COVID-19 Impacts on Energy Availability in an Electricity Utility

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Abstract: *Various industries have undertaken studies to determine the impact of the virus on their long-term sustainability, since the COVID-19 outbreak. This study focused on the impact of the virus on the energy sector and the ability of the national electricity supplier to be able to deliver on their mandate, if human resources were affected. A system dynamics method was used to build a simulation model for scenario analysis. Based on various structural model configurations; for the purposes of understanding the time lags between the infections, critical cases, recoveries and mortality, the qualitative system dynamics model was sufficient. This did not however, provide the quantitative results that could be used for future trending. Using an approach based on logistic equations provided a more quantitative analysis of the distribution of infections and deaths in the various age groups within the provinces. If the provincial rates (infection, recovery and mortality) had been used for determining the distribution of infections within the organisation, the results would have been misaligned. Model results indicated that the impact of mortality had a much more significant effect on the Energy Availability Factor (EAF), than a loss in productivity when employees were sick due to the COVID-19 virus.*

Keywords: System dynamics; COVID-19; Energy Availability Factor; electricity

1. Introduction

In 2019, the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), causing the coronavirus disease 2019 (COVID-19) was first detected in the Wuhan City, Hubei Province of China. Since detection until the 22nd January 2021, the disease has resulted in 2,102,276 deaths and 98,160,577 infections globally (Worldometer, 2021). South Africa (as at 22nd January 2021) reached 1,380,807 infections and 39,501 deaths. Besides the high mortality rates nationally and globally, the International Monetary Fund (IMF) estimated that the virus would have resulted in a 4.4% shrinkage in the global economy in 2020 (IMF, 2020), accompanied by unprecedented increases in unemployment, poverty, greater income inequalities, and disruptions to primary, secondary and tertiary economic sectors.

In South Africa, Eskom SOC (an electricity utility established in 1923) supplies over 44 GW of electricity through 387,633 km of high-, medium- and low-voltage lines and underground cables and is a key enabler of economic activity, with its 40,000 strong workforce. Due to the potential impact of COVID-19 on resource availability, a research project was initiated to develop a system dynamics model to provide insight into expected trends in terms of COVID-19 infections and mortality rates. The loss of employees as well as downtime due to the recovery and quarantine periods for those infected, was then linked to the Energy Availability Factor (EAF) for the power generating stations.

2. Literature Review and Problem Context

2.1 Mathematical modelling of epidemics

Elsevier records indicate that there are well over 2,500 studies (Sihombing, Malczynski, Jacobson, Soeparto, & Saptodewo, 2020) which emerged in 2020 on the COVID-19 virus in the subject of health, biology and clinical studies, with some covering mathematical and modelling and estimations. Mathematical modelling of epidemics can be traced back to 1766, when Daniel Bernoulli developed a model to analyse the mortality due to smallpox in England (Blower & Bernoulli, 2004). In 1772, Lambert followed up on Bernoulli's work and included age-dependent parameters (Dietz & Heesterbeek , 2002). In 1911, Ross (1911) introduced a systematic approach for mathematically modelling epidemiology using a set of equations to approximate the discrete-time dynamics of malaria through the mosquito-borne pathogen transmission.

Kermack and McKendrick then expanded on Ross's work after which they suggested probability of infection of a susceptible population is linked to the number of contacts with infected individuals (Serfling, 1952). Figure 1 illustrates the types of mathematical models which have since emerged (Siettos & Russo, 2013). The three main categories include:

1) Statistical-based models,
2) Mathematical or mechanistic state-space models, and
3) Empirical or machine learning-based models.

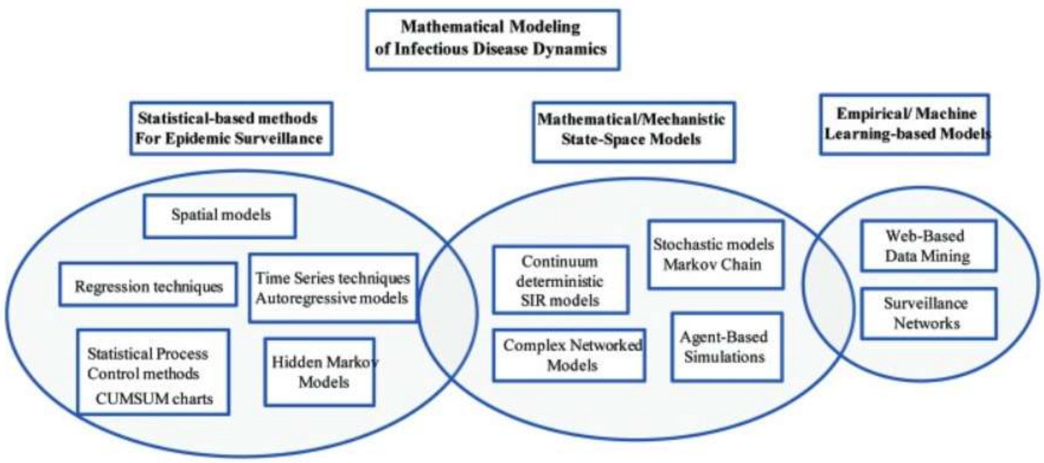


Figure 1: Map of Mathematical Models for Infectious Diseases Modelling (Siettos & Russo, 2013)

