Drone Response Service (DRS)

A SIMULATION IN THE NETLOGO ENVIRONMENT

AGENT-BASED MODELLING

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This study will develop an agent-based model (ABM) to simulate the operation of drones within a Drone Response Service (DRS). This will act to characterise the operation of a DRS system, which will then be used as an initial business due diligence test to determine the viability of operating such a service in an urban environment.

Section 1 describes the DRS. In section 2, a research question will be formulated to set out the modelling objectives of the ABM (described in section 3). Section 4 will analyse the effect of changing individual (relative to default parameters) and multiple (relative to an urban environment) factors.

SECTION 1: DRS

A DRS entails autonomous emergency response drones responding to car accidents within an urban environment. The purpose of the drones is to provide a live video feed of accident sites for:

a. Responding emergency personnel
b. City traffic and policing services
c. Insurance providers

Cloud-based analysis of the video feed, supported by state-of-the-art machine learning techniques, will provide insights as to the features of the accident in real-time. These features may include (but are not limited to):

i. Number of injured persons, and the severity of their injuries
ii. Number of cars involved and the extent of their damage
iii. Traffic flow impairment

Recommended courses of action and relevant evidence (if applicable) may then be forwarded to all pertinent parties (a – c).

SECTION 2: RESEARCH QUESTION

Under what conditions does an emergency DRS

(a) retain its entire drone fleet,
(b) respond to the highest percentage of accidents and
(c) operate profitability over a specified period

simultaneously.

The conditions refer to:

(a) environmental factors *(refer to accident and patch parameters in Table 1)*
    - Weather
(b) business and legal constraints *(refer to drone parameters in Table 1)*
(c) drone-build *(refer to drone business and legal parameters in Table 1)*
(d) economic
    - Costs of buying and maintaining drones
    - Income earned per accident response

SECTION 3: MODEL SUMMARY

The DRS was modelled in *Netlogo*. A full description of:

a. Agents
b. How the model works
c. Display console
d. Things to notice and try

may be found in the model's information page.

A short description of the agents, the profit measure, the model's order of operation and drone programming flowchart is provided below.

Agents

A summary of the model's agents is provided in *Table 1*.

Table 1: DRS Model Summary

AGENT TYPES	Drones	Accidents	Patches
Description	Autonomous UAVs equipped with cameras that provide a video feed of an accident site.	Car accidents that occur randomly on roads throughout the city, with differing levels of severity.	Patch agents consist buildings, obstructions and roads. Buildings act to obstruct drones flying below their height level. Obstructions prevent drones from flying within their airspace. Roads are set at ground level.
Properties	• **state**: ○ "unavailable", "available" or "recharging" • **energy**: battery capacity remaining	• **time remaining**: time after which responding to the accident provides no value • **emergency level**: severity of the accident [low, mid, high]	• **height**: height of a building (property of buildings only)
Behaviours	• Fly avoiding obstacles • Search for accidents • Return to base • Recharge	• Appear randomly throughout city • Disappear after a specified time	
Parameters	Battery - Capacity - Minimum level at which the drone returns to be recharged - Rate of charge and discharge Business and legal: - Location of drone base - Drone flight height	- Car accident frequency - Maximum accident waiting time for accidents of different severity levels	- Building height range - Number of no-fly zones (i.e. obstructions)
Measures	% of initial drones operational	% of accidents responded to	

