Human Behaviour and Continuous Food Supply in a Semi-Permanent Refugee Settlement

An exploration of policies for a network of Food ATMs in interaction with uncertain beneficiary behaviour in the context of the Bidi Bidi refugee settlement in Uganda

Master thesis submitted to Delft University of Technology in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

in

Engineering and Policy Analysis

Faculty of Technology, Policy and Management

by

Daan van Beek

Student number: 4245342

First supervisor: Dr. T. C. Comes

Second supervisor: Dr. T. Verma

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Supporting code can be found on: https://github.com/daanieo/FATM_ABM

Chapter 1

Executive summary

Over the last couple of decades, refugee flows have been telling us a story of increasing numbers that are unlikely to go down anytime soon. The region of Eastern Africa only is home to 2.7 million people finding refuge in refugee settlements that are not often associated with permanency. UNHCR handbooks and many competent authorities state that refugee camps are of temporary character and as a result we observe a significant similarity in post-disaster food assistance and food assistance in a quasi-permanent settlement.

The subsequent disparity between the way of organising food distribution and the needs of the population is the main motivation for the development of Food ATMs. This novel method of food distribution is based on allowing beneficiaries to determine how food is withdrawn to suit their own lives. A key point on how beneficiaries will use the Food ATM is a population's perception of the Food ATM. For instance, alleged food shortages might move people to hoard food and consequently undermine whole-system performance. Assumed similarities in literature on panic-buying events suggest that a combination of behavioural factors is a key vulnerability.

Since a system of Food ATMs has not been implemented before, a conceptual design was made by 1) acquiring information through expert consultation on the design of an individual Food ATM and 2) the creation of an optimisation model forming an optimal network of Food ATMs. In order to analyse the interaction between a system of Food ATMs and beneficiaries, the current set of Operation Research (OR) models with stochastic or game theory-based formulation of food demand had to be expanded. For this purpose, concepts from research on panic-buying and emotion-related social interaction were used. This research contributes with the union of these concepts in a geo-spatially explicit Agent-Based Model, replacing current OR models' top-down formulation of demand with an agent-based bottom-up formulation.

This enabled 1) increasing the understanding of interaction between a supplier of recipient of food assistance and 2) analysis of proposed operational policy in the context developing the Food ATM. Following 2), this thesis provides policy recommendations that have been made based on subsequent quantitative and qualitative investigation of model results.

This thesis represents a first step to investigate the effects of individual behavioural factors in the realistic context of improving food distribution in the Bidi Bidi refugee camp in Uganda. New insights taught the relevance for further research, most notably on the relation with the bigger humanitarian supply chain, information diffusion between beneficiaries and the strategy for a population's adoption of the Food ATM.

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Chapter 2

Introduction

2.1 Refugees in permanently temporary settlements

Over the last couple of decades, refugee flows and subsequent refugee settlements have been telling us a story of increasing numbers that are unlikely to go down anytime soon. Many complicated events are causing new refugee flows. The region of Eastern Africa only is already to home to 2.7 million refugees today. This region has been plagued by conflict and other difficult circumstances for decades. For example, Kenyan refugee camps are inhabited by Somalis who fled for terrorist groups and today the majority of refugees originate from South Sudan. The looming threat of ethnic tensions in neighbouring Ethiopia or potential consequences of climate change by no means reduce the number of displaced people in the future.

The longevity and seemingly chain-linked nature of these problems ask for mitigating measures. This does not mean that solving the drivers of refugee flows, such as failed harvests, squeezed supply chains due to conflict, etc. is not on top of the list. In reality, it can already be observed how refugee camps are used differently than originally intended. All over the world, most refugees who are currently residing in refugee camps have been living in such a camp for a decade (Butele and Mitschke, 2017). For example, 70 year-old Palestinian or 10 year-old Syrian refugee camps in Jordan, displaced Rohingya finding refuge in Bangladesh and Uganda giving permanent refuge to more than a million South Sudanese. However, relating refugee camps to permanency is often a politically sensitive subject. Subsequently, permanency is something we do not associate very often with refugee camps: UNHCR handbooks and many competent authorities state that refugee camps are of temporary character. As a result, refugee camps *are not designed for permanency.*

In more recent years, the design problems of refugee camps have been getting attention from researchers. Refugee camps are often intentionally built in remote locations. Adequate infrastructure, ranging from food to waste water treatment to cooking fuel, tends to be (completely) absent and due to the remoteness relatively expensive to construct (de Rooij et al., 2016). Work also has been commenced to improve tents or sometimes patch-work buildings that were never meant for years of habitation (Harrouk, 2020).

Often, refugee communities are perceived as a burden for society. Events such as food riots often scapegoat refugee communities, to the extent that people are displaced (Athumani, 2020). Hence, it is important that the influx of refugees can *provide benefit* the local population. One aspect of benefiting the local population is economic development. Social research tells us that (besides the physical circumstances from last paragraph) the unstable environment tends to be a significant setback for any (economic) development. Thus, redefining the refugee camp as a (quasi-)permanent settlement corresponds better with reality and allows for better action (Turner, 2015).

2.2 Food security as a condition for stability

The prospect of a more stable environment stands with food security as one of *the* conditions for basic survival. Lots of refugee camps have some food distribution system already set up. In general, the aim is to make use of existing infrastructure to provide food assistance. That is, providing financial assistance in order to enable for local development and economic benefit of farmers (WFP, 2018). However, in many cases the food-supply infrastructure is not adequate for stable supply and one has to resort to *in-kind* food assistance: providing rations of various types of foods.

In-kind food distribution tends to have a very comparable nature in very different circumstances. For example, after a disaster occurs, big bags with weeks worth of food are distributed among the population in need. Usually, some weeks or months after disaster struck, original infrastructure is set back in place and food assistance can be scaled down. Remarkably, in many refugee camps that have been existing for years, this very same method is applied as well. One can imagine that the instability that results from such methods does not bring the "sense of normalcy" refugees long for Oka.

Having observed the similarity between post-disaster food assistance and food assistance in a quasi-permanent settlement, it is safe to say that there is a disparity between the way of organising food distribution and the needs of the population. In order to understand the consequences of current methods, we will first be examining the case study as a typical situation. The case study that will later be the used as a provider of concrete examples is the Bidi Bidi refugee settlement, located in Northern Uganda. As stated before, this refugee camp has grown fast over the last 10 years, rapidly filling the previously sparsely populated Yumbe region of Uganda. As of now, the settlement has grown to be one of the biggest in the world with more than 250,000 inhabitants on a surface of more than 250 sq km.

2.3 Defining food security in a semi-sustained settlement

In order to understand the problem to its full extent, one has to look further than the term's 'traditional' definition, which can rather be defined as the *Availibility* of food. Hence, the four pillars of food security are introduced: 1) availability of food, 2) access to food, 3) proper utilisation, and 4) stability of the aforementioned (EC-FAO Food Security Programme, 2008). The key point here is, that all four elements have to be fulfilled *simultaneously* in order to ensure food security. Besides conditions to fullfill, these four points also provide structure to identify possible improvements.

2.3.1 Availability of food

Might sound somewhat obvious as a goal, but the sheer number of possible food sources does require separate coverage. In recent years, in-cash (or market-based) food assistance has gained popularity amongst humanitarians because of various reasons. Firstly, it enables moving away from allegedly paternalistic in-kind food distribution (Hidrobo et al., 2014; Hoddinott et al., 2014; Sabates-Wheeler and Devereux, 2010). In other words, simply *enabling beneficiaries* to be responsible for their food prevents unnecessary meddling in their lives. Secondly, as the name 'market-based intervention' suggests, the food market is expected to provide food. A very desirable side-effect is the stimulated local food production and subsequently the local economy. Lastly, the 'market' is expected to provide food which is only *bought* by beneficiaries allegedly simplifying the distribution process.

Despite its promises, it must be said that quite some difficulties in implementation exist. Firstly, the existence of a (relatively) stable supply chain providing food at reasonable prices. A World Bank report warns for "challenging [implementation] in the presence of weakly-integrated or poorly-competitive markets" (Gentilini, 2014). Succesfull pilots have mainly been conducted in middle-income countries *with* a stable food market. This might prevent positive result from being replicated in more challenging low-income countries (Hoddinott et al., 2014). One example is mentioned by Barusya: in Uganda, experts warn for possible competition over resources with the poorest locals (2018).

In order to bypass food distribution, providing refugees with a plot of land to rely on for food production has long been a cornerstone of Uganda's open-door refugee policy. Anticipating on the case of the Bidi Bidi refugee settlement, this strategy is starting to show signs of limited sustainability with land getting more and more scarce, which is already leading to disputes and tension (Barusya, 2018; Betts et al., 2019). On top of that, a UNHCR report mentions that 73% of questioned refugees owning land claim that farming their plot does not provide enough to sustain their household (UNHCR, 2019).

All in all, it seems that the more precarious the context, the more challenging it is to provide food assistance. Self-reliance and purchases on the local market can in many cases only provide partly. As a result, external donors and complex supply chains are will still be necessary to provide for more 'traditional' in-kind food assistance.