2.2 System dynamics modelling of epidemics

Simulation models fall within the realm of mathematical models and enable a better understanding of the system in a dynamic, quantitative, and graphical format and generally allow for the rapid assessment of a virus. System dynamics is a mathematical computer based simulation methodology. It provides a useful setting to explore feedback — how the states of a system (the levels or stocks) influence (or "feedback" to) the flows that alter those states. System dynamics modelling has been applied to issues of population health since the 1970s and include amongst others the following topics:

1. Disease epidemiology including work in heart disease, diabetes, HIV/AIDS, cervical cancer, chlamydia infection, and drug-resistant pneumococcal infections (Levin, Roberts, & Hirsch, 1975).
2. Substance abuse epidemiology covering heroin addiction, cocaine prevalence, and tobacco reduction policy (Homer , Ritchie-Dunham, Rabbino, Puente, Jorgensen, & Hendricks, 2000) (Homer J. , 1993).
3. Patient flows in emergency and extended care (Dangerfield, Fang, & Roberts, 2001);
4. Health care capacity and delivery in such areas as population-based health maintenance organization planning, dental care, and mental health (Wolstenholme, 1996).

System dynamics has been able to integrate the dynamics for multiple interacting diseases and risks and allows scenario analysis based on changing policies.

2.3 Mathematical modelling of epidemics

The typical Susceptible-Infectious-Recovered (SIR) model has been used to show how individuals move from a fixed population into a susceptible stock and then recover, but can get re-infected. (Smith & Moore, 1999). The Kermack-McKendrick model was first used in 1927 and is the simplest model (

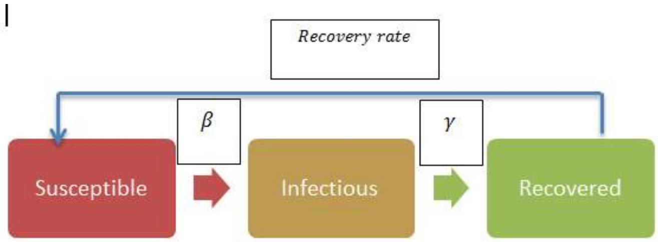


Figure **2**) showing this flow and makes use of coupled non-linear ordinary differential equations (Kermack & McKendrick, 1927).

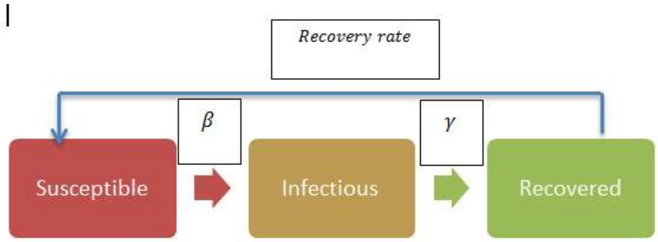


Figure 2: SIR Model

Since the outbreak of the COVID-19 virus, several initiatives were undertaken to model elements relating to the pandemic (System Dynamics Society, 2020). Other work like that of Froese (2020) added additional variables to model the COVID-19 virus, and built on the SIR model structure. An incubation period was included since most infectious diseases have a period during which the infection does not spread – the population during that period was then referred to as *Exposed*. The model also provisioned for mortality and not just recoveries. The trends obtained from including the additional dynamics included a lockdown period of 100 days and R_0 was changed from 5 to 0.5 around day 50. Fatality rates and age dependent factors were also included.

In a study by Ibarra-Vega (Ibarra-Vega, 2020), a conceptual system dynamics model was created for the coronavirus outbreak based on a population of 100,000 inhabitants. This model included scenarios where the quarantine periods were changed. The model consisted of 4 stocks: the *Susceptible*, *Infected*, *Recovered*, and *Deaths*. The conclusions were that each city had different characteristics, such as the population, economy, transport, and health systems which changed the levels of daily contacts.

In a study by Sy et al. (2020), system dynamics was used to generate scenarios based on various policy considerations. The model built upon the basic Susceptible-Infectious-Recovered (SIR) model and captured the relationships, feedbacks and delays in a disease transmission system. Some policies included the construction of additional health facilities and quarantine centres, however this policy change alone would have only mildly resolved the situation and could not be effected in low income countries which did not have the financial means to construct the additional infrastructure, let alone resource it. Based on the models results, the most effective strategies focussed on avoiding exposure to the virus from even happening; focusing on increasing healthcare capacities only delays the inevitable system collapse as its effectiveness assumed people getting infected first.

The Office of the Chief Economic Advisor to the Government of India worked with Professors Jayendran Venkateswaran and Om Damani of the Indian Institute of Technology, Bombay, in order to understand the spread of COVID-19 in India through a System Dynamics SEIR epidemiological model approach (Venkateswaran & Damani, 2020). They partnered with researchers at Stanford University. The results from this study indicated that even with an extended lockdown, pockets of the epidemic would persist and caused resurgence in infections. The model results also indicated that testing together with contact tracing and isolation would be required in order to contain the infections in the long-term.

Epidemic models are conventionally used for projections, rather than for forecasts. Record and Pershing (2020) used system dynamics to understand epidemic forecasts based on the premise that there was two way feedback between the forecast output and human behaviour. The conclusions were that an overestimate in the forecast could improve the outcome, and lower the infection peak, but an underestimate in the forecast could indicate a greater response time can be accommodated. This study was interesting because system dynamics is generally not used for forecasting but for comparing various policies, whereas statistical methods are better suited to forecasting trends based on empirical data, however forecasting was done using a system dynamics method.

