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Towards a new approach for managing pandemics: Hybrid resilience and bowtie modelling

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ABSTRACT

Pandemic viruses have historically caused tremendous damage to lives and livelihoods. The coronavirus, COVID-19, has proven to be a significant issue around the world. In this paper it is argued that systems of controlling similar types of disasters need to be improved through learning from past experience and from others, as well as through improved modelling for better decision making. In doing so, the focus will be on resilience modelling and learning from incidents. Therefore, in this paper, first the introduction deals with hybrid approaches in operational research highlighting the differences between hybrid modelling and hybrid models. Second, an introduction to mathematical modelling of epidemics is provided and how such modelling leads to certain types of public health modelling is demonstrated. Third, resilience modelling will be discussed as a complimentary type of modelling, where concepts related to robustness, redundancy, resourcefulness, and rapidity are introduced. Fourth, resilience modelling will be extended to new principles taking COVID-19 as an example for the analysis. Fifth, the analysis will then be used to compare degrees of resilience for different countries. Finally, other modelling approaches for managing – and learning from – pandemics, in terms of root cause analysis, bowtie modelling and safety barriers, are proposed.

1. Introduction

What could have been done to mitigate and manage a pandemic from an operational research perspective? In this paper, it is hypothesised that resilience modelling can offer a valuable tool for decision analysis related to public policy. In doing so, the approach followed in this paper will utilise relevant metrics regarding risk, reliability, and operations disciplines. The paper is organised as follows; the impact of COVID-19 pandemic is first outlined. This is then followed by a brief introduction to mathematical modelling for pandemics outlining their benefits and limitations with regard to decision-making. Resilience modelling is then formally introduced, combined with risk and reliability analysis. A comparison between different countries in their ability to cope is then provided as way of illustration on how such modelling of resilience can be of value.

2. Characteristics and impact of the COVID-19 pandemic

Almost 100 years ago, the world was engulfed by the Spanish Flu epidemic which infected around 500 million people worldwide; at the time this was thought to be a third of the world’s population. This has been followed by major pandemics such as SARS 2002–2004, H1N1 in 2009, Ebola between 2014 and 2016, and now COVID-19. However, we are still struggling with how to model such pandemics in order to become more resilient.

The world has suffered immense damage from COVID-19 virus that can be characterised as a perfect storm and a typical ‘wicked problem’ as a result of its scope and scale. Such a pandemic disaster ticks all the boxes with respect to ‘wickedness’; a term coined by Rittel & Webber (1973) which relates to problems that are very difficult or even impossible to solve because they involve many changing, interdependent, and undefined factors. This is true given the experiences with the Corona virus (Covid-19) in terms of multiple waves, multiple emerging variants of the disease, and the variety of available vaccines. COVID-19 is also characterised by a high risk priority number (RPN); a measure used in the reliability domain to prioritise risk of failure characterised by its three governing variables of severity (lethality), frequency (spread of the disease), and diagnosability (likelihood of detection). The impact of the COVID-19 pandemic also fits well with creating a typical example of a VUCA environment (an acronym for volatile, uncertain, complex, and ambiguous situation). It also caught the world by surprise as a ‘black swan phenomenon’ (although some may argue that it is more like ‘a
A ‘black swan phenomenon’ is a term used to describe an event that comes as a surprise, which is often associated with characteristics of rarity, extreme impact, and retrospective predictability. Conversely, a ‘black elephant’ signifies a known event that was ignored (Taleb 2010).

Such characterisations prompt the need for two paradigm shifts. The first is the prioritising of resilience over efficiency, such as the case of the emphasis, for example, on operations and supply chain management with regard to a shift from just-in-time to a just-in-case mind set. The second shift requires the embrace of uncertainty, shifting the emphasis more towards seeking the generation of scenarios, rather than seeking solutions per se. Thus, these are a prompt to embrace a scenario-based decision-making process in order to assess the pros and cons of each scenario. In other words, there is a need for a shift of emphasis from a probability-based attitude to risk assessment to a possibility-based attitude, as argued by Labib and Harris (2015) in their study of the triple hybrid cascading hazards of earthquake, tsunami, and nuclear power plant generation failure in Japan in 2011.

In this paper, it is hypothesised that investigating what lessons can be learned from other disciplines in terms of modelling, and learning from countries’ experiences using these as examples of best practice, can create a significant impact on the way we manage pandemic disasters. In doing so, we utilise a set of techniques, in a hybrid approach, that can help to focus on the causal factors and enable identification of safety barriers and key lessons in a logical constructed model.

3. Introduction to mathematical modelling for pandemics

Mathematical modelling of infection transmission is based on dividing the population into ‘compartments’ (Bailey 1975). Policy decision making in pandemics tends to rely on the Susceptible-Infectious-Removed (SIR) modelling approach in epidemiology and its variations. Variations of transmission models presented as flow diagrams have been summarised by Baussano et al. (2014) as shown in Fig. 1.

Such an approach has been criticised for its limited scope, and further been extended to include variations such as the SEIR and SEIRV methodologies, where the ‘E’ and ‘V’ are compartments of ‘Exposed’ and the ‘Vaccination’ respectively.