2.3.2 Access to food

Represents how easy it is for people to get food *on the household level*. That is, the availability of food, as discussed in the previous paragraphs, focuses more on food on a systemic level. For beneficiary households, this does not automatically imply receiving food. For example, market prices for foods can be too high for beneficiaries to afford.

More related to in-kind food distribution, it is often the physical barriers that limit reduce the ease of access of food. In many cases, a monthly food distribution event is organised at a single location. The sheer size of the operation almost inherently causes chaos and capacity problems. As a result, queues are sometimes days' long. On top of that, the received rations account for a month's worth of food, that has to be transported over significant distances. All in all, it can be said that this single life-line event leaves especially the most vulnerable (bigger families, elderly) in a precarious position.

2.3.3 Proper utilisation

Entails the correct consumption of food in terms of variety of diet, preparation and good care of the rations. It is thought that the method of food distribution plays a big role in the ability of beneficiaries to make proper use of their food rations. One example is correct preservation of food. Research conducted among farmers does show that improved storage facilities can prevent up to a third of food going to waste over a month (Costa, 2015). Realising that proper storage facilities for food are virtually absent on a household level in such camps, it is fair to assume that a significant part of the distributed food is either lost or degraded.

2.3.4 Stability

Of the aforementioned) is the last dimension. The EC-FAO Food Security Programme's main focus lies on on external factors, such as political and/or social instability or adverse weather conditions (2008). Notwithstanding this, for the sake of this research the definition of such stability has to be extended. It is thought that the performance of choice-based systems highly depend on (external) social stability and trust. In other words, hoarding behaviour of essential goods (food, petrol) is likely to occur when people have little faith in the availability of the good at a later point in time.

2.4 Research problem

Qualitatively, the current problems regarding the aforementioned four dimensions of food security leave sufficient room for a system of Food ATMs to improve upon. A pivotal element of the Food ATM offering a better solution to individual beneficiaries is the choice-based nature of the system. Inherently hereto, the behaviour of beneficiaries can also have negative effects. Especially in the light of panic buying and hoarding as a result of collective behaviour with seemingly minor (Upton and Nuttall, 2014) or major (Dulam et al., 2020) events at their root.

The research problem to analyse beneficiary behaviour can be divided into two parts. Firstly, a the physical appearance of a system of Food ATMs will be designed, being approached as a 'classic' Facility Location Problem (FLP) with the goal to reduce the distance between beneficiaries' homes and the Food ATMs. Secondly, to study the effects of beneficiary behaviour an Agent-Based Model (ABM) has been built.

ABM is a tool to analyse a system in which *interaction* between a system's parts gives the system its inherent properties. In the case of a food distribution system by means of the Food ATM, the interaction between system elements results in multiple self-reinforcing feedback loops. A feedback loop entails how

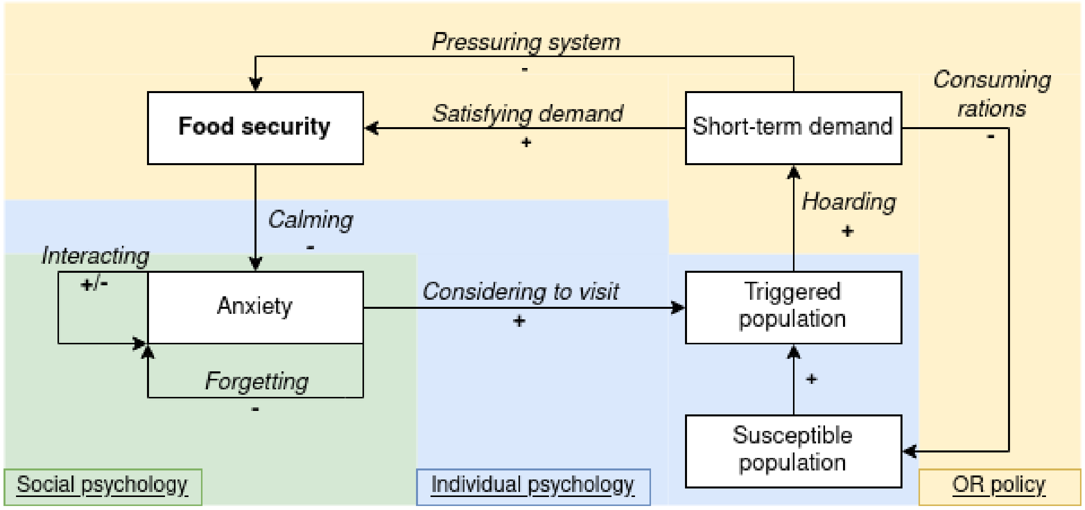


Figure 2.1: Problem causality; categories according to research discipline

a dynamic can be aggravated because it causes a sequence of events on their turn strengthening this dynamic. Figure 2.1 shows a simplified abstraction of the feedback loops that lie at the base of possible undermining food security. The multiple feedback loops suggest a system potentially highly sensitive to disruption. Research in the analogous field teaches how panic buying psychology is based on a population's expectation of how the world will develop. The most concurrent example of an unexpected surge in demand was that for toilet paper after lockdowns were announced all over the world. Although hoarding toilet paper was perceived as a relatively harmless event, other events of unexpected hoarding behaviour by consumers was taken more seriously. For example, an in retrospect inconvenient advise by the UK Energy Secretary to "keep [your car's] tank 2/3 full, but do not panic" partly caused the 2012 UK fuel crisis that lasted for weeks (Upton and Nuttall, 2014).

Also in the humanitarian field, research has been conducted on how similar dynamics prohibits humanitarian aid efforts. Bunce wrote how rumour spreading is an increasing factor that we have to reckon with (2019). Especially regarding food, people can show extreme behaviour. In Kampala, Uganda's capital, alleged theft of food upon lowering food rations led to food riots and the killings of three children (Athumani, 2020). In the light of such chain reactions it is important to gather more knowledge on the role of food distribution, or more specifically operational policy with regards to food distribution, in these dynamics.

Figure 2.1 shows how the various system elements are linked to each other, causing various feedback loops among them. These relations can be divided in three categories according to research discipline: 1) Social psychology, 2) individual psychology and 3) Operations research policy. 1) Social psychology captures the social interactions between people such as diffusion of information (or, in some cases, misinformation) about the system. Authors such as Gao and Liu and Herrmann et al. have covered methods to integrate such concepts from social psychology in Agent-Based Modelling (2017; 2013).

2) Individual Psychology entails the layer between the distribution system and the targeted beneficiaries. From expert consultation it was raised that the (individual) behaviour of people regarding to a system of Food ATMs is a potential risk for the stability of food distribution. Moreover, insights from panic buying-related research (Upton and Nuttall, 2014; Dulam et al., 2020) help describing how beneficiaries perceive the performance of a Food ATM. An example of such insights is that, based on the population's characteristics, food security (or the lack thereof) translated into decreased (or increased, respectively) anxiety.

Finally, literature on 3) Operations Research models in the humanitarian field show that a population's demand of food is often considered as a static goal to be satisfied. This, however, can be argued to be a dynamic consequence of action. In other words, instead of looking at food as something that 'simply' needs to be brought to a population in need, it can be argued that the formation of demand and eventual consumption of food depends on the distribution method itself. This dynamic is the direct consequence of taking individual behaviour into account. This also justifies why most literature does not cover this point: when looking at OR in a post-disaster setting, food distribution are reactive campaigns to help those in need. For this reason, the goal is to guarantee food delivery and not to integrate individual behaviour as that is not a key factor in this type of research.

As a main point in this thesis, it is assumed that the design of a system of food ATMs (and thereby operational policy) sets an environment in which the social (1) and individual psychology (2) influence dynamics. Hence, it is argued that operational policy influences the performance of the system by influencing such behavioural elements. Taking into account that this is not covered in OR research in the humanitarian field, there is room for a scientific contribution in this area. This leads to the following main research question:

What operational policies show robust performance incorporating the influence of beneficiary behaviour on the performance of a system of Food ATMs in the context of a semi-sustained refugee settlement?

2.5 Report structure

The content of this report is structured as follows. First, relevant examples from literature will be discussed. The main goal of the literature is to learn from what other scholars have done, and where the relevance of their research stops a research gap is identified. The answer to the research question as formulated above will have to cover this gap.

Secondly, the methodology is discussed. This is a vast chapter starting with the design of the Food ATM. In this section, results of brainstorm sessions will be discussed and how (the lack of) data sources influences the further research approach. Then the conceptualisation and the model formalisation will be explained. Lastly, the experiment design is discussed.

Chapter 3

Literature review

A literature review has been conducted to assess the current state of literature regarding 1) the warehouse location problem, 2) the last-mile, 3) perceived behaviour in humanitarian models, 4) perceived behaviour in other models and 5) social behaviour in other models.

Warehousing coincides with the notion that the Food ATM stores food temporarily. The last mile entails the moment where the food changes hands from the distributing authority to beneficiaries. Perceived behaviour in humanitarian/other models means behaviour *that results in action.* It seems that scholars in other fields incorporate behaviour to a further extent than in the humanitarian field, justifying the distinction. Lastly, social behaviour in other models entails behaviour with respect to others not resulting in physical action.