There are several other system dynamics models which were developed to consider various scenarios and changes to parameters influencing the infection rates, however, it is clear that even capturing the complexities of these dynamics is challenging and dependent on the environment in which the pandemic is occurring.

In this study, a system dynamic simulation model was built to understand the South African national infection rates per province and within age groups. The results were then further explored to determine whether the same rates could be used as a proxy for determining the infections and mortality within the electricity utility. More importantly, the impact of infections and mortality on the energy availability needed to be interrogated and understood to support operational and strategic planning.

3. Methodology

A system dynamics modelling process was followed, which included the following steps (Sooknanan Pillay, 2018):

- *Project Inception*: Establish the focusing question linked to the system problem, alignment with business strategic objectives, literature scans.
- *Concept to Context*: Determine the modelling timeframe, understand the historical trends of variables, develop a diagrammatic framework with upstream and downstream variables
- *Boundary Setting*: Requires collaboration and ideation sessions, develop causal loop diagrams, define a model boundary chart.
- *System Analysis*: Preliminary computations
- *Model Development and Design*: Modules and sub-modules, state variables, initial conditions of stocks and parameterization, mathematical linkages of variables, engagement platforms for scenarios.

After the simulation was developed, various scenarios were run to generate projected infection rates and mortality as well as the impact on Eskom's human resources on EAF.

3.1 Causal Loop Diagram

Part of the system dynamics process involves the construction of a causal loop diagram which illustrates the cause and effect relationship between variables in a system. The diagrams are subjective and qualitative but provide a tool to understand some aspects of a causal system. A possible causal loop diagram for the Covid-19 infections is shown in Figure 3.

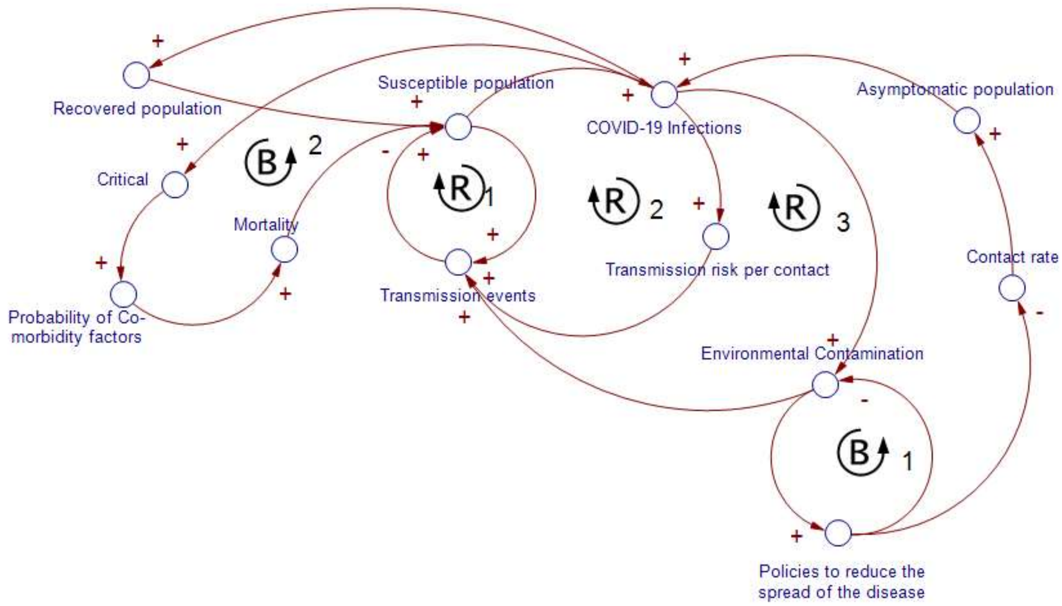


Figure 3: Causal Loop Diagram – Spread of COVID-19 Infections

Starting with Reinforcing Loop R1, an increase in transmission events (e.g. social gatherings, public transport, shopping, student interactions etc.) will result in an increased number of people susceptible to the COVID-19 virus. The greater the susceptible population, then the higher the number of transmission events. With Reinforcing Loop 2, if there is an increase in the number of susceptible people, the risk of transmission per contact is higher which then facilitates more transmission events and again results in a higher number of the susceptible population. Reinforcing Loop R3 comes into effect when a high number of infections result in greater environmental contamination and increases the number of transmission events. Environmental contamination is balanced with balancing Loop B1 since policies can be introduced to curb the spread of infections. The other Balancing Loop 2 serves to decrease the pool of susceptible people due to the reduction in population numbers when mortality increases especially when comorbidity factors of those who are critically ill.

3.2 System Architecture Map

A system architecture map (SAM) provided a high level view of the dynamics within the system, it did not display causality as in a causal loop diagram but it provided an indication of the sub-systems that would make up the simulation model. The SAM for the Covid-19 infection system is shown in Figure 4. Susceptible people were either symptomatic or non-symptomatic. If the population was symptomatic, they remained as an active case or they recovered after a period of isolation. The active cases recovered after a quarantine period or became critical thus resulting in death (especially if they have comorbidity factors) or they recovered after a period of medical treatment.

