There are also modelling studies developed for different containment measures and COVID-19 shows the effect of control measures (Ferguson et al., 2020). However, the task is challenging due to the limited data available at early stages of the pandemic that introduces both systemic and statistical errors (Dehning et al., 2020).

While early strategies in the Maldives relied on preventing the introduction of the disease into the country, through a number of measures at ports of entry linked to quarantine and isolation of arrivals, the strategies adopted changed with confirmation of the first imported case in the country (Ministry of Health, 2020). This included a number of containment measures, including closure of schools and government institutions. Even at this early stage, like in many other countries, attempts were made to model the COVID-19 and forecast the epidemic parameters in a situation where the disease is introduced, and local transmission pursues in the Maldives.

The purpose of the modelling was to provide a yardstick to plan containment interventions in the Maldives, particularly Male' area to mitigate and reduce health effects of COVID-19 pandemic. The approach and methods applied to forecast and track the COVID-19 epidemic in the Maldives is described here, including the parameters and assumptions made in making real time adjustments to forecast the epidemic parameters with the mitigation and suppression interventions that were being introduced as the epidemic progressed. In fitting the model to the local population, the different living arrangements of foreign migrants and locals were central to the greater Male'area population.

Literature Review

When the physician Kermack and biologist McKendrik added rates of mortality and rates of birth to standard epidemics, epidemic models were firmly established as applications of interest in the mathematical literature (Kermack et al., 1927). Thus, compartmental models began and have been used as early as 1920s to analyse numerous influenza and other epidemiological outbreaks (Brauer, 2008). This is by far the most common method mathematical modelling used by epidemiologist and is widely used to address practical questions using ordinary differential equations (Pellis et al., 2011).

Thus 'general stochastic epidemic modelling' is usually used for understanding of epidemics referred to SIR (Susceptible, Infected or Recovered) compartment modelling (Clémençon, Chi Tran, & de Arazoza, 2008). SIR model has been used widely to understand MERS-CoV (Hyuk-Jun & Chang, 2017), SARS (Tuen Wai et al., 2003) and the spread of the dynamic epidemics.

The variant of SIR (S-Exposed-IR) is another mathematical tool used in understanding the dynamics and spread of infectious diseases (Höhle & Feldmann, 2007). Dynamic SEIR compartmental models provide a tool for predicting the size and duration of both uncontrolled and managed outbreaks—the latter in the context of interventions such as case detection, patient isolation, vaccination and treatment (Getz et al., 2019). Modified SEIR has also been used to model the COVID-19 (Li et al., 2020).

Another modified version of SIR is S-I-R-Death (SIRD) where the model considers fatalities, similar to Ebola modelling (Osemwinyen & Diakhaby, 2015). As COVID-19 mortality reported is high at 2.3% in certain countries (Anastassopoulou et al., 2020), the SIRD model is opted in this paper for early epidemic forecasting of COVID-19.

Methods

To forecast the COVID-19 epidemic in the Maldives, SIRD compartment model was used which represent the number of susceptible, active cases, recoveries, and fatalities respectively was used. The four variables, $S(t)$, $I(t)$, $R(t)$, and $D(t)$, represent the numbers of people in each component at a particular time (day).

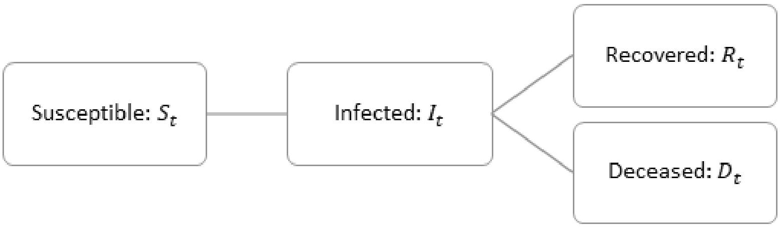


Figure 1. Model used for the epidemic projections

The susceptible (S) becomes infected at rate “β” when they come in contact with the infected and there will be depletion of the susceptible population. They are removed from the population with recovery at rate γ or death at the rate τ. The dynamics of the epidemic is given by the non-linear differential equations below (dots denote time derivatives), as used by Lin, Muthuraman & Lawley (2010).