3.1 Warehouse location problem

The idea of storing supplies either in anticipation of an event or simply as a node in transporting supplies from A to B is a prevalent sub-field in supply chain research. A remarkable difference in research is the considered scale: Balcik and Beamon; Dufour et al.; Charles et al., for example, attempt to optimise warehouse locations and sizes on a global level (2008; 2018; 2016). This in contrast to others trying to tackle a warehousing problem at regional (Zokaee et al., 2016; Grace et al., 2017; Peters et al., 2016) or even local level (Vitoriano et al., 2011; Rancourt et al., 2015; Crooks and Wise, 2013).

From these publications, it can be observed that the considered scale is a determining factor for the considered problems of a Warehousing problem. On a global level, the focus seems to be on tendencies rather than individual disasters: historic data is used to illustrate the overall concentration of demand for relief supplies (Balcik and Beamon, 2008; Dufour et al., 2018; Charles et al., 2016). With a more detailed estimation of demand for relief supplies when considering a smaller region, the importance and comprehensiveness of the terrain and beneficiaries seems to increase. That is, data on population, roads (Peters et al., 2016; Maghfiroh and Hanaoka, 2017; Zokaee et al., 2016; Grace et al., 2017; Rancourt et al., 2015; Vitoriano et al., 2011) and simulating human behaviour (Crooks and Wise, 2013; Burkart et al., 2017; Muggy and Heier Stamm, 2015) is more extensively used when the warehouse fulfills a last-mile function.

3.2 The last mile

In this subsection the literature stating having researched the 'last mile' is considered. Although making use of the same terminology, it must be stated that scholars' perception of this concept can differ hugely. In vehicle routing models, inaccessible distribution points due to broken links stand central, rather than the consequences thereof (Ferrer et al., 2018; Maghfiroh and Hanaoka, 2017; Battini et al., 2014). Essentially, the interaction between distribution points and beneficiaries is considered out of scope. Others do consider a relation between beneficiaries and distribution points, for example in the form of coverage (Grace et al., 2017; Zokaee et al., 2016).

An extension of such coverage is described by Rancourt et al. (2015). Rancourt et al. argues that accessibility is not a binary state, but rather an appeal on beneficiaries' means. For example, distance can be covered by paying for transport, leading to a trade-off between food aid and a financial burden (Rancourt et al., 2015). A 2017 model review paper also calls for such “ease of access” by looking further than the distributor's point of view (Boonmee et al., 2017), or even “to the time it is ready for consumption at the food aid recipient's home” (Roubert et al., 2018).

3.3 Perceived behaviour in humanitarian models

A literature review by Muggy and Heier Stamm states the importance of going further than the classic assumption of beneficiaries without choice or distance being the dominant consideration (2014). Burkart et al. attempts to catch the choice of beneficiaries by differentiate on *attractiveness*. This results in a so-called *Competitive Location Model* (CLM), where a probability of a visit estimated (2017). Generally, these delivery points are considered non-interactive: delivery point characteristics do not depend on the behaviour of a beneficiary (or: visitor) (Gorji, 2015).

Other scholars do attempt to capture interaction between beneficiaries and facilities. For example, Muggy and Heier Stamm incorporates choice by means of Game Theory (2020). In this game, the score for the beneficiary decreases when choosing for a certain facility: the facility loses attractiveness upon being preferred by beneficiaries.

Others take an agent-based approach, explicitly mentioning the possible influence of behaviour, in particular information sharing (Crooks and Wise, 2013; Fikar et al., 2017). Crooks and Wise intentionally made the model's agents simplistic, allowing for easier analysis of the influence of data (2013). Fikar et al. on the other hands, incorporates information sharing between agents for optimisation purposes (2017).

3.4 Perceived behaviour in non-humanitarian models

Concepts to incorporate human behaviour are used more often in other fields. For example, stochastic modelling of people's preferences by Baviera-Puig et al. (2016) is very similar to Burkart et al.'s (2017). This geo-marketing model incorporates more circumstantial factors, such as the location's outside connections (Baviera-Puig et al., 2016). Comparable coupling of data can also be observed in other modelling approaches. For example, an ABM in a research on the accessibility of healthy food to low-income urban population incorporates information on location, social capital and preferences to attempting to mimic relevant human behaviour (Widener et al., 2013).

Besides preference, panic-buying is a particular type of behaviour where insufficient system performance leads to changing customer preference, further disrupting the system (Dulam et al., 2020; Upton and Nuttall, 2014). Dulam et al. focuses explicitly how a disruption leads to more disruption: a one-dimensional interaction between stock inventories (thus: availability of desired goods) and the consumer's reaction as a result (2020). Upton and Nuttall perceives consumers as being part of a scale-free social network, incorporating the human-to-human psychology behind to understand a supply chain disruption (2014).

3.5 Social behaviour in other models

More in-depth information on the spread of these rumours can be found in literature on information diffusion. All reviewed models used a Susceptible-Infected (SI) approach: the dominant conceptualisation of rumour spreading (Gao and Liu, 2017; Herrmann et al., 2013; Shang, 2014; Zhu et al., 2019; Zhang et al., 2011; Nekovee et al., 2007; Zhao et al., 2011; Mazzoli et al., 2018). The SI-approach means that a 'susceptible' person is 'infected' with a certain belief/opinion. Uniqueness of the agent is said to be important, also given the fact that among reviewed literature only one scholar does not use an ABM approach. This is confirmed by Shang, who finds that a limited number of unique non-spreading agents can stop diffusion altogether (2014).

Interaction between individuals resulting in diffusion of information is said to happen due to *contagion* and *mirroring* (Gao and Liu, 2017; Herrmann et al., 2013). The former entails spreading information either mouth-to-mouth or through some kind of medium, whereas the latter entails an agent mirroring someone's behaviour and/or ideas. The difference lies in the perception of why agents mirror or are contaged, namely personality traits or probability. Besides agent interaction, Gao and Liu also argues that an agent can form ideas itself by perceiving the environment (2017).

3.6 Research gap and questions

Analysing the available literature on a Facility Location Problem in humanitarian context yielded the knowledge that behaviour of the recipients has limited presence in the modelling field. Existing models take into account how humanitarian infrastructure can be designed given certain behavioural factors (Burkart et al., 2017; Muggy and Heier Stamm, 2020; Crooks and Wise, 2013; Fikar et al., 2017). These models are of stochastic nature, describing demand not as a matter of choice for the targeted population, but as passive reception in a post-disaster situation.

In the case of the Food ATM, choice is a fundamental element and should therefore be considered as reactive on the system. Research in other fields does show the effects of collective human behaviour: the potential to significantly disrupt supply chains (Dulam et al., 2020; Upton and Nuttall, 2014). Hence, in order to meaningfully describe the formulation of demand for continuous food supply by means of the Food ATM, a bottom-up agent-based model approach is proposed, instead of 'traditional' top-down stochastic formulation.

Moreover, possible influence of information spreading in social networks as a driver for this behaviour is undeniable (Upton and Nuttall, 2014; Gao and Liu, 2017). This potential risk is also recognised by humanitarians (Bunce, 2019). Recalling the alleged importance of behaviour as shown in Figure 2.1, it might be fruitful to explore its effects and driving forces more in depth. In the context of designing operational policy for a system of Food ATMs, the main research can be formulated as follows:

What operational policies show robust performance incorporating the influence of beneficiary behaviour on the performance of a system of Food ATMs in the context of a semi-sustained refugee settlement?

Further structuring parts of the research, a set of sub-research questions is introduced:

1. What Key Performance Indicators can be identified to evaluate the performance of a system of Food ATMs?

In order to analyse the performance of a system, one has to come to a set of metrics allowing for evaluation. Such metrics will be chosen in such a way that they reflect the system's focus. For example, reactive (post-disaster) food distribution is likely to focus on *whether* people get food, whereas systemic (long term) food distribution can also consider *how* people receive food.

2. How can a system of Food ATMs be defined given the physical environment provided by the case study?

As the main research question states, the goal is to evaluate the influence of behaviour *on a system of Food ATMs*. That implies a system has been designed in some way. Lending concrete examples from the case study, various designs for systems of Food ATMs will be used as 'input' for the behavioural analysis.

3. What factors of beneficiary behaviour affect, or are affected by, a system of Food ATMs in a semi-sustained refugee settlement?

As stated before, optimisation is inherently subject to input bias. To avoid (or rather, minimise) the effect thereof, various behavioural factors will have to be identified separately. This allows for transparency and a broad exploration.

4. How can the effects of this interaction on system performance be investigated by means of an ABM?

The notion of *interaction* between facilities and beneficiaries is essential to the necessity of evaluating this problem by means of an Agent-Based Model. In this modelling technique, the focus lies on decision-making on micro level. In the case of beneficiaries, this means individual decisions that lead to systemic changes, which on its turn changes these individual decisions.