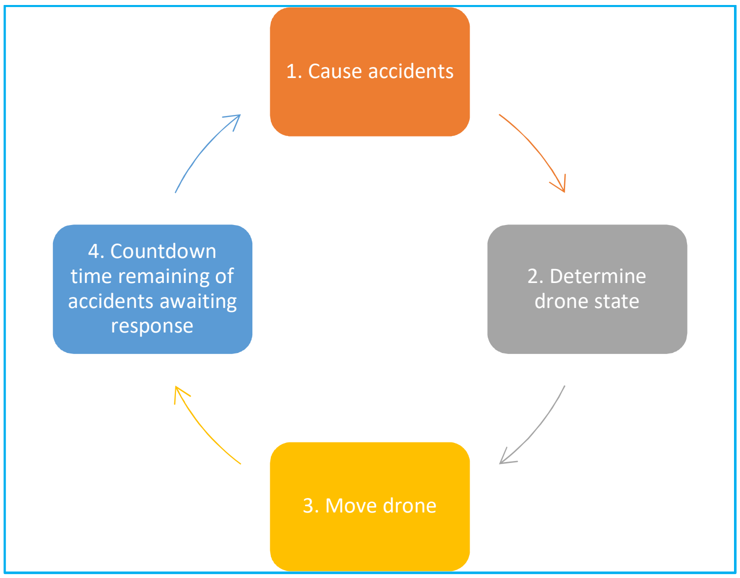
Profit measure

A profit measure incorporating the economic conditions is also included. The user is able to set the revenue earned from responding to accidents (by severity), as well as the initial and maintenance costs associated with purchasing and operating the drones respectively.

Time-order of operation

The order of *actions* has a material impact on the model's outcome. *Graph 1* depicts the order used in the model.

Graph 1: Model - Order of operation

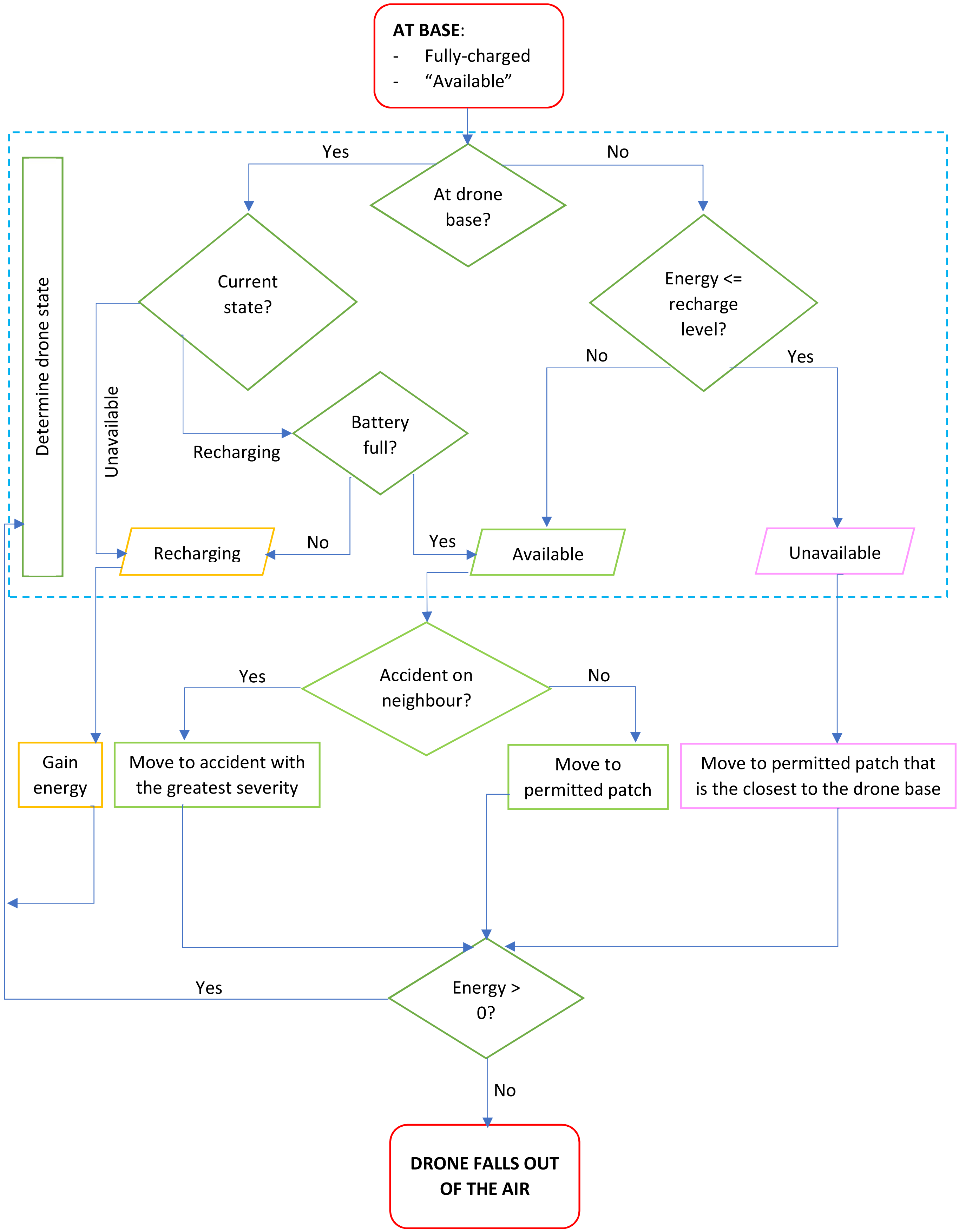


Rationale:

