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RELIEF FOOD SUPPLY NETWORK SIMULATION

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ABSTRACT

Research into simulation modelling to support disaster management has focused on large disasters. In some regions, there are frequent small-to-medium scale disasters, which require daily decisions to be made. These are typically described as routine emergencies. For example, in Indonesia's West Java province, on average, there were 4.6 disasters per day between 2016 and 2020. This paper presents a simulation model of relief food distribution to refugees in a region that is vulnerable to multiple disasters on a daily basis. To illustrate how the model can support disaster management decision making, we use the West Java case. The model demonstrates that the current warehouse locations and routing heuristic can cope with the demand; however, improvements are needed to cope with an expected increase in the demand due to an increased number of disasters as a result of climate change and a growing population.

1 INTRODUCTION

This paper presents a simulation model of the relief food distribution to refugees in a region that is vulnerable to multiple disasters on a daily basis, which is a part of the Relief-OpS project (www.southampton.ac.uk/relief-ops). To illustrate how the model can support disaster management decision making, we use a case from West Java province in Indonesia (Figure 1), using data collected between 2016 and 2020. West Java province is chosen because it has the highest multi-disaster risk in Indonesia (Amri et al. 2016) due to the population size, population density (population size of over 46 million people in the area of 37,000 km^2), high contribution to Indonesian GDP and being the center of rice production in Indonesia (rice is the main staple food in Indonesia).

The literature differentiates between routine emergencies and disasters (Altay and Green 2006; Anaya-Arenas et al. 2014). The difference is often related to the scale of the impact. For example, Altay and Green (2006) consider major emergencies, disasters and catastrophes collectively as disasters while Faharani et al. (2020) use the number of casualties. Hence, based on the number of casualties, the same event (e.g.

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earthquake) could be considered as an emergency, disaster or catastrophe depending on the number of casualties. Routine emergencies can typically be handled by the affected community themselves or by a single government agency, while disasters put an enormous stress on the community and government resources, and in the larger disasters, additional resources are needed. Altay and Green (2006) further note that government agencies typically have standard procedures to deal with routine emergencies. However, to deal with disasters, they may need to carry out non-standard procedures. In agreement with Altay and Green, Galindo and Batta (2013) set the following criteria for a disaster: the event seriously disrupts the functioning of a community, exceeds the community resources to cope with the event, and requires several non-local agencies to work together using non-routine or non-standard procedure. Hence, there is a clear separation between routine emergencies and disasters in the literature.

Figure 1: Indonesia (© OpenStreetMap contributors) – West Java province is highlighted.

Salkowe and Chakraborty (2009) discuss disaster definition from the political or administration perspective which is relevant to the case of Indonesia. The Republic of Indonesia comprises 34 provinces. Each province is divided into a number of municipalities (cities and regencies). After the 2004 tsunami, Indonesia formed Badan Nasional Penanggulangan Bencana (BNPB), which is responsible for disaster management at the national level, from setting mitigation and preparedness policies to coordinating response and recovery operations. The provincial and municipality governments each form their own Badan Penanggulangan Bencana Daerah (BPBD) to directly deal with disasters in their administration regions. When a disaster happens in a municipality, the mayor of the city (or regent for regency) will declare an emergency status and the municipality's BPBD will coordinate with relevant agencies to respond to the disaster. If a disaster covers multiple municipalities then the governor will declare an emergency status and the province's BPBD will coordinate with relevant agencies to deal with the disaster. If the resources in a regional government are overwhelmed then they will escalate the coordination to the higher government level (e.g. from municipality to province, and from province to national). Hence, in this case, the definition of disaster in Salkowe and Chakraborty (2009) is relevant, i.e. an event is considered a disaster when a regional or national government declares it as a disaster and triggers the emergency procedure. Based on the data that we will discuss in Section 3, the number of refugees ranges from 0 to tens of thousands per disaster, which suggests that what is known as routine emergencies in the literature can be declared as disasters in practice. Furthermore, standard procedures exist for BNPB and all BPBDs to coordinate the response and recovery operations following a disaster of various scales, including the escalation procedure.