The basic idea of such modelling is to use a system of differential equations to model the different states (compartments) and combine them with a curve in order to come up with suitable policies to reduce movements from S to I by reducing a measure called \(R_0\) (referred to as \(R_\text{note}\), or the basic reproduction number. \(R_0\) is defined as the average number of secondary infections produced when one infected individual is introduced into a host population where everyone is susceptible (Dietz and Schenzle 1985), and it is considered the threshold for many epidemiological models (Hethcote and van den Driessche 2000). It also involves improvement of the movement from I to R ‘in order to flatten the curve’ (Sinkala et al. 2020).

**Basics of the SIR modelling:**

\[
S(i) + I(i) + R(i) = N
\]

\[
At \ t = 0; \ S(0) = S_0, \ I(0) = I_0, \ R(0) = 0. \tag{2}
\]

\[
\frac{dS}{dt} = -aSI \tag{3}
\]

\[
\frac{dI}{dt} = aSI - bI \tag{4}
\]
$$\frac{dR}{dt} = bl$$

(5)

where:
- $a =$ transmission coefficient (which relies on conditions).
- $b =$ recovery coefficient (which relies on disease).

The three equations that characterise $dS$, $dI$, and $dR$ can be illustrated in Fig. 2.

Accordingly, the inflection point of the I curve in Fig. 2 is $\frac{dl}{dt} = 0$, which causes Eq. (4) to be rewritten as:

$$aSI - bl = 0$$

(6)

Hence, at $t_0$, the basic reproduction number $R_0$ can be obtained as follows:

$$R_0 = \frac{aS_0}{b}$$

(7)

Therefore, in terms of public health policy, $R_0$ is a function of:
1. Transmission coefficient; $a$ (which depends on conditions), for instance washing hands.
2. Recovery coefficient; $b$ (which depends on the disease), for instance Intensive Care Units (ICU).
3. Susceptibility; $S_0$, (which depends on the ability to resist), for instance availability of vaccines.

Such approaches are supposed to help decisions related to triage management for the entire population (Burkle 2006). However, existing compartmental mathematical modelling has been recently criticised in that it cannot explicitly capture important related factors such as effects of testing, contact tracing, and isolation (Sturniolo et al., 2020), and hence there is a need for a more holistic model. In addition, these existing models tend to produce lagging types of indicators that look back at whether the intended results were achieved, rather than leading types of indicators that look forward at future outcomes. Furthermore, and as will be shown in this paper, hybrid modelling of resilience provides a much richer modelling and in-depth decision analysis that can lead to better decision making. One of the main differences between the two approaches is that epidemiological compartmental mathematical modelling tends to take a differential form, whereas the proposed resilience modelling takes an integral form.

Hybridised approaches can be classified in terms of both model and modelling. Such classifications were originally suggested by Shanthikumar and Sargent (1983), where hybrid models are procedural; therefore, an output of one model becomes an input to the subsequent model, and so on—see Stephen and Labib (2018), and Labib and Read (2015) as examples of such a hybrid model approach. Whereas in hybrid modelling different models are deployed and they act independently to study the same problem. In this paper, hybrid modelling is proposed where it is argued that in addition to the classical epidemiological based modelling, the utilisation of resilience modelling can enhance the decision making for managing pandemics.

4. Resilience modelling

There have been quite a few comprehensive reviews and books dedicated to definitions of resilience among different disciplines (e.g. Sutcliffe and Vogus, 2003; Hollnagel et al., 2006; Walker and Salt, 2012; Francis and Bekera, 2015; Hosseini et al., 2016; Masys, 2015). Generally, resilience can be characterised by abilities to absorb, adapt, and restore (Francis and Bekera 2015). Such characterisation will be further extended later on in this paper to include prevention and learning, and other elements. Having so many definitions for resilience across many disciplines demonstrates that it is not easy to define as a concept. In a similar analogy it is as difficult to define the ‘soul’ as explained by Charles Handy (1998). Accordingly, one can similarly argue that ‘resilience’ is ‘one of those concepts that, like beauty, evaporates when you try to define it, but like beauty it is instantly recognizable when you meet it’ (Handy 1998, pp158). The main idea of resilience is analogous to a spring that will deform under load and after absorbing the load it then bounces back (Yokomatsu and Hochrainer-Stigler 2020); and in material science, a resilient material has combined properties of strength and flexibility, or ductility as opposed to brittleness. The origin of the word ‘resilience’ comes from the Latin word ‘resilio’ that means ‘to rebound’.

The concept of the resilience triangle originated from the work of Bruneau et al. (2003), and was then mathematically modelled by Tierney and Bruneau (2007). Resilience was formally defined by Attoh-Okine et al. (2009) as the area of the triangle divided by the total area of the rectangle of the sides of maximum performance (represented as 100% on the Y-axis) versus the time frame that lies between the times of the initial disruption (at $t_0$) and the full recovery (at $t_1$), as shown in Fig. 3.