5. Based on the ABM, what are the effects of various policies under relevant scenarios?

Having implemented the system elements responsible for interaction, relevant scenarios will firstly have to be identified. Relevancy of scenarios can firstly be determined according to the system state. That is, scenarios which result in an undesirable system state and therefore need policy intervention. Secondly, recall how the system's dynamics are conceptually built on a plethora of feedback loops. Consequently, relevancy of scenarios is arguably also determined by *which factors* contribute to the state of the system. In order to subsequently converge to design of robust policy, the performance of policies will have to be analysed under these various scenarios.

6. How can the model results be translated into an advice for decision-making?

Upon identifying certain behavioural factors that are either on themselves or in combination of influence on system performance, one will have to interpret the meaning in 'real life'.

Chapter 4

Methodology

In this chapter the methodology will be discussed. Although the research goals can be generally applied, real examples are needed to challenge one's proposed methodology.

4.1 Case study and available data

The reason for a separate subsection on the design of the food atm is due to its conceptual stage. That is, the estimated running costs, the food the food ATM is ultimately supposed to distribute is all unkown. For the sake of reprehensibility of the research it is important to list such assumptions.

Secondly, due to the fact that in the humanitarian field one often has to deal with scarce availability of data. Even to an extent, that one's ocnceptual ideas cannot be executed merely ebcause of the fact supporting data does not exist. The availability of supporting data and its consequences for methodology is discussed.

Hence, a case study will be this research's over-arching concept: the envisaged implementation of Food ATMs in the Bidi Bidi refugee settlement. Yin's work teaches that the situation in which a case-study would be the way to go is characterised by little control over events, and when the focus is on a contemporary phenomenon within some real-life context (1994).

In many fields, the availability of data can be overwhelming nowadays and therefore decisions in the analysis of data mainly focus on determining what story the data tells. In the humanitarian field though, the situation is couldn't be more different. Data-driven modelling techniques can be limited in their usefulness because of the absence of correct input data. This means that the chosen methodology has been adapted to the availability of data.

In the Bidi Bidi refugee settlement, a pilot programme is being developed to explore the possibilities and practical implementation of the Food ATM. Simultaneous to the development of this pilot programme, the design team also started to quantitatively design the Food ATM. That is, facility size and estimated serving capacity of a facility has been thought of. One (usually very) important factor of design that has not been taken into account for this research is operational cost. Firstly, knowledge on costs of operational policy is non-existent. Secondly, a facility having a target population inherently fixes the number of facilities that one needs given the size of a population.

Key dimensions of a Food ATM:

- Target service population: 2,500 households
- Average serving capacity: 3 people per 10 minutes
- Target food storage: 15,000 kg per facility

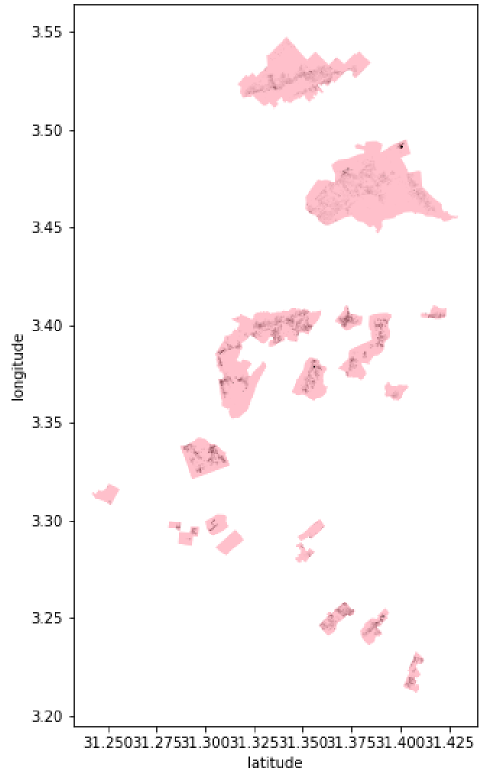


Figure 4.1: Buildings and Zones in Bidi Bidi (HOT)

4.1.1 Spatial distribution of population

As will be further elaborated upon in section 4.2.2, the problem of finding optimal placement of Food ATMs is approached as a variation of a Facility Location Problem. Instead of focusing on minimising transportation costs, the focus lies on minimising the distance between households and *a* facility. A logical prerequisite to compute the distance between a household and a potential location of a Food ATM is the location of households.

It must be stressed that actual detailed data on the location of refugee homes is non-existent. The Humanitarian OpenStreetMap Team (HOT), an NGO “to humanitarian action and community development through open mapping”, has completed a mapping project of the Bidi Bidi refugee settlement (Humanitarian OpenStreetMap Team, 2021). By means of geo-sensing (manual or automatic interpretation of aerial footage), the shape and location of building is translated into a digital format. The resulting data is further complemented with information on the type of buildings of other points of interest. On-site teams, often consisting of settlement inhabitants with local knowledge, are charged with this task.

Figure 4.1 shows in pink the camp's 5 ‘zones’: within the perimeters of these administrative regions refugees are assumed to settle. The buildings show themselves as small black dots. UNHCR (the UN-commission on Refugees) reguarly publishes population data with per zone.

Table 9.1 shows these numbers in more detail. Besides the number of buildings that is counted per zone, and the number of people residing in each zone according to UNHCR population data, a third category is added: the scaled number of buildings. Anticipating on the model conceptualisation: a building is initialised as one household agent, but initialising all buildings results in a too computationally expensive model. Hence, the number of buildings is scaled down.

Name	# bldings (original)	share	# bldings (scaled)	share	# households (pop data)	share
Zone 1	13,134	0.179	427	0.185	7,399	0.172
Zone 2	10,148	0.139	295	0.128	8,420	0.197
Zone 3	25,096	0.343	826	0.358	11,254	0.263
Zone 4	8,276	0.113	248	0.107	6,067	0.142
Zone 5	16,538	0.226	509	0.221	9,601	0.225
Total	73,192	1.000	2,305	1.000	42,741	1.000

Table 4.1: Number of buildings on map and number of households in population data (UNHCR and Government of Uganda, 2020)

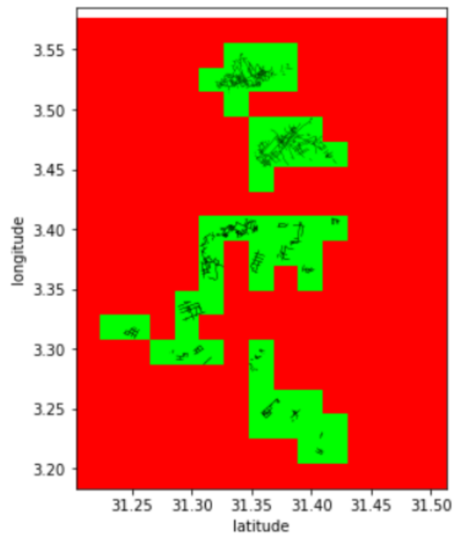


Figure 4.2: Access grid (15×19) and roads in Bidi Bidi (HOT)

Further, it can be observed that the share of the number of buildings for each zones roughly coincides with the share of population as stated by the UNHCR population data. Hence, it is thought that the geo-sensed buildings realistically illustrate the distribution of the settlement's inhabitants.

4.1.2 Roads for accessibility

The Food ATM is envisaged as the last link of the supply chain before food is handed over to the beneficiary. A Food ATM on its turn is supplied from a central warehouse by truck. Hence, proximity to a road is important in the consideration whether a location is appropriate. Besides geo-sensing buildings, HOT has also worked on locating roads in the settlement.

Figure 4.2 shows a 15×19 grid, of which for every cell it has been determined whether a road falls in that particular cell. Whereas the figure shows relatively large cell sizes for visualisation, modelling purposes require a more detailed 250×324 grid.

4.2 Methods: approaches and tools

This section describes and motivates the methods, concepts and tools supporting the formulation of an answer to the research questions. The section is subdivided into three parts, corresponding with the three modelling approaches. Firstly, the *Multi-model approach* will be discussed: how, given the current design phase, a system of Food ATMs can be designed by means of an optimisation and function as a basis for the agent-based simulation model. Secondly, the *Optimisation* approach will be further elaborated upon by a breakdown of used tools and concepts. Lastly, this is also done in a similar fashion for the *agent-based model*.

4.2.1 Multi-model approach

The multi-model approached is based on the perception of the environment in which the Food ATM is supposed to be implemented in as a complex system. It is notoriously difficult, if not inherently impossible, to boil down a complex system to the relevant elements. This can be avoided by making use of a relevant case study, also in this case the over-arching provider of concrete examples and realistic complexity.

Figure 4.3 shows how case-study related data feeds in the optimisation. Pilot programmes of individually functioning Food ATMs are set up, and thus it is thought that some convergence on design has been reached. Functioning of Food ATMs in a network is thought to be largely determined by the physical environment: proximity to facilities is thought to be easily measurable and also vital a vital aspect.

The complexity of the system is a direct result from its users. That is, non-linear human behaviour being essential to determine the system's performance will have to be analysed. Being approached as a complex system, we move away from attempting to design a good system towards questioning "What happens to the system if...?".