Small-to-medium-scale routine disasters are very common in Indonesia. For example, in West Java province alone, on average, there were 4.6 disasters per day between 2016 and 2020, forcing around 23,800 people to become refugees annually. The daily frequency shows the characteristics of routine emergencies but the high uncertainty of the events, locations and impacts bears the same characteristics of disasters. Furthermore, administratively, Indonesia BNPB and BPBDs deal with both disaster categories using shared resources. The literature tends to separate routine emergencies and disasters. Hence, there is a need for research that considers the situation where government agencies use shared resources to deal with both routine, small-to-medium scale disasters and rare, large-scale disasters. How should a model (or models) be developed to support the disaster management decisions in this context? Our research project, Relief-OpS aims to address this challenge.

The remainder of this paper is organized as follows. We will show the gap in the research into simulation modelling for relief food supply chain in Section 2. In section 3, we will explain the West Java case that we will use to illustrate how our simulation model can support relief food distribution decision making. Subsequently, the model will be presented in Section 4. In Section 5, we will discuss the results of preliminary experiments and how it can be useful for decision makers. Finally, we will close our paper with conclusion and future work.

2 LITERATURE REVIEW

The International Federation of Red Cross and Red Crescent (IFRC) defines Disaster Management (DM) as “the organization and management of resources and responsibilities for dealing with all humanitarian aspects of emergencies, in particular preparedness, response and recovery in order to lessen the impact of disasters”. Sendai Framework for Disaster Risk Reduction 2015-2030 puts a stronger emphasis on disaster risk management acknowledging the importance of risk management and strengthening resilience against disasters. The disaster management problems are characterized by high stochasticity due to the randomness of the events, scales, locations and impacts. Hence, modeling and simulation (M&S) can play an important role.

Prior to 2006, the application of Operational Research / Management Science (OR/MS) – which includes M&S – in disaster operations management had not reached a critical mass (Altay and Green 2006). However, they noted that the number of papers published in the 90s had more than doubled from the previous decade. Several years later, Galindo and Batta (2013) repeated Altay and Green’s survey. Although they had not observed any drastic changes or developments in the research direction, the number of publications had increased significantly. Since then, research into M&S for disaster management has been plentiful, resulting in several literature review papers as shown in Table 1.

Several scholars review the literature by focusing on a specific modeling method such as optimization (Caunhye et al. 2012; Özdamar and Ertem 2015), stochastic models (Hoyos, et al. 2015), evolutionary models (Zheng et al. 2015), big data analytics (Akter and Wamba 2019), artificial intelligence (Tan et al. 2020) and simulation (Barnes et al. 2019). Other scholars review the models based on disaster management activities such as shelter and evacuation (Esposito Amideo et al. 2019), mass casualty management (Farahani et al. 2020), asset prepositioning (Sabbaghtorkan et al. 2020) or integrated activities such as disaster operations management (Altay and Green 2006; Galindo and Batta 2013; Hoyos et al. 2015) and humanitarian logistics (Caunhye et al. 2012; Özdamar and Ertem 2015; Boonmee et al. 2017). Disaster operations management is defined as the set of activities that are performed before, during, and after a disaster with the goal of preventing loss of human life, reducing its impact on the economy, and returning to a state of normalcy (Altay and Green 2006). Humanitarian / emergency logistics is defined as the process of planning, managing, and controlling the flow of resources to provide relief to affected people (Caunhye et al. 2012).

Table 1: Literature review on M&S for disaster management.