Hence Resilience as a percentage can be obtained as follows:

$$Resilience = \frac{\int_{t_0}^{t_1} Q(t)\,dt}{100(t_1 - t_0)}$$

(8)

In other words, more resilience is achieved by reducing the area of the triangle. Further developments of the resilience triangle model have been achieved by the introduction of the concepts of Robustness and Rapidity, which were formalised by Shinozuka et al. (2004) as follows:

$$Robustness = B - C$$

(9)

$$Rapidity = \frac{A - B}{t_1 - t_0}$$

(10)

These concepts were extended into the R4 framework of resilience by Tierney and Bruneau (2007, pp15), where:

- Robustness—the ability of systems, system elements, and other units of analysis to withstand disaster forces without significant degradation or loss of performance.
- Redundancy—the extent to which systems, system elements, or other units are substitutable, that is, capable of satisfying functional requirements, if significant degradation or loss of functionality occurs.
- Resourcefulness—the ability to diagnose and prioritise problems and to initiate solutions by identifying and mobilising material, monetary, informational, technological, and human resources.
- Rapidity—the capacity to restore functionality in a timely way, containing losses and avoiding disruptions.

It is worth noting here that out of the R4 framework so far, only
robustness and rapidity have been formulated mathematically within the resilience triangle. It is also worth mentioning that such resilience view is in line with the comprehensive reviews of the phases of disaster operations management in terms of preparedness, mitigation, response and recovery (Altay and Green, 2006; and Galindo and Batta, 2013), as well as business continuity and disaster recovery planning (Sahebjamnia et al, 2015).

5. Extended resilience modelling

In this paper, and in the wake of COVID-19 crisis, five further analytical developments and variations are introduced as additional principles to the classical resilience triangle; (1) the principle of continuity, (2) the principle of vector analysis, (3) the principle of curvature analysis, (4) the principle of antifragility, and (5) the principle of moving upstream. When describing each of these principles, there will be an attempt to link them to the COVID-19 pandemic, by way of illustration.

5.1 Principle of Continuity: in terms of continuity, in this model in Fig. 3, note that the point on the horizontal time axis at the very right end of the figure (point E) is considered as the same point as the left end of the figure (point P). This is similar to the map of the world, where although the globe is round, we consider the extreme west and the extreme east on the map as the same line; and crossing that line in reality cause a whole day shift in the time zone. The same analogy applies to resilience, where the ‘adapt’ phase is equivalent to a ‘learning’ phase, since it will inform the ‘plan’ phase against future disasters and enable us to extract generic lessons (Labib and Read, 2013). In the case of COVID-19, this means learning to mitigate against the second wave or any future pandemic. And there is clear evidence that countries who had experienced pandemics such as SARS and MERS have been better prepared for COVID-19, for instance South Korea, where they passed legislation that facilitated effective track and trace systems, having improved their public health emergency preparedness and response by drawing on their experience with the MERS outbreak in 2015. Thus, the idea is that ideally suffering should produce perseverance and endurance; these are good ingredients of resilience which constitute learning to cope with future similar incidents. Also, it is helpful to note that rapid learning is an important concept here and does not only occur as a reflection at the end of a crisis, or as a sort of a briefing at the end of a project, but rather learning needs to occur even during the recovery phase itself, otherwise second or third waves of the pandemic may be experienced. Thus, one needs to differentiate between the ‘on-the-go’ type of learning versus the reflective type of learning; in other words, by using the single and double loops learning originally defined by Argyris and Schön (1978), which argues that single-loop learning occurs whenever an error is detected and corrected without questioning the underlying values of the system, whereas double-loop occurs when we examine and alter the governing variables.

5.2 Vector Analysis: in terms of the principle of vector analysis, each side of the resilience triangle is a vector; which is defined as ‘a quantity having a direction as well as magnitude’ (Oxford Dictionary). For example, redundancy in terms of maintaining safety stocks helps firms to gain time during disruption (Zsidisin and Wagner, 2010), and hence causes a change in the direction of the vector during the damage/absorption stage. In the comparative analysis of different countries with respect to the impact of the COVID-19 pandemic on lives (death toll or cases of the disease) and livelihood (e.g. GDP, recession, employment, etc.), it is clear that the magnitude and slope of both damage and recovery vary among different countries. Many countries in Europe such as France, Italy, Spain, and the UK as well as the USA have experienced an exponential surge in number of infections. However, the case of South Korea outperforms many other countries as evidenced by Fig. 4, which compares the six countries in

Fig. 4. Deaths attributed to COVID-19 in USA, UK, France, Italy, Spain, and South Korea (Vertical Axis Scale Logarithmic and Raw Numbers) Source FT (28/5/2020).
terms of raw numbers of death on a logarithmic scale. Note that in Fig. 4, the y-axis is upside down compared to Fig. 3, as it indicates the death tolls. https://ig.ft.com/coronavirus-chart/?area=usa&area=gb&area=fra&area=ita&area=esp&area=kor&area=Regional=usny&area=Regional=usnj&cumulative=0&logScale=1&perMillion=0&values=deaths