(1) Accidents should occur prior to the drones being deployed/moving. The drones' existence is driven by the existence of the accidents. This occurrence may or may not take place with a particular probability.
(2) Depending on a drone's location and energy level, the drone's state may be determined. The state determines what movement is made in the following step.
(3) If the drone is:
    - "available": The drone will move towards a neighbouring patch that contains one of the most severe accidents. If no accidents are present, the drone will move to a random neighbouring patch.
    - "unavailable": The drone will move towards an allowable patch that is closest to the drone base, and that neighbours its current location.
    - "recharging": The drone will remain at the drone base until its battery is full.
(4) If a drone has not moved to an accident's location, its viable time remaining will decrease by 1.

The process then repeats itself until no drones are remaining.

Drone programming flowchart:



SECTION 4: ANALYSIS AND INSIGHTS

20 user-defined parameters are present in the model. The potential scope of the analysis forced this study to prioritise the analysis of a 6-factor subset. Each factor may depend on a single or multiple parameter/s. The 6 factors are (*Netlogo parameter names are shown in italics*):

(1) Accident frequency: *accident-frequency*
(2) Conditions: *conditions*
(3) Refuel energy level: *refuel-energy-level*
(4) Number of drones: *num-drones*
(5) Drone base position: *x-drone-base*, *y-drone-base*
(6) Battery size and efficiency: *battery-capacity*, *charge-rate*, *discharge-rate*

SECTION 4A studies each individual factor's influence on the model measures (i.e. research questions). A scenario testing procedure will then be performed in *SECTION 4B*. This entails modifying multiple factor parameter values simultaneously to recreate real-world operating scenarios.

SECTION 4A: INDIVIDUAL FACTORS

Analysis

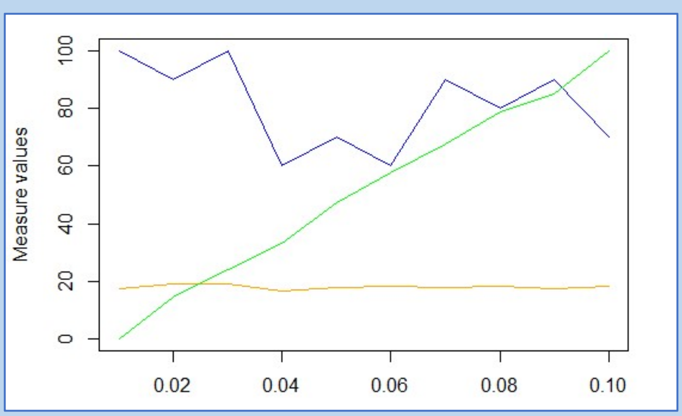
A default parameter basis is chosen (*refer Appendix A*). Each experiment's iteration is 30 000 ticks in length. The x-axis of the graph output refers to all factor parameter values assessed. The profit measure value is rescaled to lie between 0 and 100. Abbreviations and associated graph colours for the model measures are detailed in *Table 2*.