Review paper	**What is being reviewed**	**Review Method**
Alsnih and Stopher (2004)	Simulation tools for mass evacuation with road network	Tool analysis
Altay and Green (2006)	Models used for disaster operations management (activities performed before, during and after a disaster)	Content analysis
Li et al. (2011)	Covering models for emergency response facility location	Content analysis
Caunhye et al. (2012)	Optimization models for emergency logistics (facility location, relief distribution, casualty transportation and other operations)	Content analysis
Galindo and Batta (2013)	Models used for disaster operations management	Content analysis
Anaya-Arenas et al. (2014)	Relief distribution network models	Systematic review, content analysis
Hoyos et al. (2015)	Stochastic models used for disaster operations management	Content analysis
Özdamar and Ertem (2015)	Humanitarian logistics models	Content analysis
Zheng et al. (2015)	Evolutionary optimization for disaster relief operations	Content analysis
Boonmee et al. (2017)	Facility location optimization model	Content analysis
Akter and Wamba (2019)	Big data analytics in disaster management	Bibliometric and network analysis
Barnes et al. (2019)	Simulation models in disaster management	Bibliometric analysis
Esposito Amideo et al. (2019)	Optimization models for shelter location and evacuation routing operations	Content analysis
Mishra et al. (2019)	Simulation models in disaster management	Content analysis
Farahani et al. (2020)	Models for mass casualty management	Content analysis
Sabbaghtorkan et al. (2020)	Asset prepositioning models for disaster operations	Systematic review, content analysis
Tan et al. (2020)	Artificial intelligence for disaster management	Content analysis

Altay and Green (2006) identified that the most commonly used method was mathematical modeling. A few years later, mathematical modeling still dominated the literature (Galindo and Batta 2013; Hoyos et al. 2015). The mathematical models have been developed based on well-known optimization problems such as location problems (Li et al. 2011; Boonmee et al. 2017; Caunhye et al. 2012; Anaya-Arenas et al. 2014; Zheng et al. 2015; Farahani et al. 2020; Sabbaghtorkan et al. 2020), routing problems (Caunhye et al. 2012; Anaya-Arenas et al. 2014; Özdamar and Ertem 2015; Zheng et al. 2015; Farahani et al. 2020), inventory problems (Sabbaghtorkan et al. 2020) and their integration; for example, location routing problem (Caunhye et al. 2012; Anaya-Arenas et al. 2014; Farahani et al. 2020), location inventory problem/location allocation problem (Sabbaghtorkan et al. 2020) and inventory routing problem (Caunhye et al. 2012). Barnes et al. (2019) specifically review the use of simulation modeling and has found it to be limited. Mishra et al. (2019) review papers on simulation modelling in disaster management between 2000 and 2016. The scope of the review is rather broad, which includes the modelling of physical behavior of flood water or soil erosion, and the spread of disease, wildfire or panic. Even with this broad scope, the number of papers is relatively low. If we look at the number of articles that focus on the modelling of the disaster operations, it is even more limited.

The above reviews show that there is a lack of simulation modeling work to support disaster management decisions. In the disaster management literature, simulation is used mainly to validate mathematical models (Galindo and Batta 2013), to evaluate the performance of a system or combine it with heuristic algorithms to provide near optimal solutions (Li et al. 2011; Zheng et al. 2015), and mostly for the disaster response phase (Hoyos et al 2015). Agent-based simulation has often been used to model evacuation planning and emergency responses (Mishra et al. 2019). In fact, several mass evacuation simulation tools have been reviewed by Alsnih and Stopher (2004). The reviewed tools have the capability to model access to a road network that is shared by emergency personnel and evacuees.

In summary, the literature has highlighted several research gaps. First, the use of simulation is lacking (Barnes et al. 2019). Secondly, the use of empirical data is lacking (Galindo and Batta 2013; Hoyos et al. 2015; Esposito Amideo et al. 2019; Farahani et al. 2020; Sabbaghtorkan et al. 2020). Empirical data is needed to embed more realism into the models by providing better parameter estimation based on valid historical data and more realistic assumptions. Empirical data also allows us to have a better understanding of disaster management problems. Thirdly, there is a need for models that are linked to GIS-based platforms (Esposito Amideo et al. 2019). Finally, although heuristics/rules of thumb are more effective in helping decision makers to make quick decisions in the scene of disaster, few papers propose or evaluate such heuristics (Farahani et al. 2020). This paper aims to close the gaps by developing a simulation model with parameters that are estimated using empirical data.