Pareto optimal solutions that were found by the optimisation algorithm will be analysed for relevance and subsequently provide a basis for the simulation model. It can also be observed that 'Relevant behavioural concepts' are extracted from the case study. This entails how the context of the Bidi Bidi refugee settlement can act as a validation for **possible behaviour**.

4.2.2 Optimisation

As stated before, the location problem of the Food ATM is comparable a Warehousing problem with warehouses of which the capacity is free to choice. Hence, the approached as a modified *Capacitated Facility Location Problem* (CFLP).

The over-arching programming tool is the Python programming language. This language is widely used in various fields and allows for the use of a great variety of third party libraries, all open-source. For reading and conducting operations on geo-spatial data, GeoPandas is used. To conduct the optimisation the Platypus optimisation library is used. This library provides in multi-objective optimisation and in a wide variety of evolutionary algorithms and analysis tools.

As stated before, the model will be programmed in Python and thus the further use of libraries available in Python are preferred. For optimisation, the choice has been made for the Platypus optimisation package because of its extensive documentation and the availability of multiple optimisation algorithms. This library's default optimisation algorithm is the so-called 2nd generation Non-dominated Sorting Genetic Algorithm (NSGA-II). Given the reasoning that the problem is a variation of a UFLP, similar optimisation models also made use of this particular algorithm (Harris et al., 2009).

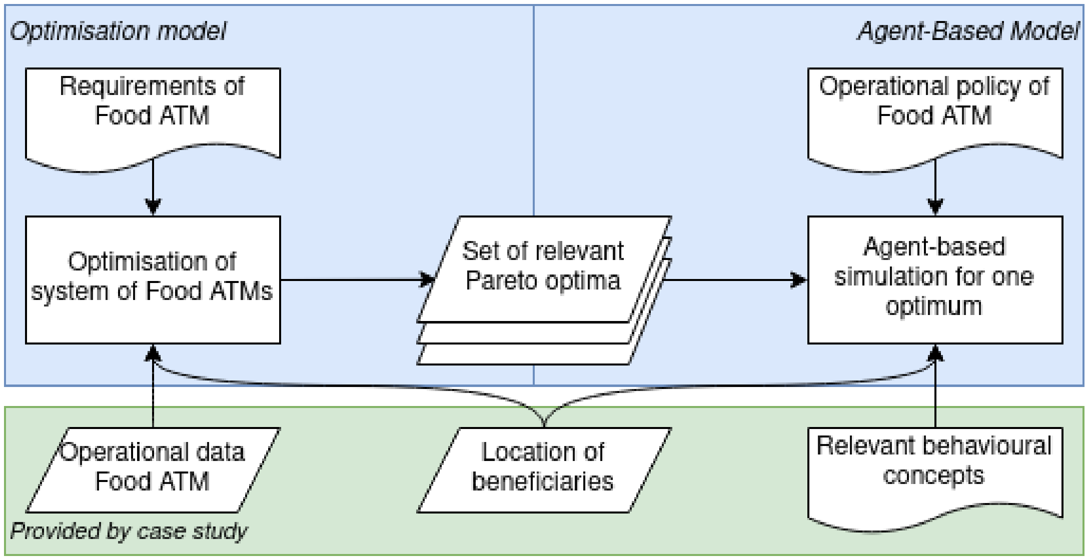


Figure 4.3: Flowchart illustrating model design and use of case-study

Although particular documentation states that its approach can be considered as outdated, it is still used as a good option for optimisation (pagmo development team, 2020). The relative simplicity of this optimisation problem enables to move the focus away from computational efficiency. As stated in its introduction paper, the algorithm does perform well in finding the "true Pareto efficient front" (Deb et al., 2002).

In order to assess the performance of the algorithm, the usage of the Hypervolume metric is introduced. This statistic, natively provided in the Platypus library, shows the "dominated portion of the objective psace as a meausre for the quality of the Pareto set" (Zitzler et al., 2007). Since one approximation of the Pareto front dominates another results in a higher value for the Hypervolume, the metric can be read as follows: a higher value suggests a better approximation of the true Pareto front.

4.2.3 The Agent-Based approach

The over-arching concept to describe food distribution by means of a sytem of Food ATMs is the agent-based philosophy. Modelling a system based on agents advocated the "creation of individuals with their own attributes and behaviours" (Crooks et al., 2017). This follows the notion that the behaviour (and thus, performance) of a system can only be explained by scoping down the behaviour of the individual. Recall the concept of panic buying. This can be related to human beings "situated in some environment [...] capable of flexible, autonomous action in that environment in order to design objectives" (Wooldridge, 1997).

Besides these notions of Autonomy (individual decisions), Heterogenity (unique human behaviour) and Explicit space (the environment in which they operate), Interaction is considered as an important element (Crooks et al., 2017). Interaction is behaviour that exists as a result of communication between two agents. Recall Figure 2.1, the Causal Loop Diagram elaborating on various system elements. People are assumed to change their behaviour as a function of other people's behaviour and system performance: interaction between agents. In short, it can be said that the considered system does correspond to these descriptions when an agent-based approach is valid. Subsequently, an Agent-Based Model is chosen as tool.

Although ABMs are increasingly popular in various domains, these types of models tend to be critiqued for not being scientific, lack of reproducibility and limited transparency. In order to overcome such challenges, a standardised set of steps is followed, as described in (Van Dam et al., 2013).

With increasing popularity of ABMs, a larger variety of packages and libraries have been developed for the purpose of agent-based modelling, all with their specific characteristics and use cases. Due to the importance of geography in this model, GAMA is the preferred tool. This is a Java-based package which is described by the developers as “a modeling and simulation development environment for building spatially explicit agent-based simulations” (Taillandier et al., 2019).

4.3 Computational Framework

The report has its main focus on *qualitative conceptualisation* of the to be modelled system and the *quantitative results* of the computational model. In order to gain insight in how various software tools support the conceptualisation and model execution this computational framework is presented. The figure shows which steps have been taken and how they feed into each other, starting with Data preparation (section 4.1), combining various data sets in order to form concrete examples of realistic scenarios. This feeds into the optimisation and agent based model, whose conceptualisation is extensively discussed in sections 4.4 and 4.2.3. Lastly, an implementation in Python by means of the Message Passing Interface (MPI) has been developed. Due to its technical nature, no chapter has been dedicated hereto. The implementation was developed with the goal of facilitating experiment generation and saving model results in efficient binary files.

4.3.1 Reproducibility

Reproducibility as one of the traditional pillars under scientific research is of natural importance. However, especially in the context of Agent-Based Models, which are often subject to critique of being subjective or non-scientific, reproducibility is pivotal. Besides the fact that full model functionality is presented in this report, all supporting code is published in a Github repository.

Along with the publication of the raw code, manuals and a Readme are supporting third parties in reproducing results and/or making use of concepts presented in this research. The Git repository can be found on: https://github.com/daanieo/FATM_ABM