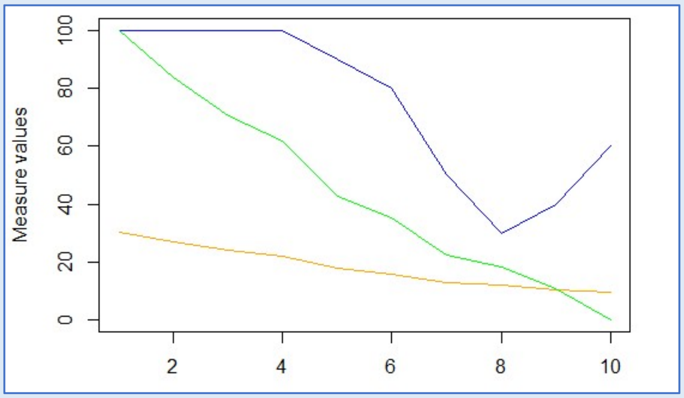
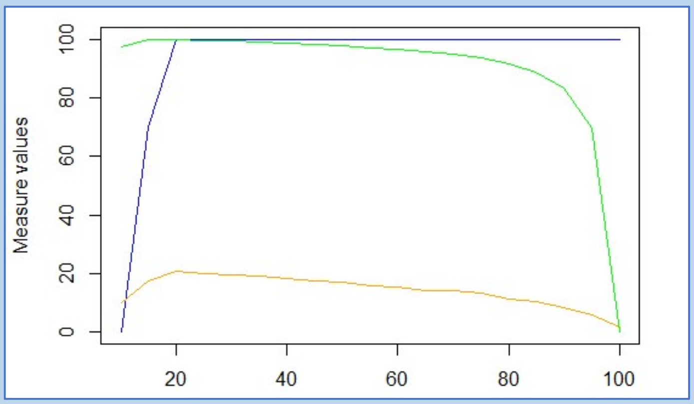
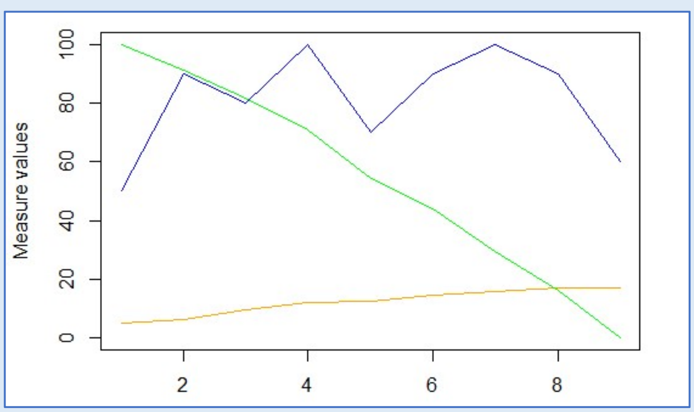
Table 2: Model measures – Abbreviation and corresponding graph colour

Profit measure	Abbreviation	Colour
Percentage drones remaining	**PD**	
Percentage of accidents responded to	**PR**	
Profit	**PFT**	

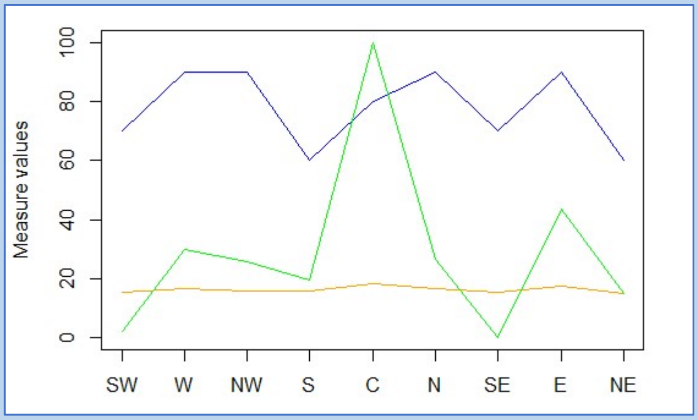
Each factor's parameter values were altered individually. The model measure output for each factor configuration, as well as the analysis thereof, is shown in *Table 3*.

Table 3: Single parameter factors

	Average measure values (10 repetitions)	Analysis
Accident frequency		The **PD** exhibits a sizeable reduction at certain accident frequency levels (i.e. 0.04 – 0.06; 0.10). Although sharing no apparent correlation to the measure, accidents in the drone's neighbouring patches may be drawing the drone out further from the drone base. **PR** seems unchanged. This suggests that although the DRS misses more accidents, the ratio missed remains constant. PFT increases linearly with accident frequency. A viable DRS depends on a *high accident environment* to drive profitability.