3 RELIEF FOOD DISTRIBUTION CASE IN WEST JAVA

We limit the scope of our model to the most common disaster types in West Java (flood, landslide, tornado, wildfire and earthquake). These disaster types contribute to more than 90% of the refugees. Table 1 shows the number of disasters and refugees data from West Java Regional Disaster Management Agency (BPBD Jawa Barat). The number of refugees is the number of people who are evacuated due to the high risk or whose houses are seriously damaged. This is different from the number of affected people, which includes fatalities, injured and those who can still live in their homes or with their friends or families (i.e. use the community's resources). The data shows the high variation in the number of events and refugees. The most common disaster type is landslides (40% of the total events), where on average more than one event happened everyday between 2016 and 2020. The number of tornado disasters shows an increasing trend. Flood has generated the highest number of refugees, followed by landslide. The proportion of the number of disasters between different disaster types is shown in Figure 2.

Table 1: The disaster types in West Java – Number of events and refugees (2016 – 2020).

	Disaster	**2016**	**2017**	**2018**	**2019**	**2020**
Number of events	Flood	211	183	159	164	280
	Landslide	464	673	753	302	569
	Tornado	179	332	302	489	439
	Wildfire	241	620	569	389	35
	Earthquake	38	284	1	17	43
	Total	1,133	2,092	1,784	1,361	1,366
Number of refugees	Flood	25,972	6,729	9,883	6,174	47,384
	Landslide	2,692	2,246	7,575	578	6,788
	Tornado	196	261	1078	105	49
	Wildfire	252	428	0	0	0
	Earthquake	0	3	140	0	227
	Total	29,112	9,667	18,676	6,857	54,448

West Java province comprises 27 municipalities (9 cities and 18 regencies). Due to the difference in topography, geology, land use and other environmental characteristics, the probability that a disaster type occurs varies between municipalities as shown in Figure 3. For example, Garut is more likely to suffer from an earthquake than any other disaster types. To take another example, around 50% of tornadoes happen in Bogor Regency, Bogor City and Sukabumi Regency.

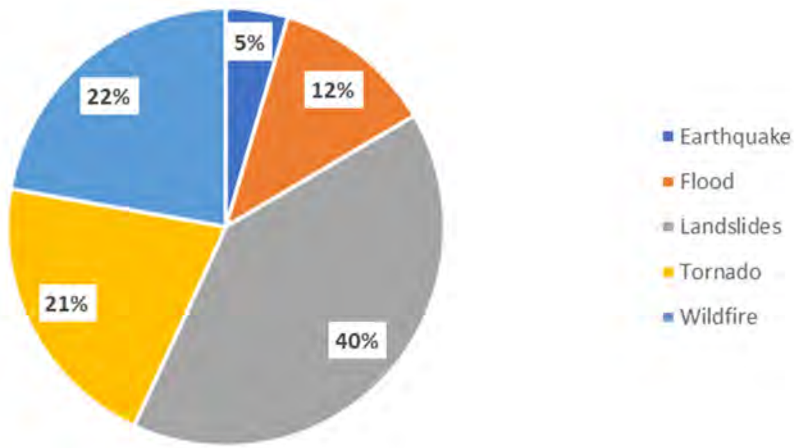

Figure 2: Proportion of the number of events per disaster type in West Java (2016 – 2020).

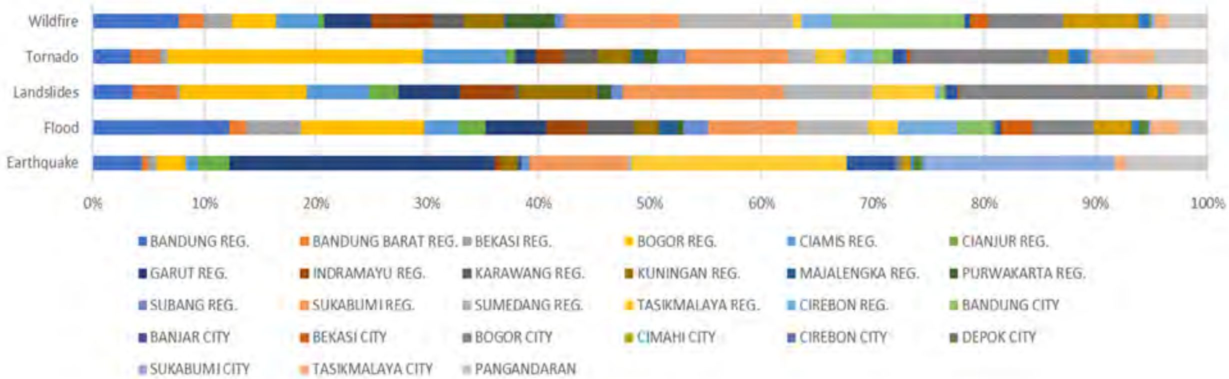

Figure 3: Proportion of affected municipalities per disaster type in West Java (2016 – 2020).