5.3 Curvature Analysis: In terms of curvature analysis, there is an inherent assumption in the resilience triangle with respect to assuming all the sides are straight lines, as shown in Fig. 3. However, in reality each of the lines (vectors) can be considered as non-linear. In the field of reliability, the concept of the deterioration in performance of equipment has been modelled as a curve in the P-F curve introduced by Nowlan and Heap (1978), where the performance of equipment deteriorates over time, which can be attributed to it being either an ageing system or caused by adverse internal or external conditions. The same concept of deterioration that leads to a complete failure is also conceptually illustrated by Vaughan (1996) in her analysis of NASA’s Challenger shuttle disaster, where design deviation flaws attributed to the O-ring where being gradually perceived as a normal situation and an acceptable risk instead. This becomes the new norm and over time people tend to abandon the initial design specifications, thus a near-miss situation becomes ‘normalised’; hence the term ‘normalisation of deviance’ (Vaughan 1996), and in the case of the shuttle this eventually led to a catastrophic situation. Also, Bonstrom and Corotis (2016) represented the resilience triangle as nonlinear. Ayyub (2014) developed mathematical modelling that captures the non-linearity of the resilience triangle, as shown in Fig. 4. Here deterioration in performance can also be described as a degree of becoming more vulnerable. For example, reflecting on why the UK has suffered more from COVID-19 compared to other countries, one can attribute the fragmentation and delay in decision-making to response as an outcome of similar fragmentation in the preceding negotiation and decision-making related to Brexit. In addition, other countries who have experienced polarisation and deep political divisions have also been affected badly by the pandemic especially when decision-making in terms of response has been delayed.

Moreover, vulnerability that leads to deterioration can be due to a by-product of too much belief in previous success, which can lead to unjustified optimism (Labib and Read, 2013). The World chess champion, Garry Kasparov in his reflection on why he was beaten, at his peak performance stage of his career, by an opponent (Kramnik) states that ‘My weakness was a refusal to admit that Kramnik had out prepared me – preparation was supposed to be my strong suit. Each one of my successes up to that moment was like being dipped in bronze over and over, each success, each layer, making me more rigid and unable to change, and more importantly, unable to see the need to change’ (Kasparov, 2017, pp61).

According to Fig. 5, the crisis occurs at time $t_i$ and the failure $f$ lasts for a duration of $ΔT_f$ until time $t_f$. Recovery then takes place for a duration of $ΔT_r$ until time $t_r$. Hence, total disruption

$$ΔT_i = ΔT_r + ΔT_f.$$ (11)

Three different characteristics of failure events can take place, according to Ayyub (2014);

Brittle failure ($f_1$), Ductile failure ($f_2$), and Graceful failure ($f_3$). Looking back at Fig. 4, it can be seen that countries differ in their failure rate characteristics, where both the US and the UK tended to follow a brittle pattern as compared to South Korea, which followed a relatively ductile pattern.

Also among the different types of recovery, they can take the form of either; Better than new ($r_1$), As good as new ($r_2$), As good as old ($r_3$), or Worse than old ($r_4$). Obviously, the performance (Q) in the figure can represent either lives or livelihood, and it is important to make sure that improving one of them should not be at the cost of affecting the other. Note that the special case of $f_1$ (brittle), and $r_2$ (as good as new—but in a straight line), is actually the classical resilience triangle shown in Fig. 3.

5.4 Principle of Antifragility Analysis: this concept is about systems that actually ‘benefit’ from disorder, and was originally conceived by Taleb (2012), who related it to his earlier concept of the ‘black swan’ (Taleb 2010). It was also analysed in the context of risk analysis by Aven (2015). Its main idea is inspired by the principle of physical training, where a sports person becomes better by imposing stressors (training exercises). The antifragility is depicted in Fig. 5 as recovery type $r_1$ (better than before), whereas the fragility is shown as $r_4$ (worse than before). The role of simulation exercises (SimEx) is intended to provide equivalent staff and (inter/intra) organisational training to prepare for...
large scale incidents. However, in the case of COVID-19, a SimEx called Cygnus was conducted in 2016 in the UK and involved all major government departments, the National Health Service (NHS), and local authorities across Britain. Cygnus simulated a pandemic of the H2N2 influenza virus; a very similar situation to COVID-19. However, despite a remarkably similar scenario, the UK COVID response showed a clear knowledge gap when putting the learning into practice. Moreover, such a simulation exercise had been criticised in the media because it involved mainly public health issues and ignored the incorporation of financial and economic related aspects to mitigate against the impact of the pandemic (Nuki and Gärden 2020). In addition, antifragility can be assessed through the concept of High Reliability Organisation (HRO) and its five principles (Weick and Sutcliffe 2007), which can be measured (Agwu et al. 2019) as an indicator of antifragility and resilience.

In the context of Covid-19 pandemic, it has been observed that one of its remarkable positive impacts has been the accelerated innovations in on-line education and remote working. Ayyub (2014) then proposed to measure resilience as:

$$\text{Resilience(Re)} = \frac{T_f + F \Delta T_f + R \Delta T_r}{T_f + \Delta T_f + \Delta T_r}$$  \hspace{1cm} (12)

where for any type of failure ($f$) profile, $F$ is measured as follows:

$$\text{Failure}(F) = \int_{t_0}^{t_f} \frac{fdt}{\int_{t_0}^{t_f} Qdt}$$ \hspace{1cm} (13)

Similarly, for any type of recovery ($r$) profile, $R$ is measured as follows:

$$\text{Recovery}(R) = \int_{t_0}^{t_r} \frac{rdt}{\int_{t_0}^{t_r} Qdt}$$ \hspace{1cm} (14)

Ayyub (2014) then proposed that failure profile ($F$) can be considered as a measure of both robustness and redundancy. Also, recovery profile ($R$) can be considered as a measure of both resourcefulness and rapidity, where these terms where originally conceptualised by Tierney and Bruneau (2007). Note here that this is also consistent with the way resilience is defined as ability to prepare, adapt, respond, recover, learn, and grow from disturbances; whereas robustness is defined as the ability to resist the effects of disruption.