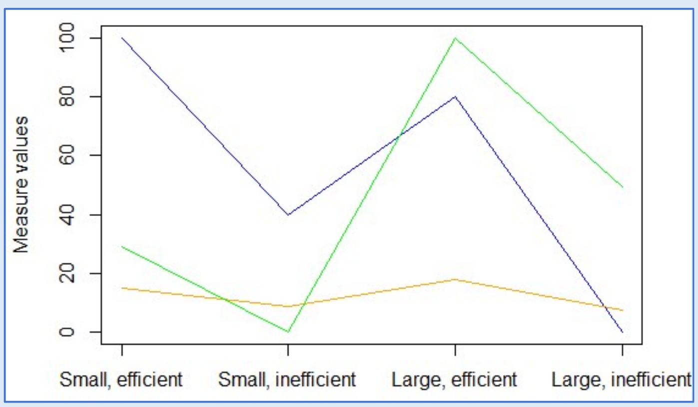
Conditions		The allowable weather conditions vary from good (1) to bad (10). Poor conditions seem to decrease **PD**, **PR** and **PFT**. The **PD** appears to spike up after 8. As poor conditions reduce drone speed, it emerges that the drone is unable to move far from the drone base, thereby reducing the probability of it running out of battery. **PR** exhibits a decreasing reduction in its measure value as conditions worsen. The slow drone speed may inhibit most movement beyond a point when accounting for the scale of other parameter choices. The lower **PR** heavily reduces **PFT**.
Refuel energy level		Drones' survivability seems ensured when the refuel energy level is greater than 20. This minimum level of 20 appears to maximise the DRS's "available" time, and is therefore also associated with the model's highest **PR**. When the refuel energy level is too low, drones may be unable to return to base, thereby resulting in their demise. As fewer drones are operational, the **PR** is negatively affected. When the level is too high, the frequency to which drones return to base is increased, thereby reducing "available" time, **PR** and **PFT**. **PFT** looks to only fall after a refuel level of 70. As the refuel energy level tends to 100, drones are increasingly prevented from leaving far from the base. This causes **PR** and **PFT** to tend to 0.
Number of drones		**PD** is difficult to compare across differing numbers of drones, as the percentage outcomes differ in scale (i.e. An experiment containing 1 drone may have a **PD** of 0 or 100, whereas a 2-drone analogue may have a 0, 50 or 100 **PD**). The number of drones should not impact **PD** as they operate independently. **PR** increases steadily as the number of drones increases. This is intuitive as the spatial reach of the DRS expands with the number of drones that are operational. The almost linear decline in **PFT** is largely attributable to the high initial cost of drones. A longer experimental timeframe may allow these drones to recoup their costs and attain profits.

Drone base position



Drone bases located in the environment’s corners (SW, NW, SE, NE) tend to have lower **PD** on average, relative to the center (C) and its cardinal locations (N, S, E, W). Some anomalies to this relationship occur due to the drones being unable to centrically expand from the base at non-center locations. The **PR** does not appear to differ vastly at different base locations. This may be caused by the random spread of accidents across the environment space. The **PFT**, when the base is located at C, seems to exceed that of all other locations. Cardinal locations also exhibit better **PFT** than their corner counterparts. A possible explanation for different profit levels being earned is that less time is spent recharging. Drones tend to be closer to more central drone base locations at all times. When a recharge is required, a shorter distance must be travelled to the drone base. This increases the battery remaining upon arrival, reducing the time required to recharge.

Battery size and efficiency



Efficient batteries [*charge-rate* = 1, *discharge-rate* = 0.5] give the drone more “time” to return to base and are therefore associated with higher **PD** scores, relative to inefficient batteries [*charge-rate* = 1, *discharge-rate* = 1]. A larger efficient/inefficient battery is associated with a lower **PD** score relative to a smaller battery of the same efficiency status. This may be caused by the distance away from the drone base that a drone is able to travel on such a battery.

An efficient battery offers longer flying times, thereby enabling the DRS to receive better **PR**. Larger batteries achieve this to an even greater extent. **PFT** appears to increase more by a larger battery size, than if the battery is more efficient. An expanded operating space is the likely cause thereof.

Insights

Based on the analysis, the following insights may be drawn:

Accident frequency: The **PR** remains fairly constant as accident frequency increases. Profitability is strongly driven by a “higher accident environment“.

Weather conditions: The DRS may not be able to operate profitability in poor weather conditions. However, there is a strong positive correlation between poorer weather conditions and accident frequency in practice. The increase in the number of accidents may offset the losses incurred by a limited DRS reach. The capability of drones flying in poor conditions should be explored further.