Each municipality is divided into several districts (known as Kecamatan in Indonesia). The total number of districts in the province is 627 (on average, 23 districts per municipality). The ideal level of detail in our model is at the district level. This is because we focus on daily disasters that are typically small to medium in scale (i.e. affecting 1 to 5 districts) which is a small fraction of a municipality area. If we choose a more detailed level (i.e. sub-district or Kelurahan), there will not be enough data points in each sub-district and the quality of data deteriorates as many data points do not include sub-district information.

By law, the Indonesian government is required to provide assistance (including food supply) to those affected by a disaster for up to 14 days after a disaster strikes. This emergency period may be extended when needed. For this, the Indonesian government sets aside a national budget known as CBP (Cadangan Beras Pemerintah) to stock rice to be distributed to refugees during the disaster response operations. The state logistics bureau West Java division (known as BULOG wilayah Jawa Barat) is responsible for the inventory management of CBP rice. The rice is stored in warehouses in West Java. When a disaster forces people to become refugees, the municipality government whose administration area covers the location of the disaster will instruct BULOG to make the rice available at the nearest warehouse and will arrange the transportation. If a disaster affects more than one municipality then it is the provincial government who will instruct BULOG and arrange the transportation.

The data on the number of refugees per disaster type in each municipality between 2016 and 2020 are available. Table 2 shows a fraction of the data (due to the space constraint, we do not show the other disaster types and 17 other municipalities). The column "count" shows the number of disaster events between 2016 and 2020. The columns "min", "avg" and "max" show the minimum, average and maximum number of refugees per event, respectively. It shows that the disasters in various scales have been declared by the Indonesian government (e.g. some disasters do not generate any refugee and some other disasters generate tens of thousands of refugees).

Table 2: The number of refugees per event for flood and landslides in ten municipalities (2016 – 2020).

	Flood				**Landslides**			
Municipality	**Count**	**Min**	**Avg**	**Max**	**Count**	**Min**	**Avg**	**Max**
Bandung Regency	122	0	5,756	12,609	121	0	27	54
Bandung Barat Regency	15	0	2	10	134	0	216	620
Bekasi Regency	49	0	184	552	7	0	18	60
Bogor Regency	111	10	211	366	383	1	1,322	6,212
Ciamis Regency	30	1	85	262	191	0	8	36
Bandung City	33	0	0	0	18	0	0	0
Banjar City	6	0	0	0	36	0	2	9
Bekasi City	28	0	2,210	11,041	6	0	1	7
Bogor City	55	1	10	52	568	0	35	86
Cimahi City	34	0	24	132	33	0	2	9

There are challenges in collecting these data. This is partly due to the inconsistency in the reporting (e.g. number of refugees can be reported in the number of people, number of households, or both) and most data are available in Excel or PDF/scanned files. The problem with the Excel files is that it allows free text entry to the spreadsheets; hence, there is bound to be some inconsistency and non-standard entries in the data (e.g. cell that is supposed to contain number may contain the unit as well). This is especially problematic when the Excel files are entered by all municipality-level BPBDs. These data collection issues are common in a simulation project (Onggo and Hill 2014).

Figure 4 shows the network that we will use in the model. Each node in the network represents one district and each edge represents the shortest path between a pair of districts. A node shown in green indicate that there is a BULOG warehouse in that district. Clusters of districts in the network shows the location of the big cities, for example, the cluster in the center of the network is where the province capital (Bandung City) is located. To form this network, we need to combine the district data and the road network data. This process is challenging because the official road network data in West Java is unavailable from the local government. Thus, we gather the road network map from open source Geographic Information System (GIS) called DIVA-GIS (http://diva-gis.org/) and construct the road network data between each district manually from the map. Unfortunately, the district information in the open source GIS is incomplete. Hence, we can only represent the transportation network between 432 (out of 627) districts in West Java. However, based on the spatial distribution of the nodes that covers the whole province, the network can be used for our purpose. We represent the transportation network as an undirected graph with 432 nodes, of which 30 nodes have a BULOG warehouse. The network shows that most warehouses are located in the north where the majority of centers for rice production are located.