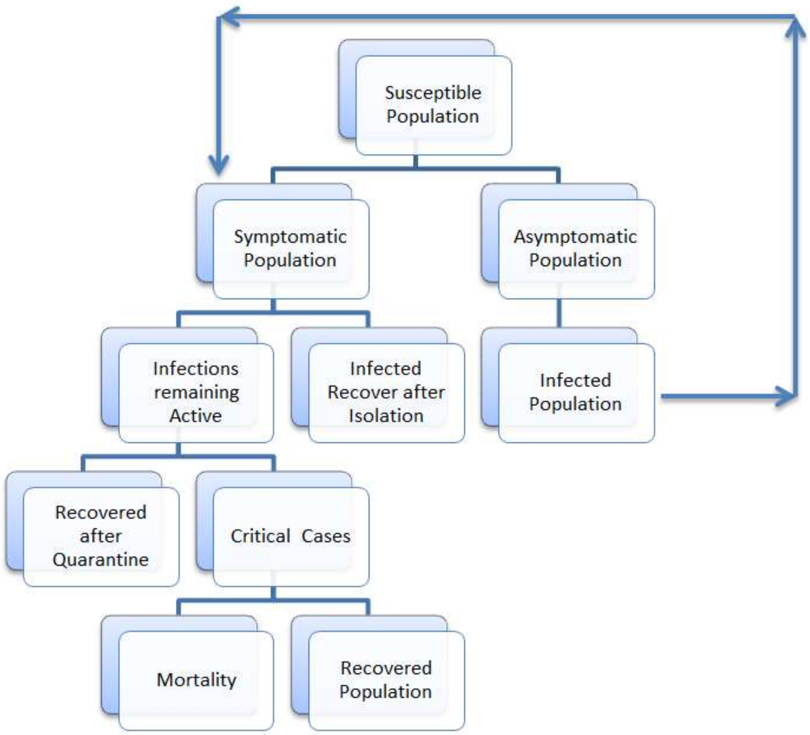


Figure 4: System Architecture Map of COVID-19

3.3 System Analysis

Before commencing with the development of the simulator, data analysis was conducted. South Africa has nine provinces: Gauteng, Kwazulu-Natal, Western Cape, Eastern Cape, Limpopo, Mpumalanga, Free State, Northern Cape, and North West. To develop the national model, the age group of the population per province was obtained and summarised as shown in Table 1 based on population statistics from StatsSA (2019).

Table 1: Provincial Age Group Population Statistics (Stats SA, 2019)

POPULATION	0-19	20-29	30-39	40-49	50-59	60-69	>70
Gauteng	4,656,237	2,992,858	3,032,291	1,928,870	1,295,952	474,169	446,687
KwaZulu-Natal	4,544,746	2,067,103	1,813,980	1,130,085	800,470	306,529	381,310
Western Cape	2,190,133	1,181,482	1,242,411	877,370	665,477	419,558	267,843
Eastern Cape	2,822,215	1,020,900	941,233	646,959	519,213	223,865	361,375
Limpopo	2,516,519	997,769	909,179	605,957	421,368	160,280	240,929
Mpumalanga	1,768,802	825,828	799,459	502,686	338,662	119,252	145,304
Free State	1,078,152	488,847	470,895	322,388	244,860	94,905	112,326
Northern Cape	469,793	204,966	210,933	143,646	105,365	41,286	55,029
North West	1,512,691	663,004	688,758	473,064	336,196	124,075	139,856

The national number of COVID-19 infections, deaths and recoveries was summarised per province and included in Table 2.

Table 2: Provincial COVID-19 Statistics (18/01/2021) (Flevy, 2021)

POPULATION	INFECTIONS	RECOVERIES	DEATHS	ACTIVE CASES
Gauteng	230,834	223,705	4,872	2,257
KwaZulu-Natal	124,325	115,555	3,268	5,502
Western Cape	119,980	110,862	4,422	4,676
Eastern Cape	104,125	94,310	3,934	5,881
Limpopo	18,016	17,074	476	466
Mpumalanga	30,459	29,292	610	557
Free State	58,120	46,751	1,618	9,751
Northern Cape	22,502	18,661	301	3,540
North West	34,033	30,248	510	3,275

Table 3 shows the rate calculations for the various provinces.

Table 3: Provincial COVID-19 Rates (18/01/2021)

	Gauteng	KwaZulu-Natal	Western Cape	Eastern Cape	Limpopo	Mpumalanga	Free State	Northern Cape	North West
MORTALITY RATE	0.02110	0.02628	0.03685	0.03778	0.02642	0.02002	0.02783	0.01337	0.01498
INFECTION RATE	0.01556	0.01125	0.01752	0.01593	0.00307	0.00676	0.02066	0.01827	0.00864
RECOVERY RATE	0.96911	0.92945	0.92400	0.90573	0.94771	0.96168	0.80438	0.82930	0.88878
ACTIVE FRACTION	0.00977	0.04425	0.03897	0.05648	0.02586	0.01828	0.16777	0.15731	0.09623

Based on the number of employee infections and deaths per province, calculated with data obtained on the 15th of January 2021 (Mkalipe & Pule, 2021), the infection and death rates were calculated as presented in Table 4.

Table 4: Adapted Eskom Employee Statistics (Mkalipe & Pule, 2021)

Province	Death Rate	Infection Rate
Eastern Cape	0.041044776	0.108282828
Free State	0.015625000	0.041410547
Gauteng	0.022388060	0.051568212
KwaZulu Natal	0.008333333	0.064188286
Limpopo	0.023809524	0.053804766
Mpumalanga	0.011707317	0.097442723
North West	0	0.064848485
Northern Cape	0	0.060859189
Western Cape	0.010335917	0.084942932

The Eskom employees rates were different to the provincial rates and the simulator built in both values to calculate what the projected impact would have been is national trends were assumed.