5.1. Principle of moving upstream

A book entitled Upstream starts by with the following short story:

‘You and a friend are having a picnic by the side of a river. Suddenly you hear a shout from the direction of the water—a child is drowning. Without thinking, you both dive in, grab the child, and swim to shore. Before you can recover, you hear another child cry for help. You and your friend jump back in the river to rescue her as well. Then another struggling child drifts into sight… and another… and another. The two of you can barely keep up. Suddenly, you see your friend wading out of the water, seeming to leave you alone. “Where are you going?” you demand. Your friend answers, “I’m going upstream to tackle the guy who’s throwing all these kids in the water”’. (Heath, 2020, pp1).

In the book, which has been written prior to the Covid-19 pandemic, the author is defining ‘upstream’ actions in terms of intentions aimed at prevention of problems prior to their occurrence. The term upstream is preferable to preventive or proactive because the stream metaphor nudges us to extend the resilience modelling approach proposed in this paper into focussing more on solutions. Upstream also means a systematic approach towards reduction or mitigation of harm caused by those problems. For example, teaching kids to swim is an upstream strategy to prevent drownings. Reflecting on COVID-19, we extend this way of thinking with respect to the resilience triangle shown in lines PA and AB in Fig. 3, where it is now clear that we need to enhance education in schools related to hygiene and coping with the prevention of the spread of viruses.

The upstream concept can also relate to both space and time. Being nearer to the source of risk can also be conceptualised as ‘psychological distance’, which is the real or perceived distance between a person and the risk (Zwickle and Wilson 2014). Psychological distance is expressed as either the real or the perceived distance between the person and the object, which could be a risk, message, or idea. The greater the distance between the two, the greater the abstraction of the idea; conversely, the closer the distance, the more concrete the idea. The domain of psychological distance is expressed in one of four ways, temporal (time), spatial (physical distance), social (relationship), and hypothetical (potential) (Zwickle and Wilson 2014). Hence, the same authors propose to ‘bring the risk closer to the individual’. This can be done by making an abstract risk more concrete in terms of communicating it; in other words, by making the risk more personal and ‘bringing it closer to home’. This can be done, for example, by focussing on the local, as opposed to the global impacts predicted to occur. With COVID-19, the communication of its risk could have followed the same approach, which tends to be more related to systems thinking. Again, reflecting on COVID-19, it is now clear that those countries which were both geographically and culturally ‘near’ to the source of pandemic as a risk in the Far East, easily accepted the wearing of face masks, whereas it took some time to convince Western cultures to follow such a tradition as it was initially perceived as a restriction of personal freedom. Heath (2020) argues that downstream decisions are narrow, fast, and tangible, whereas upstream decisions are broader, slower, and hazier. Nevertheless, when upstream decisions are effective, their impact is both significant and sustainable. This does not discount the importance of downstream decisions as there is always a need to respond to the hazard. However, it is generally observed that allocations of resources, as a public policy, tend to be more downstream and hence they are asymmetrical.

An interesting point however, in Fig. 5, is point ‘B’, which is the deflection point, or the moment of bouncing back from a failure to a recovery profile. The question is: what causes it to happen? And further, what makes the recovery profile ($r$) take the subsequent shape in terms of level and rapidity? In order to attempt to answer these questions, it is clear that point ‘B’ is where a failure profile ($f$) turns into a recovery profile ($r$)—bouncing back; where failure profile ($f$) is a function of robustness and redundancy, and recovery profile ($r$) is a function of resourcefulness and rapidity as defined earlier. In the context of COVID-19, and utilising the resilience triangle modelling approach, Table 1 provides some examples for coding for both failure and recovery.

| Examples from COVID-19 | Coding          |
|-----------------------|-----------------|
| Insufficient installed base of ventilators and related medical equipment that may keep critically ill patients from being treated | Lack of Robustness |
| Hoarding of foodstuffs triggering bullwhip effects | Lack of Redundancy |
| Difficulty of ramping up medical product manufacturing capacity | Lack of Resourcefulness |
| Lack of quick response to the crisis | Lack of Rapidity |
| Novel design of ventilators and localised production of protective gear | Adaptability—continuity |
| Digital information and connectivity which creates novel models of workflow | Adaptability—continuity |
| Collection and dissemination of information, and data analytics for policy design | Adaptability—continuity |

Table 1: Examples of Coding of Resilience for COVID-19.
outbreak. The proposed resilience modelling can be regarded as a candidate for risk analysis that can help to identify threats in advance, and prepare an effective response system to enable rapid judgments about the seriousness of a virus outbreak. It is also important to establish an efficient response plan in running tests, tracing the infections, and isolation. These measures are key factors in curbing the spread of the virus.

The concept of the resilience triangle is an intuitive modelling approach. For example, in the work related to elective surgery in the wake of COVID-19, the authors (Anderson et al. 2020) developed a systems dynamics-based scenario of the availability of hospital beds. It can be observed that the shape of their curves with respect to time are very similar to the resilience triangle, hence further work can utilise the concept of resilience modelling for such applications.