$$\dot{s}(t) = \frac{ds(t)}{dt} \quad (1)$$

$$\dot{s}(t) = -\big(\beta - u(t)\big)s(t)i(t) \quad (2)$$

$$\dot{i}(t) = \big(\beta - u(t)\big)s(t)i(t) - (\gamma + \tau)i(t) \quad (3)$$

$$\dot{r}(t) = \gamma i(t) \quad (4)$$

$$\dot{d}(t) = \tau i(t) \quad (5)$$

where $s(t) + i(t) + r(t) + d(t) = 1$, $s(t), i(t), r(t), d(t) \geq 0$.
The values used at time 0, $S(t0) = N$, $I(t0) = 2$, $R(t0) = 0$, and $D(t0) = 0$

A total population of 687,426 was used for the country based on the National Statistical Bureau’s (NBS) population projections for the year 2020 and accounting for the migrant population of 100,000 (National Bureau of Statistics, 2018). For Male’ area population of 313,854 (N) was used accounting for undocumented foreign migrants and the NBS projected population for greater Male’ region, with assumed 80,000 people in communal living and 233,854 in households. These population values were used as N at different points of the epidemic. A recovery rate of 98% and case fatality rate of 2% based in the values reported in literature (Verity et al., 2020).
β is derived from product of the probability of exposure to an infected person (p) and probability of falling ill when exposed(q) based on the clinical attack rate. Probability of exposure is defined by k/N, with k is affected by the contact bubble size of a susceptible population and the compliance to containment interventions in the population (Wu & Googan, 2020; Anderson, Heesterbeek, Klinkenberg &

Hollingsworth, 2020). The size of the contact bubble was derived from the Health Protection Agency (HPA) data on contact tracing of COVID-19 cases. Probability of falling ill is maintained at constant rate of 0.15 at all instances when the model was applied (Cheng et al., 2020). Effect of containment interventions were assigned u values based on the interventions implemented informed by published literature (Ferguson et al., 2020). These two variables were the main parameters used to fit the model to the local population. The reproduction number for the model was derived from the following equation.

R_0=(β-u)/(γ*S_((t))) (6)

While this mathematical formula is used, it is important to note that β and u derived to achieve the best fit to the current context and population characteristics. As such, it is recognised that the levels of uncertainty are introduced based on the identification of the parameter and values assumed and may compound the model outputs (Capaldi et al., 2012)
A summary of containment interventions enforced during this period is described in the Table 1.

Table 1
Summary Of Containment Interventions Placed During Early Phases Of The Covid-19 Epidemic In The Greater Male Area

Time period – epidemic week	Containment intervention (Ministry of Health, 2020)
March 2020- imported cases	Closure of schools and educational institutions, mass/social gatherings, establishments, government, mosques, businesses
Week1 (day 0 - April 15, 2020)	Lockdown in greater Male' area, inter-island transport restrictions, facility based quarantine of contacts and isolation of suspected cases in addition to previous restrictions
Week 3	Communal living residences placed under monitoring as containment sites, permit based essential service access, in addition to previous restrictions
Week 5	Communal living residences placed under monitoring as containment sites, permit based essential service access, in addition to previous restrictions