The number of infected employees and the deceased were both linked to an Energy Availability Factor (EAF) structure using the equation below derived from the relationship between EAF and the Generation Division staff shown in Figure 5.

$y = -6E - 09x2 + 9E - 05x + 0.3795$

Since Generation staff makes up the core of the operations of the business, this linkage and relationship was used as a proxy to represent the impact of loss of staff on the EAF.

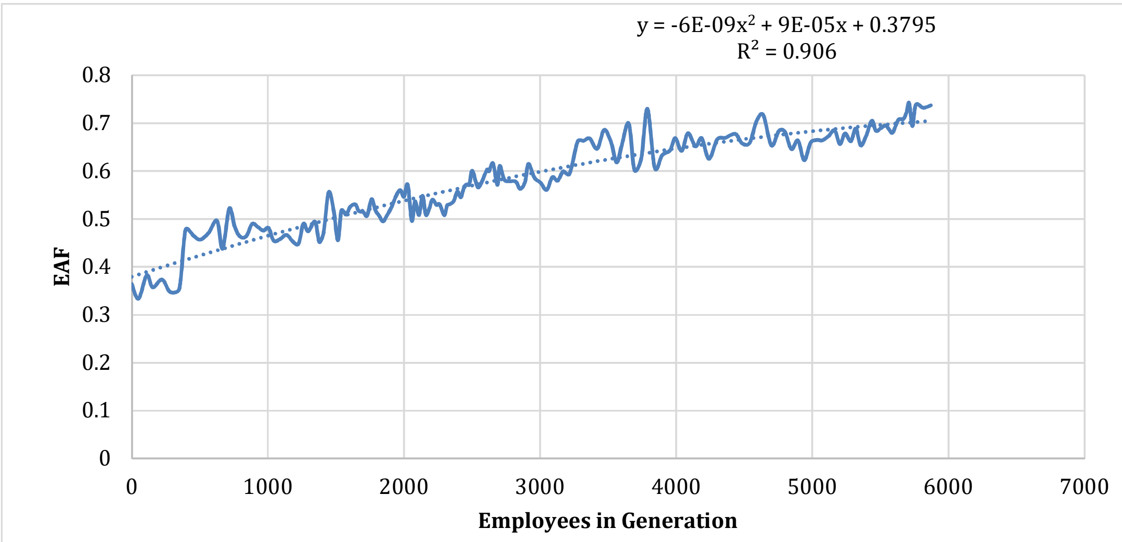


Figure 5: EAF versus Generation Staff

After the number of infected Eskom employees was calculated, the downtime due to employees being on sick leave was linked to productivity levels. The mortality numbers impacted the headcount and the Energy Availability Factor (EAF).

3.4 Model Structure

The software used to construct the system dynamics model structures was iSee Stella Architect. The timeframe of the simulation was from day 1 (1st June 2020) to day 310.

The structures that were completed include:

1) National population by age group and province;
2) National Infection chain with stocks and flows (Susceptible, Exposed, Infected, Quarantined, Critical, Recoveries and Mortality);
3) National Testing and Impact on Rates of Infection;
4) Eskom employees by age group, race, gender and province;
5) Eskom Infection chain with stocks and flows;
6) Eskom Impact in terms of productivity and human resources to deliver on its mandate.

In Figure 6 below, the model structure built was different to the previous configurations because it used logistic equations to fit the infection data in the National Infections stock.