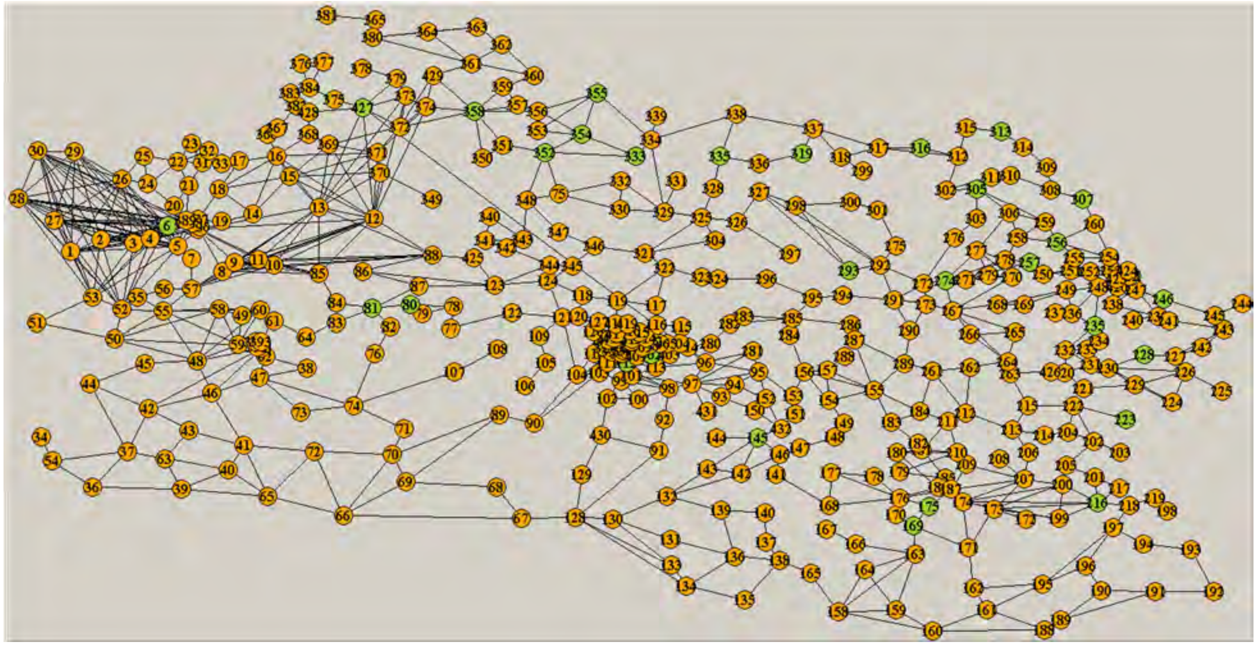

Figure 4: Road network in West Java (Indonesia).

4 RELIEF FOOD NETWORK SIMULATION MODEL

Currently, each municipality government makes an independent decision to transport relief food when a disaster happens in its administration area. Hence, the current BULOG policy is to prepare rice at the nearest warehouse to the disaster location for the municipality government to collect and distribute to the refugees. To evaluate the current relief food distribution policy, we use a simulation model. To model this policy, we assume that in the early morning (say 8 am), we already know the locations of all disasters that happen in the past 24 hours including the estimated number of refugees in each location. Then, we will assign the nearest warehouse to prepare for the rice. Each warehouse will find the optimal route if it delivers to more than one disaster location; otherwise, it will be a simple return journey. We are interested in the following key performance indicators (KPI): the amount of rice needed annually (for budgeting), how many times we cannot deliver the rice to refugees within the same day and the total travel distance. Currently, we have not included the risk of damage to infrastructure including roads and warehouses in the model. This will be included in the future.