The proposed five principles are depicted in the resilience triangle as shown in Fig. 6.

6. Extension of resilience modelling to other modelling approaches

When considering extension of mixed modelling approaches Morgan et al. (2017) provide a theoretical lens for the classification of modelling methods into mixed, enriched, and integrated approaches. Mixed methods are sequential methods, which follow each other; they are similar to hybrid modelling discussed earlier in Section 3. An enrichment of methods involves the extraction of features from another
method, and finally integration of methods involves a combination to form a new method. In this paper there is an attempt to integrate the resilience modelling to the bowtie modelling approach in a combined integrated approach.

It is appreciated that it is difficult, if not impossible, to develop a causal explanation, and relationship, in terms of its scope and level of decomposition that is acceptable to a wide range of stakeholders. Rasmussen puts it nicely as follows: “If a causal statement is not accepted, formal logical analysis and deduction will not help, it will be easy to give counter-examples that cannot easily be falsified. Instead, further search and decomposition are necessary until a level is found where the prototypes and relations match intuition” (Rasmussen, 1990). However, this does not discount the value of attempts to provide a modelling approach that aims to combine factors, highlight vulnerabilities, and investigate safety barriers for prevention and mitigation.

The bowtie modelling is a method that is named after its shape that captures causal relationships that can lead to a high risk event; in our case the exponential spread of Covid-19, which is the central ‘knot’ of the diagram, which is also a ‘top event’ in the fault tree. The means of preventing it are then derived through safety barriers, or controls, which is presented on the left side of the model. Then the consequences of the high-risk events and means of mitigating against them are then depicted on the right side of the model. The left side of the bowtie follows a deductive approach and it is mainly about causes of the threats, and the analysis focuses on means of prevention, where such analysis can be performed by techniques such as fault tree analysis. Whereas the right side of the bowtie is more of an inductive approach and it is mainly about consequences of the crisis, which could be on lives or livelihoods, and the function of safety barriers (or sometimes called controls) are to mitigate against the impact, and such analysis can be done through event tree analysis.

The bowtie diagram normally starts with a fault tree analysis on the left side where the causal factors and threats occur upstream in terms of time. On the opposite right side, event tree analysis (ETA) can be constructed where the focus is on consequences and negative outcomes that can lead to an escalation from a crisis to a disaster. Dombrowsky puts it succinctly ‘disasters do not cause effects. The effects are what we call a disaster’ (Dombrowsky 1995, 242). The analysis then proceeds to determine barriers that need to be put in place to prevent against its occurrence from the left side of the bowtie diagram, or to protect and mitigate against such consequences from the right side (Jacinto and Silva, 2010; Targoutzidis, 2010). In this paper, it is proposed to integrate the bowtie model with the resilience triangle modelling where both models share the same X-axis that resembles time, as shown in Fig. 7.

Resilience-based decision-making is in line with risk reduction and management approaches, for example, the reduction of risk through safety barriers, where prevention means reduction of the likelihood of a hazardous event, control means limiting the extent and/or duration of a hazardous event to prevent escalation, and mitigation means reduction of the effects of a hazardous event. Hence, a barrier function can be physical and non-physical, and is a function planned to prevent/avoid, control, or mitigate/protect against undesired events or accidents (Sklet 2006). Hence according to Sklet (2006), reflection on performance of safety barriers can be assessed using the following three sets of questions: (1) were there barriers that were in place and how did they perform? (2) Were there barriers in place but not used? (3) Were there barriers that were not in place but were required? Also, by incorporating the R4 framework of the resilience triangle (Robustness, Redundancy, Resourcefulness, and Rapidity) and the means of their derivation as discussed earlier, both the bowtie and resilience modelling approaches can be enhanced, and decisions related to safety barriers can be improved.

In managing pandemics such barrier analysis helps in different ways: First, it can encourage explicit investments in safety barriers. Second, it raises awareness about characterisation and validity of safety barriers for pandemics. Third, it assesses areas of vulnerability in the system and the need to incorporate new, or enhance existing, safety barriers. Finally, it helps us to think about diversifying the nature of safety barriers, such as human, physical, software, and so on, so that risk is minimised against having one type of failure mode that can affect similar barriers simultaneously.

The fault tree analysis (FTA) relies on the investigation of causal
factors in a logical and graphical way (Ericson 2015, 183) in the form of pathways. The top event of the tree is the undesirable event, namely the hazard, crisis, or in our case the exponential spread of the virus pandemic. Then causal factors need to be immediate, necessary, and sufficient. The causal factors of the undesirable event are connected in a logical way through ‘AND’, and ‘OR’ gates. The FTA has been described and incorporated to assess learning from rare events for middle managers (Labib et al. 2019). The FTA model for the exponential spread of the COVID-19 (corona) virus is depicted in Fig. 8 by way of demonstration. The two main contributing factors of the spread are infection related issues as well as governmental response. Each one of the contributing factors is then subdivided into possible causes.