Refuel energy level: Obtaining the minimum refuel energy level is critical in (a) ensuring drone survivability and (b) maximising "available" time, **PR** and hence **PFT**. This level should be dynamic to allow for changing operating conditions (e.g. weather).

Number of drones: The larger the drone fleet, the greater **PR**. The high initial cost of purchasing/building drones must be compensated for by a long working life. This will allow the drone to recoup its costs and generate profits for the DRS.

Drone base: A non-central drone base does not appear to reduce **PD** or **PR** significantly, especially in cardinal locations (relative to center). However, a central drone base seems to maximise the profits earned. This is speculated to be caused by a shorter recharge time associated with shorter return distances.

Battery capacity: A large, efficient battery produces more income and responds to the greatest percentage of accidents, without incurring many drone losses. A small, efficient battery may offer a lower yielding return, but a comparable **PR** and better **PD**.

SECTION 4B: MULTIPLE FACTORS

A potential operating environment for the DRS is Cape Town CBD. As such, the environment parameters are configured to best correlate to this environment:

Table 4: Cape Town CBD – Environment Correlation Parameters

Cape Town CBD - Environment Correlation Parameters	Parameter	Justification
Average building height	7	The buildings are deemed tall relative to a drone's flight height. The tallest building in Cape Town is 142m tall, whereas a top consumer drone can fly up to 120m in the sky.
Weather conditions	2	Cape Town has approximately 8 hours of sunshine per day, on average, throughout the year. This equates to ideal operating conditions for most of the year.
Number of obstructions	3	Cranes and restricted operational zones (e.g. above embassies, police stations) may restrict drone movement.
Drone base location	[-12, 0]	High property prices in the CBD may necessitate the base to be located on the outskirts of the city.
Drone flight height	5	This will likely be regulated. The company may wish to lower the drone flight height to improve image quality, whilst keeping the drones high enough to prevent damage thereto or theft thereof.

The number of drones employed by the company is assumed to be 9. The company is likely to maximise the presence of these drones as

a. their response to accidents drives income.
b. they can act as a marketing tool.

The scenario space has been divided into 3 scenarios.

(1) Optimistic: Better than expected
(2) Best-estimate: Expected
(3) Prudent: Worse than expected

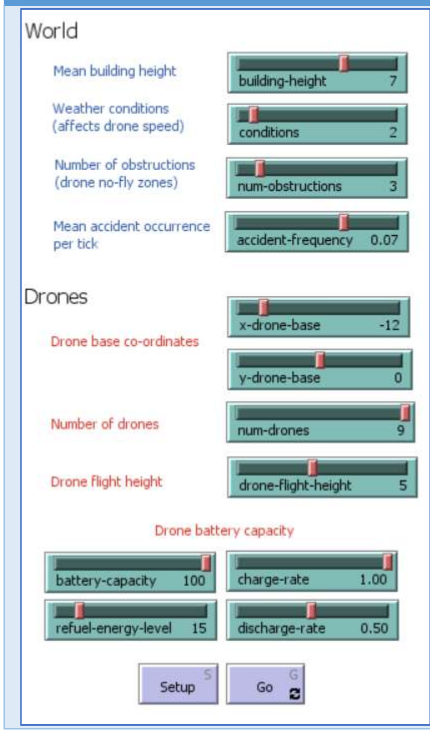
In each scenario, the expectations for:

(a) the battery settings: *battery-capacity, charge-rate, discharge-rate* and *refuel-energy-level*. These are set to reflect assumptions of battery size and efficiency.
(b) accident frequency: *accident-frequency*

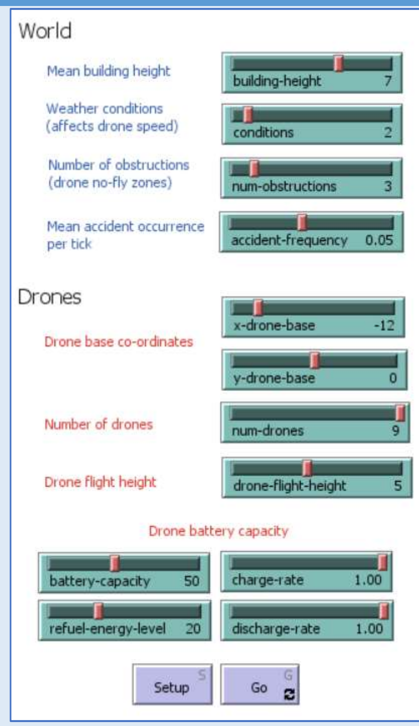
differ. The parameters chosen are shown in *Table 5*.