Based on the containment interventions on COVID-19, the following assumptions were made at different points of the epidemic regarding factors affecting k to forecast the epidemic parameters. Effect of the public health intervention (u) were derived from published literature (Davies et al., 2020; Ferguson et al., 2020; Flaxman et al., 2020) and adjusted to the Maldives islands context based on local expert opinion (Table 2). With lock down it is assumed the effect on the population would increase to 40% -60% (40% for people living in households and 60% for those in communal living as a number of these locations were also placed under monitoring) starting from the 3rd week of detection of the community case. The contact bubble size was derived from the contact tracing data provide by the HPA starting from the detection of imported cases and after the detection of community case. Adjustments to the model was made based on assumed compliance to the containment measures. This included discussion with local experts (public health and social science professionals) to arrive at a consensus on likely compliance to the measures given the living and socio-economic challenges prior to and during lockdown. As such, prior to lock down that compliance was assumed to be lower, based on observed and reported behaviour which increased markedly with the lockdown and strict enforcement. Effect of containment measure before community spread was assumed to have 20% and the effect of the interventions were assumed to take effect after 1-2 incubation periods accounting for the incubation period of 5-6 days for SAR-CoV-2 (Lauer et al., 2020). From the outset, testing capability in the country was constrained and hence, an adjustment of 25% was made to model projections to allow for observable number of infections.

Table 2

Assumptions Made On Factors Affecting Probability Of Exposure

	Imported cases	Week1*	Week3	Week5 communal	Week5 household
Containment intervention effect (u) (%)1	20	20	40	60	40
Contact bubble2	36	69	45	33	15
Compliance adjusted3	0.25	0.25	0.3	0.9	0.9
k	9	17	14	30	14

*April 15, 2020. Community case and lock down of Male' area

1Davies et al, 2020; Ferguson et al., 2020; Flaxman et al, 2020

2Derived from the contact tracing data provided by HPA, NEOC Maldives

3Derived from local expert consensus based on socioeconomic and residential conditions

Further, in forecasting the epidemic for week 5, accounts were made to sub populations, for those living in communal setting and those living in family households. This method was adopted since along with containment interventions, a number of communal living residences were placed under monitoring where social distancing measures were not possible resulting in high exposure and transmission in these residences.

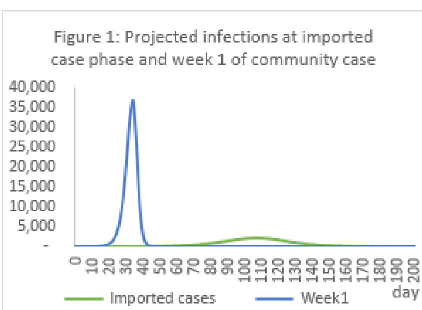
Results

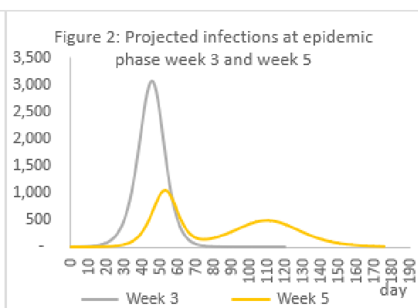
The model outputs show that at the time of imported cases with the effect of containment measures the epidemic spread is slow (R0= 1.1) over a period of 230 days. However, at the start of week 1, with the large contact bubble and low compliance to containment, estimated infections were large (152, 990) over a short period of 48 days (R0= 2.1). At week 3, re-projection with observed changes in compliance and reduced contact bubble size, the estimated infection decreased to 58,784 over a period of 101 days (R0= 1.2).
At week 5 the model projection for sub populations of Male' area showed high transmission rate among those living in communal residences (R0= 3.1) and projected 19,697 infections over a span of 21 days), while for those residing in households, the estimated transmission was lower (R0= 1.1) over a period of 11 days.

Table 3
Projected Epidemic Parameters At Different Stages Of The Epidemic In Male' Area

Time period – epidemic phase	Infections	Fatality	R0	Duration
Imported cases	25,126	251	1.1	230
Week 1	152,990	1,530	2.1	48
Week 3	58,784	588	1.2	101
Week 5 communal	19,697	197	3.1	21
Week 5 households	19,999	200	1.2	111

In the week1 model projected infections to peak with 36,766 infections in 34 days, however, week 3 model lowered the peak projected infections to 2,979 at 45 days, which was further observed to decrease at week 5 projections to 1,064 infections in 54 days.