Safety barriers can be observed as the causes of the AND gates located at the bottom of the tree, since an AND logic gates signifies that two or more things (basic events) went wrong simultaneously to cause the upper event to occur. Thus, for example the box titled ‘medical staff infection’ occurred because of both a ‘shortage of PPE’ and ‘lack of manpower’. In addition, ‘shortage of treatment’ is attributed to ‘lack of ICUs’ and ‘unavailability of vaccine’. Note here that such a diagram is not comprehensive in terms of width (all possible factors) or depth (extending to details of the root causes). However, it serves as a conceptual illustration of how a fault tree of the pandemic can be...
constructed, and then integrated to the bowtie and the resilience triangle.

Since FTA relies on a cause–effect relationships, if A causes B, it is logical to state that A happened before B, so the deeper we move downwards in a fault tree, the further back we go in time (upstream). Hence it can be argued that since the resilience triangle model has a time axis, then by incorporating FTA in a bowtie diagram and integrating it with a resilience triangle framework, a rich model can be derived for decision analysis of a crisis such as the COVID-19 pandemic. The incorporation of the FTA of the exponential spread of the COVID-19 virus in the bowtie model and its integration with the resilience triangle is shown in Fig. 9.

The left side of the whole bowtie model\(^1\) shown in Fig. 10 is focused on causal factors (or threats, shown in blue boxes) and safety barriers, or controls, are related to prevention. Whereas the right side is focused on consequences (shown in red boxes) and the safety barriers are dedicated to mitigation measures.

According to the proposed model in Fig. 10, the causal factors (threats – in blue colour) that led to the exponential spread of Covid-19 pandemic are: lack of medical staff, inability to trace infected people, ineffective virus testing, inability to combat virus spread, failure of timely right guidance and inadequate treatment.

In terms of controls (or safety barriers – in grey), availability of PPEs, and measures to prevent medical staff from being infected can contribute towards prevention of lack of medical staff. Effective software for test and trace as well as overcoming problems related to human right issues would prevent the problem of infected people not traced. Safety barriers against ineffectiveness of virus testing include improving accuracy of results, timeliness of testing, and accessibility to testing facilities. The inability to combat virus spread include wearing face masks while being involved in outside activities, avoidance of crowded public facilities, and limiting group events and gathering.

The consequences (in red) can be categorised into high transmission rates, high mortality rates, and effect on livelihoods. The consequence of high transmission rates can be mitigated against by safety barriers (in grey) such as raising awareness about severity of virus, and swift social distancing. Whereas high mortality can be mitigated against through availability of vaccine, and availability of ICUs. Effect on livelihoods can be mitigated against through business support and furlough schemes as well as extension of tax payments and reduction of rents.

Risk is defined as a triplet of answering the following three questions (Kaplan and Garrick, 1981); 1) What can happen? (in our case: threat or consequence), 2) How likely is it to happen? (in our case probability of safety barriers failure to perform), and 3) If a failure happen, what are the consequence? (in our case severity of safety barrier failure). Therefore, preventative barriers which are on the left side of the bowtie diagram before the top event ‘the knot’, can be sub-categorised into two types; ‘eliminate’ which, attempts to remove the possibility of the threat, and ‘prevent’, which attempts to avoid the top event from happening. Protective (or recovery) barriers are on the right side of the bowtie model, and these are categorised into ‘separate’, which aims to stop the top event leading to a consequence (lessens the frequency of the consequence), and ‘mitigate’, which limits the effects of the consequence (lessens the severity of the consequence). Such categorisation of all the safety barriers shown in the bowtie model in Fig. 10 are listed in Table 2 together with their performance measures.

Safety barriers in the bowtie can then be audited by classifying them in terms of their: effectiveness, reliability, success, adequacy, and presence. Such classification, with examples from Covid-19, is shown in Fig. 11. When more data is available, it could be possible to map the performance of each country with respect to the Covid-19 pandemic in terms of their controls and safety barriers.

\(^1\) Constructed using a visual software: Bowtie XP Software: https://www.bowtiiexp.com

Table 2: Categorisation of safety barriers.

| Preventive/Protective | Threat/Consequence | Barrier | Type | Possible KPI’s |
|------------------------|--------------------|--------|------|---------------|
| Preventive             | Lack of medical staff | Have proper and enough PPE | Prevent | % of stock outs |
|                        |                    | Develop proper procedures | Prevent | Feedback surveys on adequacy ad clarity |
|                        |                    | Contact backup staff | Eliminate | % of infected staff |
|                        |                    | Develop effective software | Prevent | No of tracked people |
|                        |                    | Massive communication campaign | Prevent | Feedback surveys on adequacy ad clarity |
| Ineffective virus testing | Correct results | Eliminate | Commission Research |
|                        |                    | Timely results | Eliminate | Commission Research |
|                        |                    | Efficient accessibility to testing | Prevent | Commission Research |
| Inability to combat virus spread | Wear face masks while outside activities | Prevent | Law enforcements and monitoring |
|                        |                    | Avoid crowded public facilities | Prevent | Law enforcements and monitoring |
|                        |                    | Limit group events | Prevent | Law enforcements and monitoring |
| Failure of timely right guidance | Enforce social distancing | Prevent | Law enforcements and monitoring |
|                        |                    | Massive communication campaign | Prevent | Feedback surveys on adequacy ad clarity |
|                        |                    | Increase Number of ICUs | Prevent | % per head |
|                        |                    | Support vaccine development | Eliminate | Efficacy |
| Inadequate treatment | Awareness of severity of virus | Control | Feedback surveys on adequacy ad clarity |
| Protective             | High transmission rates | Swift social distancing | Control | Law enforcements and monitoring |
|                        |                    | Area lockdowns | Mitigate | Law enforcements and monitoring |
| High mortality | Shielding most vulnerable people | Control | Commission Research |
|                        | Availability of vaccine | Control | Commission Research |
|                        | Availability of ICUs | Mitigate | Commission Research |
| Effect on livelihoods | Business support & furlough schemes | Mitigate | Feedback surveys |
|                        | Extension of tax payments and reduction of rents | Mitigate | Feedback surveys |
|                        | Working from home to keep businesses open | Control | Feedback surveys |
In analysing safety barriers, or controls, there is also a need to have diversified properties, to avoid having a common type of failure mode that can affect all barriers. Hence diversifying the nature of barriers in terms of software, hardware, backup systems, policies, and procedures in both prevention and mitigation, is a key to overcome a pandemic; there is no one silver bullet.