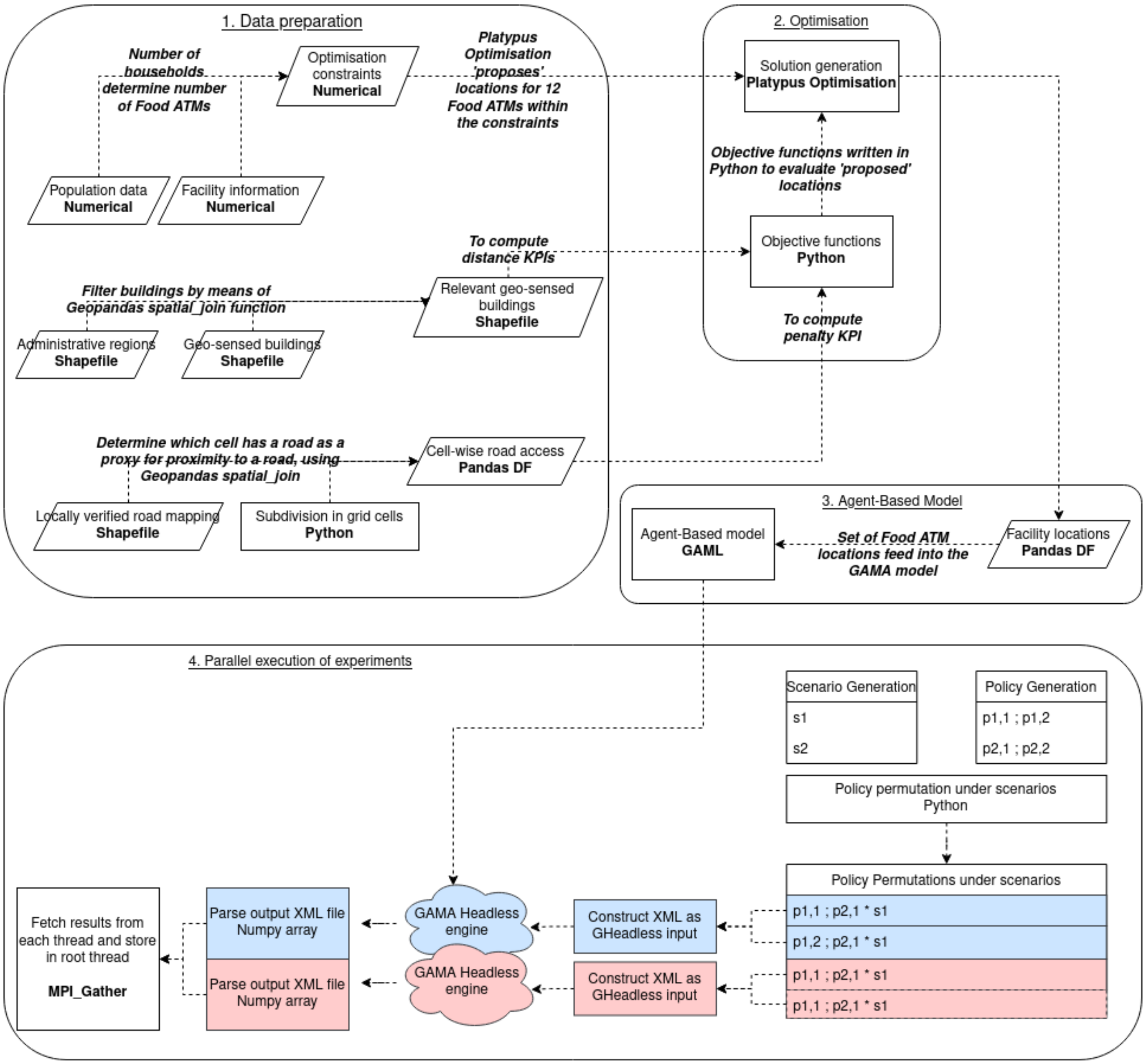


Figure 4.4: Computational framework with the four logical steps

4.4 Optimisation

Optimisation in the classic sense entails finding the optimal, i.e. 'best' solution, given a certain goal. In this case, there are two factors that oblige to adjust what one can expect from an optimisation. First, the multi-objective character of the optimisation: inherent to multiple objectives, it is impossible to find a 'best' solution. Every solution will result in a trade-ff between the considered metrics. Subsequently, the goal of the optimisation is also to gain insight in these trade-offs and what it implies for reality.

Secondly, it has to be noted that for bigger problems, the trade-off between computation expense and exploring the potential outcome space becomes more of a problem. In other words, exhaustion of the outcome space is computationally too much of an effort in order to be a realistic option. Relevant outcomes can still be found by means of intelligent algorithms (see section 4.2.2). In short, optimisation will enable us to gain insight in trade-offs by showing relevant parts of the outcome space.

4.4.1 Situation

First, one has to determine what is to be optimised: determining quantities under control and translate them to variables.In an interview it has been communicated that a Food ATM is expected to serve 2,500 households. Crowdsourced data enables us to make an approximation of the number of households in the camp: circa 29,000. In order to serve the 29,000 households, a system of 12 facilities is proposed.

As discussed in the Computational framework, a map with geo-sensed buildings exist of the Bidi Bidi refugee settlement. It is thought that these buildings can seen as a 'proxy' (i.e. an approximate substitute) for the location of beneficiaries' homes. Subsequently, varying the locations of the 12 facilities within this map can provide knowledge on a changing spatial relation between beneficiaries and facilities, potentially leading to changing results. Examples of such location-related trade-offs can be found anywhere: supermarkets in the centre of a city might bring a service closer to more people *on average*, but can leave people under-served in a city's periphery.

As discussed in the Literature review, the metric *Coverage* is a common way of evaluating the performance of a location problem in the humanitarian sector. Coverage is a metric based on a binary assumption whether a beneficiary is able to access the provided aid. In other words, for every beneficiary it is determined whether he/she has access to humanitarian aid or not. Contributing factors can vary from radial distance to broken roads. In the case of the Food ATM, people are thought to have access, but that access should be facilitated and improved. Therefore, coverage is not an appropriate metric.

Another common and also intuitive metric which is not evaluated are the system's costs. Especially in the humanitarian field reality, where financial resources are scarce, costs are important. Notwithstanding this, evaluating costs thought to contribute little information about the system's performance. The consideration of the system as 'Capacitated Facilities' and costs being independent of a Food ATM's location, costs are directly dependent on the number of facilities. Being directly dependent on one fixed input variable, it cannot be optimised and is thus not relevant for further analysis.

Three Key Performance Indicators (KPIs) have been identified to evaluate the problem:
1) Average distance follows the notion that big distances between beneficiaries and facilities are a limiting factor regarding the accessibility of food (CITE). This metric is expected to promote convergence to central locations: placement close to clusters will have a relatively high *average* impact. The distance between Food ATM and beneficiary is computed as the crow flies, a valid way of determining distances in relatively flat, evenly accessible land (Rancourt et al., 2015).

2) Maximal distance follows the notion of equity in humanitarian assistance. Computing the variance of distances between buildings and Food ATMs can also give an indication of how 'equal' the placement of facilities is. However, in case of a small number of outliers, the *overall performance* is

Metric name	Unit	Objective
Average distance	km	Minimise
Maximal distance	km	Minimise
Penalty	-	Minimise

Table 4.2: Objectives of the model's Key Performance Indicators

still likely to dominate. Hence, computing the maximal distance between some building and facility is thought to show equity best.

3) Penalty road access evaluates the proximity of a facility to a road. The need for road access is determined by the fact that food will be delivered to the Food ATM by truck. Consequently, proposed solutions with a penalty are disregarded. In order to understand the necessity to consider the penalty as a KPI rather than to set is a constraint we have to make a distinction between setting a constraint in terms of an optimisation strategy and the *technical implementation of a constraint*.

Problematically, setting multiple constraints effectively creates discontinuity in the objective functions. See Figure 4.1 where proposed solutions only *within* the fragmented zones are 'good' solutions, but will be disregarded if outside. It is known that evolutionary algorithms' (the type that has been chosen for this problem) "effectiveness is severely limited [..] when the approximating function should be discontinuous" (Fillon and Bartoli, 2007). In this case, Grace et al.'s approach to overcome similar problems by applying heuristics will be followed (2017). That is, outcomes will be manually selected *afterwards*. This KPI will thus help us to bypass the problem of the algorithm finding a 'dead end' when subdividing the outcome space.

A secondary advantage of this workaround, is that investigating such a penalty function allows us to gain insight in the entire outcome space, as if the placement of Food ATMs were not subject to such circumstantial limitations.

4.4.2 Objectives

This section will further elaborate on the formalisation of the optimisation approach. The model is formalised in three steps: 1) the objectives for each metric is given, 2) the key model variables are listed and 3) the KPIs are mathematically defined.

Table 4.2 shows the units and objectives for the three KPIs. The optimisation attempts to minimise all three KPIs.

Section 4.1 discussed various data sources and how these data from these sources are used in the model. Thus, upon initialisation information is fetched from the prepared data to initialise the list of buildings and define road access. The location for the facilities is proposed by the optimisation algorithm. So, the model is initialised with:

- $\vec{B} = \{b_0, .., b_n\}$: List of buildings b with length n
- $\vec{F} = \{f_0, .., f_m\}$: List of Food ATMs f with length m
- x_b : Latitude of a building.
- y_b : Longitude of a building.
- x_f : Latitude of a Food ATM.
- y_f : Longitude of a Food ATM.

- $R_{x,y} = [0, 1]$: For every location road access $R = 1$ or not $R = 0$.

Equations 4.1 till 4.3 calculate the radial distance between a Food ATM f and a building b as follows.

So the distance between b and f with the Earth's radius being 6373km equals:

$$d(b, f) = 2 * atan(\frac{\sqrt{Q1}}{\sqrt{1 - Q1}}) * R_{earth} \tag{4.1}$$

with

$$Q1 = sin(\Delta x/2)^2 + cos(x_b) * cos(x_f) * sin(\Delta y/2)^2 \tag{4.2}$$

with

$$\Delta z = z_b - z_f \tag{4.3}$$

for z being x or y.
The distance between building b and its (closest, among m) facility equals:

$$D = MIN\{d(b, f_0)\ , .., \ d(b, f_m)\} \tag{4.4}$$

This gives the vector of distances for n buildings:

$$\vec{D} = \{D_0, .., D_n\} \tag{4.5}$$

This gives the vector of distances for m facilities:

$$\vec{R} = \{R_0, .., R_m\} \tag{4.6}$$

Subsequently the three KPIs can be defined as follows:

$$Average\ distance = \frac{\sum \vec{D}}{n} \tag{4.7}$$

$$Maximal\ distance = MAX[\vec{D}] \tag{4.8}$$

$$Penalty = \sum \vec{R} \tag{4.9}$$

4.4.3 Constraints

Defining constraints entails setting the numerical boundaries for certain model variables. Variables subject to constraints can, for this problem, subdivided into two categories. The first are the constraints on the location of Food ATMs consisting of a latitude and longitude. These are bound by the geographical location of the camp. The second are the constraints on the variables representing the KPIs. In descending order as shown in Table **??**, the extreme values are computed based on the maximal a conceptual building and facility can have.