The main simulation loop is shown below. Lines 2-18 estimate the KPI. It starts with the sampling of the number of disasters using a Poisson distribution (line 4). Lines 5-12 sample the disaster types and number of refugees for each disaster on that day. Line 6 samples the disaster types using the proportion in Figure 2. In line 7, based on the disaster type, we sample the location of the disaster using the proportion in Figure 3. For the given disaster type and location, we can sample the number of refugees (see Table 2) using a triangular distribution rounded to the nearest integer (line 8). Next, in line 9, we calculate the demand for 14 days based on the Indonesian regulation. For simplicity, in this model, we assume that the all of the rice needed will be delivered in one go and stored at the shelter. Based on the current policy, we find the nearest warehouse to the disaster location in line 10 and add it to the set of warehouses that need to prepare for the rice on that day in line 11. Line 12 creates a list of tasks which is an instruction to deliver rice (`relief_food` kg) from a warehouse to a shelter / disaster location using a certain vehicle (this will be assigned in line 15, hence at this stage we assign -1). Lines 13-16 creates the routes and assign vehicles to the routes. For each warehouse in the set created in line 11, we filter the tasks assigned to each warehouse in line 14. Then, we run a vehicle routing optimization model and create a route for each warehouse (line 15). When a warehouse delivers to one disaster location, it will be a simple return trip. Line 16 combines all routes so that the daily KPI can be calculated in line 17. Line 18 collects the daily KPI to be used by line 19 to calculate the expected daily KPI.

```
01. kpis = []
02. for day = 0 to n_days
03.    tasks = []; warehouses = {}; routes = []
04.    n_disasters = Poisson(daily_average)
05.    for disaster = 0 to n_disasters
06.       disaster_type = generate_disaster_type()
07.       disaster_loc = generate_location(disaster_type)
08.       n_refugees = generate_refugees(disaster_type, disaster_loc)
09.       relief_food = demand(n_refugees, 14)
10.       warehouse = get_nearest_warehouse(disaster_loc)
11.       warehouses = warehouses ∪ {warehouse}
12.       tasks = tasks.append(warehouse, disaster_loc, relief_food, -1)
13.    for each warehouse in warehouses
14.       warehouse_tasks = get_tasks_for(warehouse, tasks)
15.       route = solve_vrp(warehouse_tasks)
16.       routes = routes + route
17.    day_kpi = get_kpi(routes)
18.    kpis = kpis.append(day_kpi)
19. expected_kpi = get_expected_value(kpis)
```

The model is verified by comparing the sampling processes of the inputs with what we specified in the model. At this stage, the validation is carried out by conducting sensitivity analysis on the input parameters and checking whether the outputs make sense.

This section shows that we have used the available empirical data to make the simulation parameters more realistic to answer the call from the literature that encourages us to use more empirical data for models in disaster management (Galindo and Batta 2013; Hoyos et al. 2015; Esposito Amideo et al. 2019; Farahani et al. 2020; Sabbaghtorkan et al. 2020).

5 RESULTS

We have run a one-year simulation for 30 replications. The results with 95% confidence intervals are shown in Table 3. The results shows that the expected daily travel distance is manageable, with 90% of the instances being under 177 km. The average amount of rice needed annually is 697 tonnes and 90% of the instances are under 1,470 tonnes. The results also show that the current policy to deliver rice from the nearest warehouse works because we can deliver the rice within the same day almost all the time. Given the increasing trend in the number of disasters, we run the simulation for scenarios in which the average number daily disasters increases by approximately 10% (i.e., Poisson(5)) and 20% (i.e., Poisson(5.5)). These results show that a 10% increase in the number of disasters does not lead to a significant difference in the three measures. Hence, the current warehouse locations and routing heuristic can cope with the increase. However, if the number of disasters increases by 20%, the 90th percentile of the daily travel distance and the annual amount of rice needed increase to 196 km and 3,690 tonnes, respectively. More importantly, the number of cases in which we cannot deliver the rice on the same day will also increase. If we look into the detail within a simulation run, the typical distribution of the daily travel distance is shown in Figure 5. Not only the average increases but the distributions also show that the risk of travelling farther increases as the number of daily disasters increases. This explains why the number of cases in which we cannot deliver rice on the same day increases.