Table 5: Scenario parameters

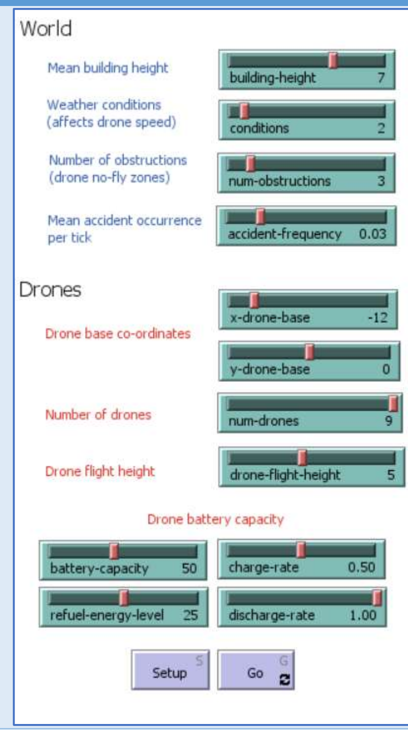
OPTIMISTIC



BEST-ESTIMATE

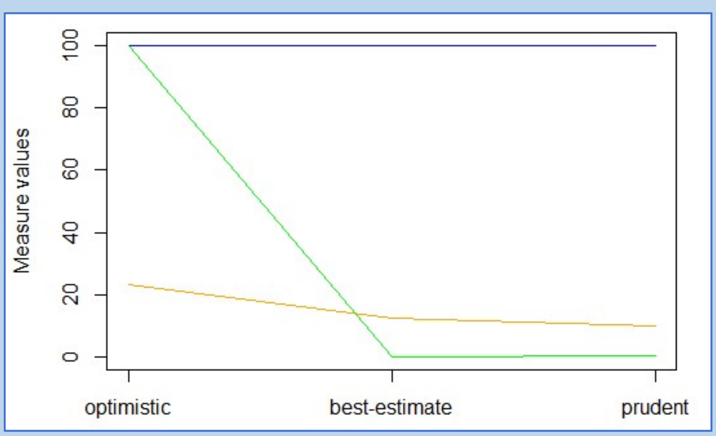


PRUDENT



Analysis

10 repetitions of each scenario were run, and the following results obtained.

	Average measure values (10 repetitions)	Analysis
Scenarios		All scenarios achieved an optimal **PD** value. The **PR** decreases as accident frequency decreases and poorer battery settings are applied. This suggests that the battery capacity and discharge rate have a large effect on accident response. An optimistic configuration yields more **PFT** than that of best estimate and prudent. An apparent anomaly seems to occur as a prudent configuration yields a greater **PFT** value than that of a best-estimate. This difference may be attributable to a slower charge rate, resulting in fewer returns to the drone base after 30 000 ticks.

Insights

The degree of uncertainty in the model's scales (i.e. temporal and physical) and parameter choices prevents one from obtaining conclusive insights into the viability of the DRS under the 3 bases. The scenario analysis appears to suggest the importance of a larger battery capacity and a smaller discharge rate on **PR**.

Conclusion

This study developed an ABM to simulate the operation of a DRS. The degree of scale uncertainty within the model prevents the user from using absolute model output to inform decisions. An analysis of the relative effect of 6 identified factors suggests that:

(a) Large, efficient drone batteries with a high drone refuel energy level allows the DRS to retain its fleet.
(b) A high number of drones, fitted with large efficient batteries and operating within good weather conditions, increases the reach of the drones and hence their **PR**.
(c) Profitability is driven by the centrality of the drone base and the frequency to which accidents occur. Factors that tend to increase **PR**, tend to increase **PFT** as well.

A possible extension to the model includes modelling the DRS as an agent, thereby allowing accident locations to be known or shared between the DRS and/or drones. More realistic model assumptions are needed to inform the viability of operating such a business.

Appendix A: Default parameter base