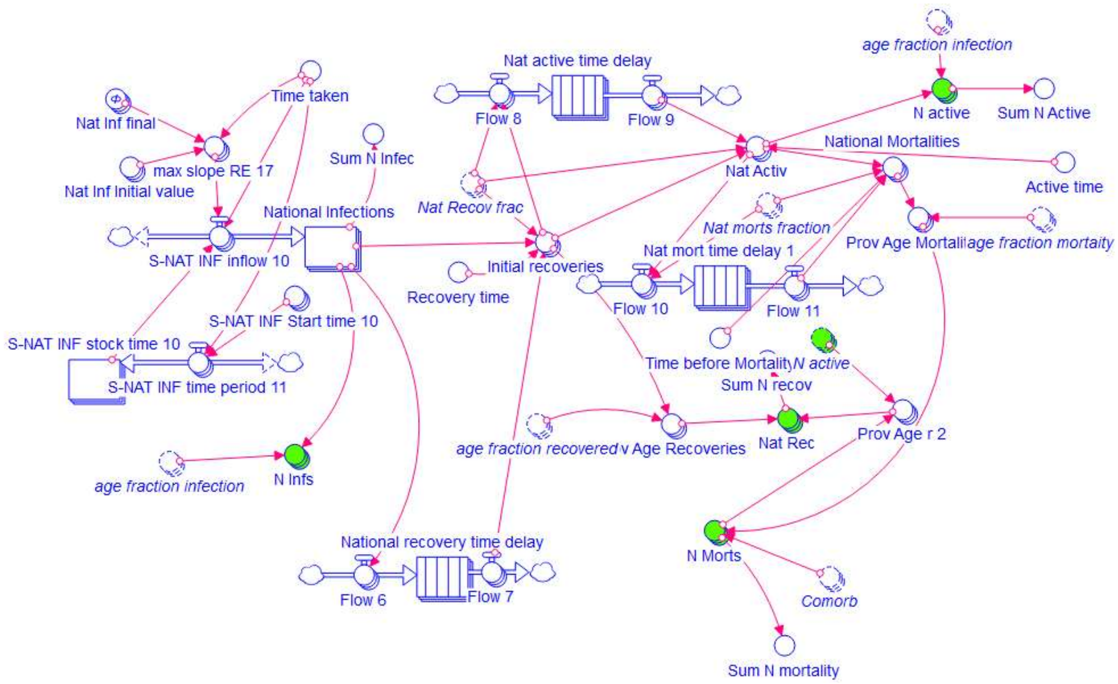


Figure 6: Provincial Infection Model

The logistics curve equation specified in Meyer (1994), allowed for asymptotic conversion to lower values, by specifying a negative value for U_1, or a positive stabilizing non-zero value by retaining a positive value for U_1.

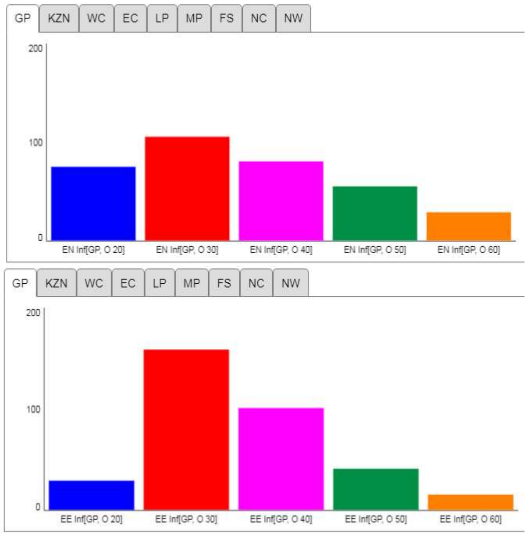
$$P(t)=U_0+\frac{U_1}{1+exp[-c(t-t_0)]}$$

where P is the dependent variable and $P(t)$ is a function of time t; U_0 is the zero offset; U_1 is the ultimate increase (or decrease) above U_0, modelled using a S-curve; c is a growth rate exponent that determines the maximum slope of the S-curve; and t_0 is the time at which the maximum slope is reached (inflection point). Time delays were introduced through conveyor structures, an example of the conveyor structure data input for the recovery of the population. The transit time was defined as the variable assigned to change the recovery period. The recoveries per province from the 1st June were entered into the provincial arrays.

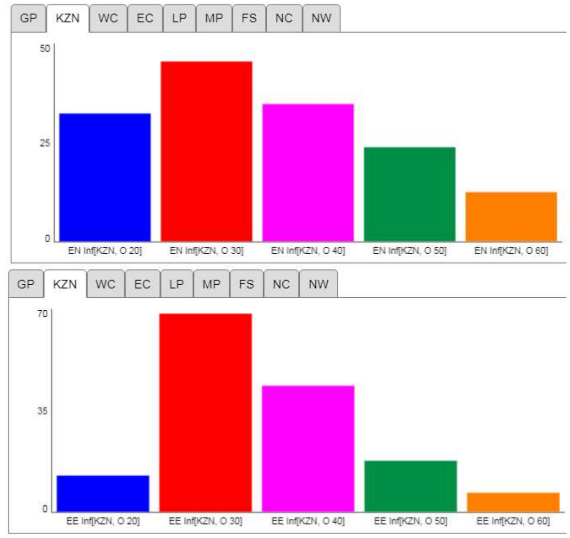
The national final infection values for target setting in the S-curve structure were based on the latest infection values obtained on the 20th January 2021.

4. Results and Discussion

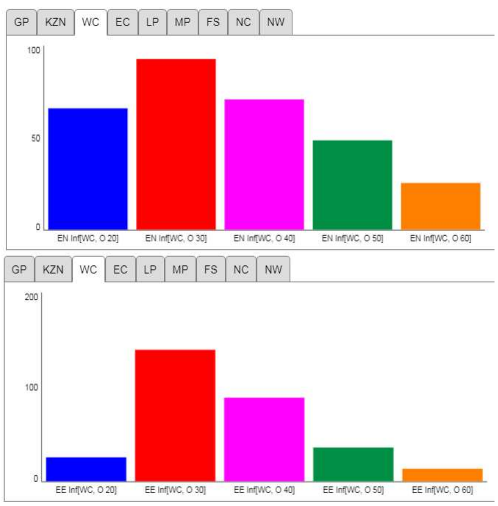
When calculating the infection spread amongst the different age groups per province in the organisation, results were generated for when the national fractions were used and compared against the results using Eskom fractions. The comparison allowed us to determine what the expectation would have been in relation to the actual dynamics within the organisation (Figure 7).