The model projections used in nowcasting (producing real time forecasts) the COVID-19 epidemic in this study was based on a compartment SIRD epidemic model and fitted to the local context and adjusted to a number of developments as the epidemic progressed. The purpose of the epidemic modelling during early phase of the COVID-19 community spread was to provide a yardstick that can guide decisions on containment interventions and preparedness as the epidemic progressed, and not assumed to be accurate, rather an approximation (Christley et al., 2013; Lipsitch et al., 2011). At the outset it is acknowledged that the outputs of the model are influenced by the assumptions and inputs used in the model. While Baysean methodologies are the tool of choice in mathematical modelling, it has been noted that in pandemic forecasts, incorporating expert knowledge in determining the choice of prior probabilities improves predictability of the models (Lipsitch et al., 2011; Desai et al., 2019). Furthermore, this allows for accounting for parametric uncertainties by applying different plausible combinations of available values.

However, adjusting the model assumptions to short term measures required a number of data inputs in daily reported numbers, accounting for data gaps and assumptions on a number of inputs to the model. In addition to pathogen and host parameters, population density, surveillance efforts are key data points that affect model accuracy (Desai et al., 2019).The key aspects that influenced the assumptions of the model input values were contact tracing, testing, the time between case detection and isolation and as importantly the behaviour of the public complying with the containment interventions. At the outset, prior to community spread, it was assumed that with the containment measures, the probability of exposure is likely to be very small. However, the results of contact tracing of the first community case noted a high level of interpersonal interactions, producing a large contact bubble of more than 100 (NEOC press, 18 April 2020) that was not expected given the containment measures in place. This prompted the revision of the projection with low compliance and high exposure scenario. However, there was limited data on movements in the Male area' and reliance was made on contact tracing data to derive compliance to movement restriction enforced. The model parameters in Week 1 with these assumptions, the infection transmission was projected to be very high, and prompted the lockdown in the Male' area (Ministry of Health, 2020). The subsequent projections based on interventions being implemented produced results that were expected in a lockdown scenario with high compliance.

Another constraint that affected the short-term projection is the accuracy of actual infected cases due to testing capacity and testing strategy adopted from Week 2 of the community case. The country has limited testing capacity and with the discovery of multiple clusters of confirmed cases living in communal residences, decision was made to recognise that a large proportion of the people in these clusters are exposed and likely to be infected, hence was not tested to confirm the diagnosis. Rather response efforts were diverted to their health monitoring and appropriate care. This approach is a common approach in resource poor setting during epidemics (Magnus, 2012). However, in modelling projections for weeks 3 and 5, reliance on reported numbers was therefore not sufficient, and assumptions were made on contact bubble size of exposed individuals in these settings and their compliance to interventions, partially informed by the rate of contacts becoming positive, which was also constrained by the long incubation period of the disease. These assumptions were thus crude as contact tracing data was the only source of information and expert judgements was used. While it can be argued that this is an appropriate model given the nowcasting scenario, greater uncertainty was introduced in the model.

Despite the uncertainty, nowcasting at different points of the epidemic can be said to be useful as it allowed decision making around resource allocation and prioritisation. For instance, COVID-19 response in the Male' area prioritised setting up of isolation and quarantine facilities for those living in communal setting and containment of selected sites along with their health monitoring(NEOC press, 22 May 2020).

Conclusion

Nowcasting the epidemic progression phase provided useful information for decision making in the early phase of the epidemic. However, producing real-time projections is challenged by the data gaps and the short duration with the accompanied uncertainty introduced due to data gaps. Precision of the forecasts can be improved with increased data availability on the epidemiological parameters, but also other data sources such as movement of the population. As the COVID-19 response moves toward easing up lockdown measures in the Male' area, inputting movement data into the model parameters will improve certainty of the model outputs and provide extremely valuable information for decision making in the coming weeks.

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Declarations:

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