Table 3: Simulation results (30 replications, 95% confidence interval).

Municipality	**Poisson(4.6)**	**Poisson(5)**	**Poisson(5.5)**
Average daily travel distance (km)	159.67 ± 3.88	173.21 ± 5.07	178.99 ± 8.51
Annual amount of rice needed (tonnes)	696.59 ± 176.16	1290.83 ± 367.99	1879.71 ± 481.85
Number of days in a year where rice cannot be delivered on the same day	0.03 ± 0.06	0.23 ± 0.18	0.17 ± 0.16

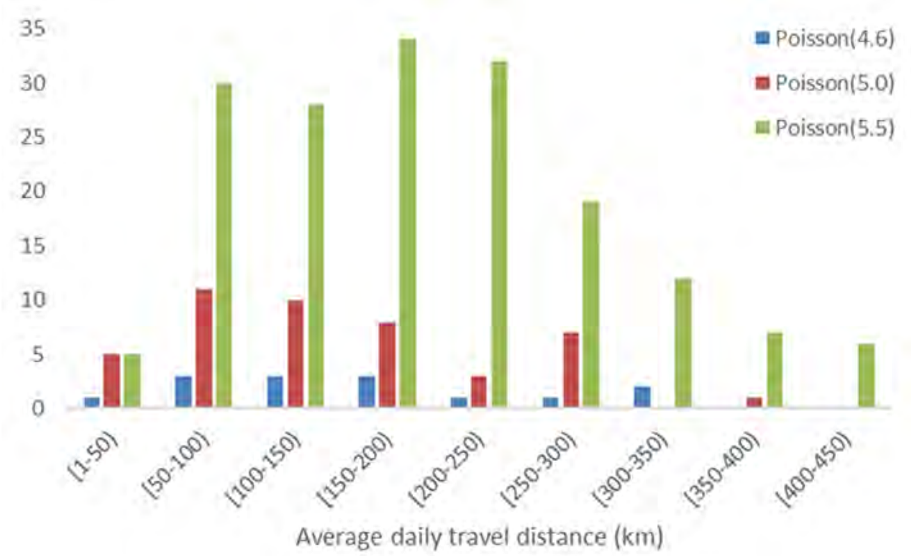

Figure 5: The distribution of daily distance travelled by all vehicles (in km).

6 CONCLUSION

Researchers have acknowledged the lack of empirical data used in models for disaster management and the use of simulation modelling in disaster management is limited. As part of the Relief-OpS project (www.southampton.ac.uk/relief-ops), we have collected data on disasters occurring in West Java between 2016 and 2020, which include disaster types, number of disasters, locations and number of refugees. This paper has shown how we use the empirical data to set the parameters of a model that simulates the food relief supply network. We have also discussed the challenges in collecting data about disasters as the required data come from multiple sources (e.g. data on the transportation network, district boundaries, warehouse locations and disasters) and in some cases is incomplete (e.g. the transportation network data does not have the complete district information). There is also inconsistency in the reporting (e.g. number of refugees can be reported in the number of people, number of households, or both) and most data are available in Excel or PDF files.

We are still in the early stages of our project. Hence, there are several directions for future work. Firstly, we will model infrastructure disruptions due the larger scale disasters. We will investigate the use of different distribution functions for the different scales of disaster. Secondly, we will need to consider the seasonality (e.g. flood and landslide occur more frequently during monsoon season) and trend (e.g. early analysis suggests that there is an increasing trend of tornado in West Java). Thirdly, we will combine the simulation model with the optimization model developed by Dang et al. (2020) to form an optimization-via-simulation model which is multi-objective, multi-period and stochastic. We will compare several algorithms to solve the model including the ones described in Currie and Monks (2021) and Onggo et al. (2020). Finally, the problem that we are addressing is relevant to other regions in the world that experience frequent small-to-medium scale natural disasters and rare large-scale disasters such as Europe (small-to-medium scale floods and occasionally large-scale floods) and Australia/US (small-to-medium scale wildfires and occasionally the large-scale ones). Hence, a similar research can potentially be done in these regions.

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