Looking at bowtie and barriers modelling in Fig. 10, it is clear that unsuccessful countries are the ones who tended to have their efforts focused on the right side of the bowtie model. Whereas, successful countries, which dealt well with the pandemic, had a balanced approach in both left and right side of the bowtie model. For example the public health simulation exercise (Cygnus) in the UK, started by the incident, and all efforts were then focused on how to mitigate against it, rather than on how to prevent it. In other words, more resources allocated to proactive and preventative measures (the upstream principle discussed earlier in resilience modelling) have clearly paid-off in reducing corrective and reactive measures taken later on. This is in line with the findings of modelling suppression versus control policies and their impact on lives and livelihoods (Adler et al., 2020), where it is concluded that early suppression of the pandemic save the most lives while infections are still low, and at the same time incurs less economic cost, compared to suppression policies few weeks later.

When analysing causes of failures it should be appreciated that such analysis is limited by the available factual evidence at the time of the analysis. The recent case of the Covid-19 pandemic is quite exciting to study as it is timely, but there are uncertainties about factual evidences as new evidence may appear later on. On the other hand, older case studies reported in the literature in learning from major disasters (eg Labib and Read, 2013) have the advantage of being ‘classical cases’ where the ‘dust has already been settled’ by now and hence generic lessons can be clearly demonstrated using the proposed techniques in a convincing argument.

7. Conclusion

Resilience as a conceptual idea is profound and considered to have a key role in dealing with disasters such as pandemics. However, there is little research on modelling resilience and integrating it with other approaches in order to systematise its operation. This paper aimed to contribute to this gap through the proposed hybrid enriched model of resilience and bowtie approaches.

In this paper, it has been argued that public policy that relies only on epidemiological modelling approaches based on compartmental analysis has limitations. It has also been shown that resilience-based modelling with the five proposed principles can enhance public policy decisions. Moreover, it has been demonstrated that the integration of revised tools and metrics that originated from risk, reliability, and operations research and management disciplines can have the potential for a significant improvement in public health policies when dealing with pandemics. The aim of such modelling is to provide a learning environment on how to absorb failure in a graceful degradation, and provides an opportunity to achieve quick recovery.

Resilience modelling has a time axis and hence can offer the answer to ‘when’ to do things, whereas the bowtie modelling, with its two sides, deals with causal analysis, and hence can provide information on the ‘how’ questions. Moreover, by combining both resilience modelling and bowtie modelling, a balance is achieved in terms of dealing with a disaster such as Covid-19 pandemic at both strategic and operational levels respectively. At a strategic level the phases of prevention of the cause, response and mitigation of the consequences are visualised and strategic milestones can be set accordingly. Whereas, through bowtie modelling more operational details of causal and barriers analysis are achieved. Such analysis helps to improve knowledge related to assessing existing barriers and the need for new or improved ones. In addition, the bowtie modelling provides insight to visualize and communicate the complexity of risks in a concise form.

Note that through the modelling based on the concept of the resilience triangle one can still capture the two fundamental strategies proposed by existing epidemiology-based modelling, which are; (a) mitigation, which attempts to focus on slowing the epidemic spread through reducing peak healthcare demand, thus protecting vulnerable population at risk from infection, and (b) suppression, which attempts to reverse epidemic growth through reducing case numbers (Ferguson et al., 2006; 2020). However, in the resilience triangle worldview, mitigation and suppression strategies are equivalent to absorption and recovery phases respectively. As has been shown in this paper, within the resilience modelling approach there are additional characterisations, and richer modelling capabilities through the R4s, the five principles, and the enhanced bowtie modelling.

For future directions of research, it is vital that public health...
simulation exercises are extended to include not just policies related to health, but also include different economic scenarios caused by pandemics. Given the complex nature of a pandemic, and the experiences with the Corona virus (Covid-19) in terms of multiple waves, multiple emerging variants of the disease, and the variety of available vaccines, the main lesson that can be learnt from all this is to embrace uncertainty rather than to confront it or shy away from it. The emphasis should be on generating possibilities of what-if scenarios rather than estimating emerging variants of the disease, and the variety of available vaccines, with the Corona virus (Covid-19) in terms of multiple waves, multiple...

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