Variable	Extreme low	Extreme high
x_f	31.3165843	31.3849562
y_f	3.5106438	3.5476851
Average distance	0	51.46549330180716
Penalty	0	12

Table 4.3: Optimisation model's input parameters

4.4.4 Verification

The necessity of verification is centred around the question whether the optimisation result is indeed the relevant result we attempted to find. Recall the nature of the optimisation problem: for 24 variables multiple objectives will have to be satisfied. The sheer size of the problem makes it too computationally expensive to analyse the entire outcome space. Making use of intelligent algorithms opens up the possibility to find relevant outcomes.

In order to verify a proposed solution, one can make use of the Hypervolume metric. This metric shows the "the dominated portion of the objective space as a measure for the quality of Pareto set approximations" (Zitzler et al., 2007). Recall section 4.2.2's description of two optimisation algorithms (NSGA-II and ε-MOEA). Solutions (and the Hypervolume performance metric|) for the same problem will be computed 10 times for both algorithms.

4.5 Conceptualisation of Agent-Based Model

In this section, we will discuss the formalisation of behaviour by means of an Agent-Based Model (ABM). The research question mentions the goal investigate behaviour on a system of Food ATMs. Recalling the Causal Loop Diagram as presented in Figure 2.1, it can be observed that the Food ATM and households show *interaction*. Also, Households are perceived as independently functioning entities: decision-making is done based on unique characteristics, such as location and properties of its members. In an ABM approach, the focus lies on this uniqueness of agents and interaction between them, and thus ABM is the modelling approach of choice.

In order to understand the goal and therefore potential use of this model, recall research question's clue: the influence of behaviour on a system of Food ATMs. The spatial part of the system has been defined by the optimisation model. Ideas and possibilities on operational policies result from brainstorming sessions, expert meetings and provided documentation. Subsequently, the behavioural elements that will be introduced in this section derive their relevance from being somehow related to these enacted policies.

The subsection Model agents will introduce the model representations of system elements, so-called *Agents*. The basic functioning and relevant properties of the *FATM Agent* (representing the Food ATM) and *Households Agent*, as well as an introduction to the Susceptible-Infected-Susceptible framework in which social interaction is embedded. Secondly, *Individual household behaviour* will be described: how 'negative events' influence the behaviour vis-à-vis the FATM Agent through its Emotional state. Thirdly and fourthly, the interaction between FATM & Households and Households & Households, respectively. The fifth section introduces a spatial and social network as a layer to define *which* Household agents interact with each other. Lastly, the Emergence of social behaviour entails how the various parts shape potentially relevant behaviour.

4.5.1 Model agents and the SIS-framework

The model knows three conceptual agents: 1) Households, 2) FATM (Food ATMs) and 3) Environment. These *conceptual* agents are not to be confused with agents representing system functionality in the GAMA Modelling Language (GAML), as elaborated upon in chapter 4.6.

The Households agent represent the members of a household in an aggregated manner. This implies that its emotional state, its physical state (i.e. food consumption and food storage) and its interaction with both the FATM agent and other households are the mere sum of its parts. In other words, the household agent does not show any behaviour as a result from interaction between its members. Such aggregation can be related to the assumption that the head of the household is responsible for food pick up, the majority of households being single-parent (UNHCR and Government of Uganda, 2020) and signs of strong hierarchy within households (Butele and Mitschke, 2017).

As stated before, agents are perceived as being (almost) unique and capable of independent decision-making. Households have an intrinsic uniqueness in the the location of their homes, but their heterogeneity also depends on other variables. The number of members and their food consumption drive their functioning at the core, where behaviour is further defined following personal characteristics and interactions with FATM agents.

At the core of the danger of panic buying lies the spreading of anxiety among households. Every household is in an *Infected* or a *Susceptible* state, respectively representing active contribution to the spread of anxiety or not. Spreading phenomena in any form are often described using a so-called Susceptible-Infected model or a variation thereof, originating from the field of epidemiology (Kermack et al., 1927). In this case, we will be working with the Susceptible-Infected-Susceptible (SIS) variant. In terms of disease, this model assumes that one becomes susceptible again after being infected. This stands in contrast to for example the SI-Recovered variant, where the Recovered is immune for further spreading. It is thought that immunity to an anxious emotional state is not at play in this case.

Representing the individual Food ATMs is the logically named FATM agent. The main function of these agents is satisfying the food demand generated by the household agents. The individual character of these agents lie in their locations ad dictated by the result of the optimisation model. Being located at different places, it is expected that the way household agents impact the performance varies per FATM agent. For example, given that households prefer the closest FATM, the demand can be bigger for an FATM closer to more Households.

Lastly, the Environment agent. Although this is an obligatory agent in GAML (by the name of *global*), this agent is counted among the conceptual agents due to its important role facilitating the interactions between agents. Its first and foremost function is the provision of geo-spatial relations: every Household and FATM agent is provided with a physical location to be covered when interacting. Secondly, as will be elaborated upon in section 4.5.4, the interaction between households can be spatially bound. The third function is making certain model elements accessible to all agents, ranging from the probability of social interaction to a Food ATM's opening hours. A detailed specification can be found in the Appendix, section 9.3.2.

4.5.2 Individual household behaviour

When discussing 'individual household behaviour', we limit ourselves to the dynamics as conceptualised within a household, without them having an effect on other system elements. The effect of household behaviour will be discussed in the following two sections instead.

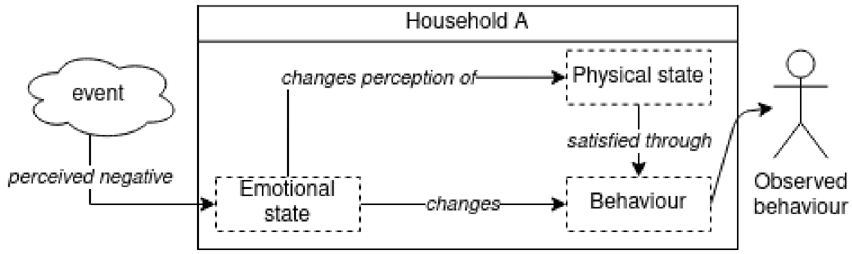


Figure 4.5: Overview the mechanism causing observed behaviour

The main driver for household action is introduced under the name of *Physical state*. This entails the food consumption pattern and a household's food storage. Given a daily ration, the number of household members the daily food consumption can be defined as follows:

$$food\_consumption = nb\_members \times \frac{ration}{30} \tag{4.10}$$

With each day passing by, on the condition of the storage of food smaller than food consumption, unsatisfied consumption is increased with the desired consumption minus the remaining quantity.

$$(\Delta unsatisfied\_consumption = \mathbf{MAX}(\ [food\_consumption - food\_storage_t], 0\ ) \tag{4.11}$$

Food consumption is subtracted from food storage, if enough and updated according to:

$$food\_storage_{t+1} = \mathbf{MAX}(\ [food\_storage_t - food\_consumption], 0\ ) \tag{4.12}$$

Secondly preceding behaviour as shown in Figure 4.5, is the emotional state of the household. Negative events are tend to trigger emotional responses for a certain period of time (Ibrahim et al., 2008). Hence, as an evaluation of the performance of the Food ATM (and indirectly, the perceived availability of food), the emotional state represents anxiety related thereto. The emotional state represents a maximally anxious household when $emotional\_state \rightarrow 1$. Thus, upon occurrence of a negative event or when unsatisfied consumption increases, the emotional state is defined as:

$$emotional\_state_t = 1 \ \textbf{with} \ timestamp = t \tag{4.13}$$

It has been observed that the impact (in terms of emotional response thereto) of an event gradually decreases over time. Hence, the emotional state is subject to a decrease over time depending on the forgetting rate α:

$$emotional\_state_{t+1} = emotional\_state_t/(1 + (t - timestamp) \times \alpha); \tag{4.14}$$

Variation in the emotional state of people brings us to its influence on behaviour. The change in behaviour after an anxiety stimulating event can often be related to (in people's perception) risk-reducing behaviour, such as stockpiling (Upton and Nuttall, 2014), information-seeking behaviour (Ibrahim et al., 2008) and information-sharing behaviour (Harber and Cohen, 2005; Rosenboim et al., 2012).