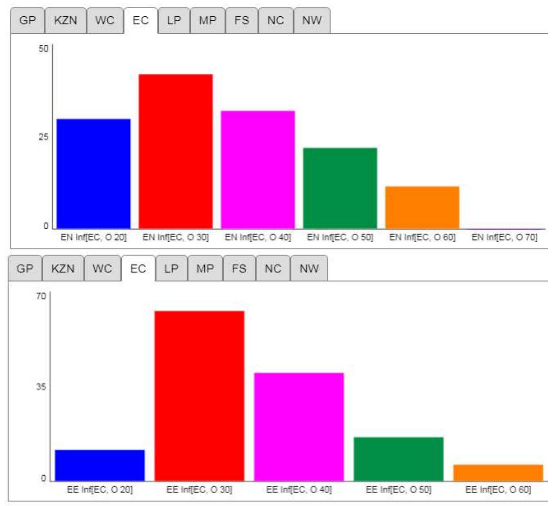
Gauteng Infections



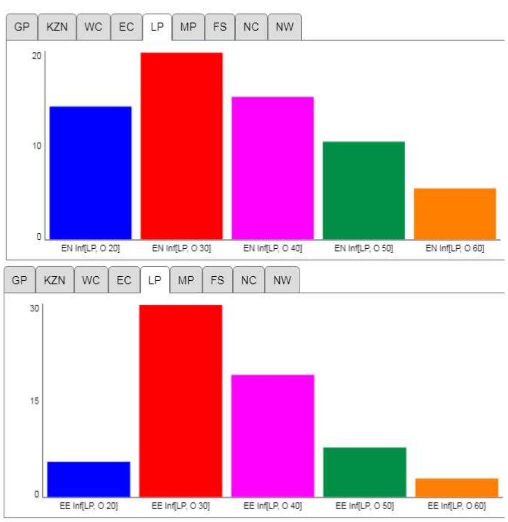
KwaZulu Natal Infections



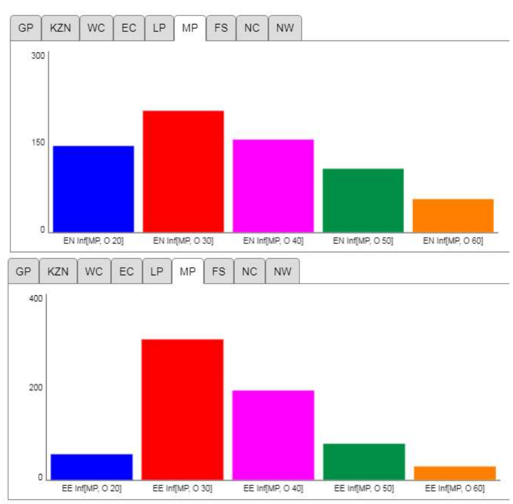
Western Cape Infections



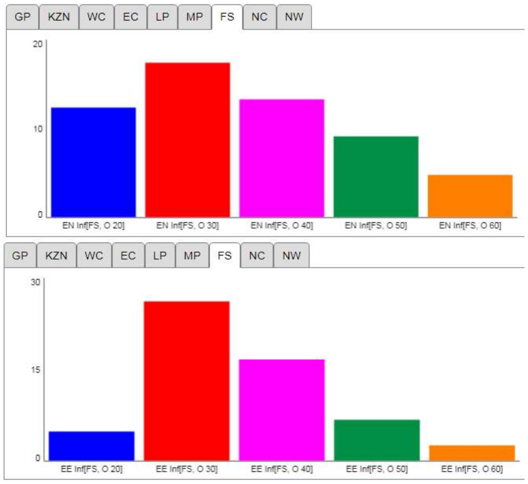
Eastern Cape Infections



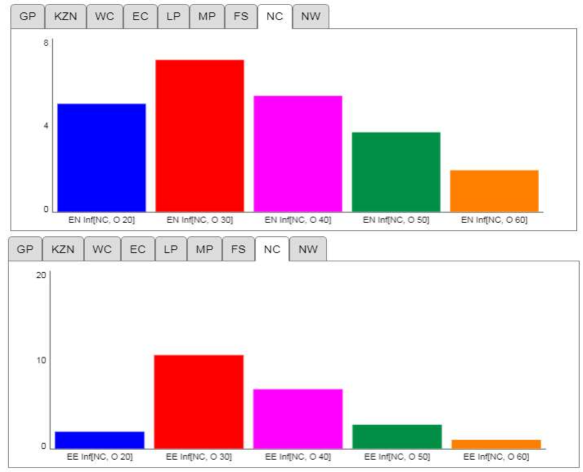
Limpopo Infections



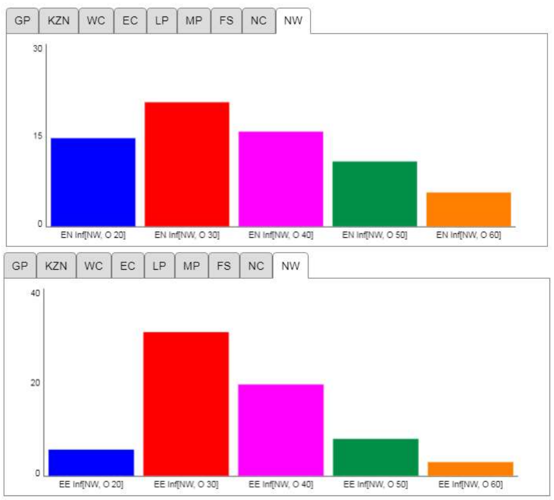
Mpumalanga Infections



Free State Infections



Northern Cape Infections



North West Infections

Figure 7: Employee Infections (Using Eskom Infection Rates and National Infection Rates)

In the case of all of the provinces, based on national age group infection rates, the 30-39 year age group would have been expected to have the highest number of infections, however, based on Eskom age fraction data, the highest number of infections would have been in the 30-39 year age group. In all instances the expectation for infections using national fractions was much higher for the 50-59 and 60-69 year age groups.

Similar graphs were obtained showing the difference in mortality. The major difference in mortality results was largely for the 20-29 year age group where expectations based on national rates indicated a higher mortality rate. When using national mortality rates, the mortality in the 50-59 year age group was a lot higher.

The number of infections as a percentage of the total number of employees as at the 13th January was 7.17%; and the mortality was 0.117%. The scenarios which were run are shown in Table 5.

Table 5: Scenarios to Calculate the Impact of Employee Infections and Mortality on the EAF

	Infection %	Mortality %
Base EAF	0	0
Scenario 1	7.17	0.117
Scenario 2	10	0
Scenario 3	0	10
Scenario 4	10	10

The Base EAF simulator run did not include any mortality or infections. Scenario 1 used the infection and mortality data obtained on the 13th January (Mkalipe & Pule, 2021). Scenario 2 assumed that 10% of employees were infected, with zero mortality. Scenario 3 assumed that 10% of employees fell into the mortality stock with infected employees fully recovered. Scenario 4 assumed a combination of both Scenarios 2 and 3. Results are shown in Figure 8.

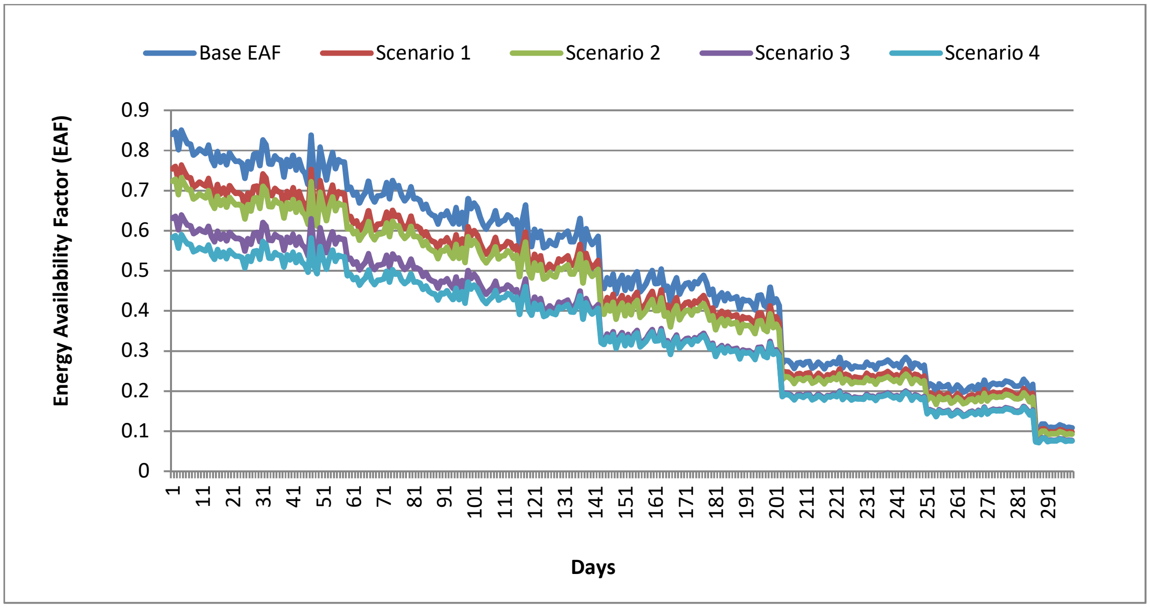


Figure 8: Results of the Impact of Employee Infections and Mortality on the EAF

Due to the dynamics behaviour of the EAF over time, the results for various periods of time are included in Table 6.

Table 6: Results of the Impact of Employee Infections and Mortality on the EAF

	EAF: 60 Days	EAF: 90 Days	EAF: 120 Days
Base EAF	0.707864	0.639596	0.560466
Scenario 1	0.635207	0.573946	0.502939
Scenario 2	0.609183	0.550432	0.482149
Scenario 3	0.531321	0.473706	0.403641
Scenario 4	0.490979	0.443628	0.388743

The results indicated that the average EAF decreased from the Base EAF by 0.0605 for Scenario 1, by 0.089 for Scenario 2, by 0.166 for Scenario 3 and by 0.195 for Scenario 4. The impact of mortality had a much more significant effect on the average EAF when compared to the impact of downtime due to employees being infected. Although the impact on the EAF is initially large, the gap between the Base EAF and the rest of the simulation runs narrows after 200 days.

5. Conclusions

The impact of mortality had a much more significant effect on the EAF than a loss in productivity with employees being on sick leave. Systems dynamics models are not well suited for exploring policies that are not parameterized in the model. The variation in terms of assumptions on the results can be quite significant. This was proven by the results obtained when national fractions were used and compared to Eskom fractions in terms of age group responses to infections as well as mortality. Depending on which fraction was used, there was a different trend in the possible age group distributions of both infections and mortality. If the national provincial rates (infection, recovery and mortality) had been used for determining the age group and provincial distribution of infections within the organisation, the results would have been unexpected and misrepresented.

For the purposes of understanding the time lags between the infections, critical cases, recoveries and mortality, the qualitative system dynamics models were sufficient. These could not however, provide the quantitative results that could be used for future trending. Using a more quantitative approach based on logistic equations provided a more quantitative analysis of the distribution of infections and deaths in the various age groups within the provinces, however, again the difference in rates on the results would produce different infection profiles.

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