As stated before, the Physical state is the driver behind the behaviour of a Households agent. In order to satisfy the agent's demand for food, the agent will interact with the FATM agent. This is triggered by the variable $incentive\_to\_facility$: when the agent perceives its food storage to be 'too low', it will demand food. In case the case of the agent being 'Susceptible' the agent is expected to make a *rational* consideration based on size of the desired stock γ, expressed in days of food per person. Given a household is infected, this incentive is always true. Hence, $incentive\_to\_facility$ can be defined as follows:

$$incentive\_to\_facility = \mathbf{any}(\, infected?, [\, \gamma \times \frac{ration}{30} \times nb\_members > food\_storage \,]\,) \tag{4.15}$$

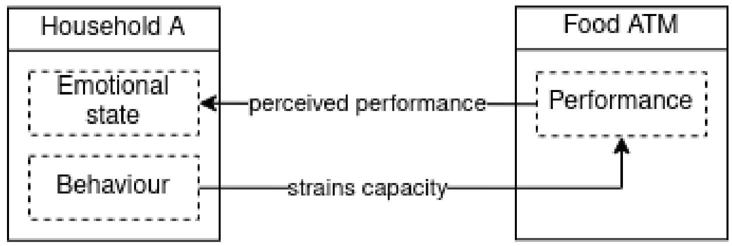


Figure 4.6: The interaction between the Food ATM and a household agent

4.5.3 Household-FATM interaction

Recall the variable $incentive\_to\_facility$ of a household agent. Upon that variable being true, the agent is moved to the FATM agent and interaction starts with the Household agent demanding food. It is assumed that the amount of food is analogous to a household's security stock γ. Also similar to the perception of the security stock is the importance of the emotional state: whether the agent is infected or not. In case it is not, the consideration is assumed to be rational:

$$food\_demanded = \gamma \times nb\_members \times \frac{ration}{30} \tag{4.16}$$

Upon being infected, the emotional state plays a big role:

$$food\_demanded = ration \times (\frac{\gamma \times nb\_members}{30} + emotional\_state \times (1 - \frac{\gamma \times nb\_members}{30})) \tag{4.17}$$

The actual withdrawal of food depends on of course the demanded quantity of food, limited by either the food in storage or the restricted amount of food.. Hence, the withdrawal and thus the quantity subtracted from storage can be described as follows:

$$\Delta food\_storage = \mathbf{min}(\ food\_demanded, food\_storage, allowed\_withdrawal\ ) \tag{4.18}$$

The second interaction between a Household and an FATM agent represents how a household experiences the visit to a Food ATM. That is, negative experiences contribute to an anxious emotional state. The criterion according to which this contribution depends on the length of the queue and the demand gap (food demanded minus food received). Recall how a household agent is unique in its way of perceiving events with the personal characteristic pc. The maximum tolerance for the length of a queue ϵ and the maximum security stock γ decrease as a function of the household agent's anxiety ($pc \to 1$). If the FATM agent perform worse than the set boundaries, the $emotional\_state$ is updated to 1:

$$(emotional\_state = 1)|\mathbf{any}(\,(\epsilon \times pc) < queue\_length), (\gamma \times pc) < (food\_demanded - \Delta food\_storage)) \tag{4.19}$$

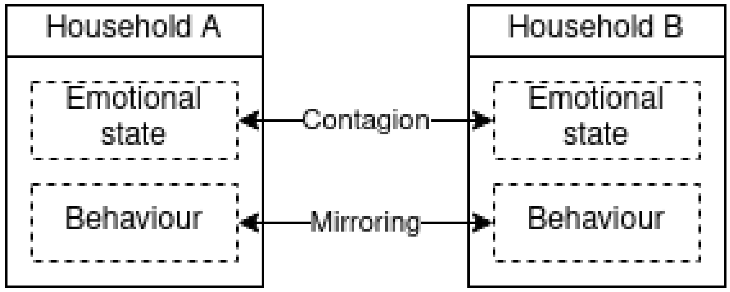


Figure 4.7: The relation of the emotional state and perceived behaviour between two households

4.5.4 Household-Household interaction

Interaction between Household agents can be categorised in Emotional contagion and Behavioural mirroring. Both dynamics contribute to collective behaviour vis-à-vis the Food ATM, be it in different ways. Emotional contagion covers the theory that social interaction between peers provoke mutual adaptation of emotions (Bosse et al., 2013) or copying emotional levels of authority figures (Tsai et al., 2011). With the concept of behavioural mirroring it is attempted to catch the dynamics that are thought to be at play when remarkable behaviour is observed. Wang et al. describes this as an agent potentially be disadvantaged by another one's behaviour (2015).

As a basis for both contagion and mirroring between Household agent i and j, one equation is used. This is given an "uncertain situation, an [agent i, red.] with a greater perception of risk (anxiety, red.) [..] amplifies the emotional impacts of others" and a lower anxiety on the other hand weakens the influence of others (Gao and Liu, 2017).

$$f(S_i, S_j) = pc_i \times [1 - (1 - S_j) \times (1 - S_i)] + (1 - pc_i) \times S_i \times S_j \tag{4.20}$$

Whether or not the interaction between two households as described in equation 4.20 occurs, depends on a couple of factors. Firstly, an agent is an active spreader when being 'Infected'. Harber and Cohen and Rosenboim et al. state that the emotional state is reflected in information-sharing behaviour (2005; 2012). Regardless of being Infected of Susceptible, an agent can be passively contaged.

Relevant interaction between two agents depends on the Infected agent's infectivity. The infectivity function follows the general talkativity β and the agent's emotional state:

$$infectivity = \beta \times emotional\_state \tag{4.21}$$

Subsequently, the infected agent's social network is consulted and relevant interaction between two agents occurs with the probability.

$$P(interaction) = infectivity \tag{4.22}$$

Behavioural mirroring occurs when an agent is Infected and is physically close to an another agent with high food demand. The underlying thought here that anxious agents pay attention to their peers when queuing. Behavioural mirroring causes infected persons be maximally anxious according to:

$$emotional\_state = 1 | (food\_demanded_i < food\_demanded_j) \tag{4.23}$$

And the subsequent food demand is updated according to equation 4.20.

4.5.5 The network layer

The social network is defined as a set of people with whom the beneficiary is in contact with, or shares something with. It is explicitly disconnected from the method of information seeking.

Recall the two ways of how information is diffused socially, 1) behavioural mirroring and 2) emotional contagion. If we take a household's social network(s) as the (only) way of describing the relation between households, it might be fruitful to make a distinction between a physically close social network and an information spreading social network, where emotional contagion is more important. For example, the assumption that people queuing are not very convincing emotionally, but *observing* hoarding behaviour might trigger it.

Besides social interactions it has been stated that people also mirror behaviour. Rather than social mrelations, it is thought that spatial relations are important. Where the social network contains people in the semi-close proximity, such spatial interactions can occur between people outside of their social network.

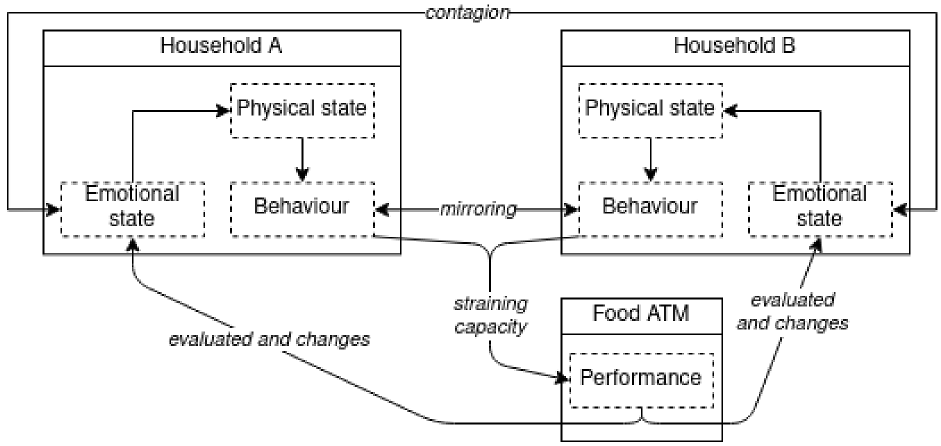


Figure 4.8: Overview the internal psychological mechanism (PM) (Gao and Liu, 2017)

4.5.6 Emergence of social behaviour

Combining the dynamics as identified in the previous section, the elements and their interaction can be listed in such a way that the problem stated in the CLD.

Figure 4.8 shows how the emotional state is influenced by occurring events and emotional contagion. The socialness of an agent is indicated with *mu*, resulting in a emotional state defined as follows:

The essential emergent behaviour here is the possible change of behaviour of Household A if Household B has a negative experience, and vice versa. Given that behaviour thought to be caused by a negative emotional state is strains the capacity more, a negative feedback loop emerges (given the right circumstances).

4.5.7 In-detail processing

In order to further explain the modelled system behaviour, a flowchart has been made of the Households and Facilities agents. The Global agent has not been considered, due to its top-level function: it only provides an environment in which agents function. In Households agent does as follows: at the start of a day food is consumed, further the food storage is checked and it is decided whether to go visit a Food ATM when it is *deemed* not to. The Facility agent's functioning is based on whether beneficiaries are in the queue: if so, they are served if the facility's food storage allows for it.

Highlighted in purple, the logic for updating the KPIs is stated: the figure shows that upon a household agent decides that food storage is inadequate, the consumption gap is added to the *unsatisfied consumption* KPI. Upon the household agent determines demand, the amount of food above a 14-day worth of food in storage is added to the *Food waste* KPI.

Highlighted in red policy related logic can be found. *Rerouting policy?* and *Manageable queue?*. An estimation of the queue's length is always made when rerouting policy is enacted, and the type of rerouting policy determines where a household agent is directed to. The logic *Serve this cycle?* is related to the number of people that are served per cycle.

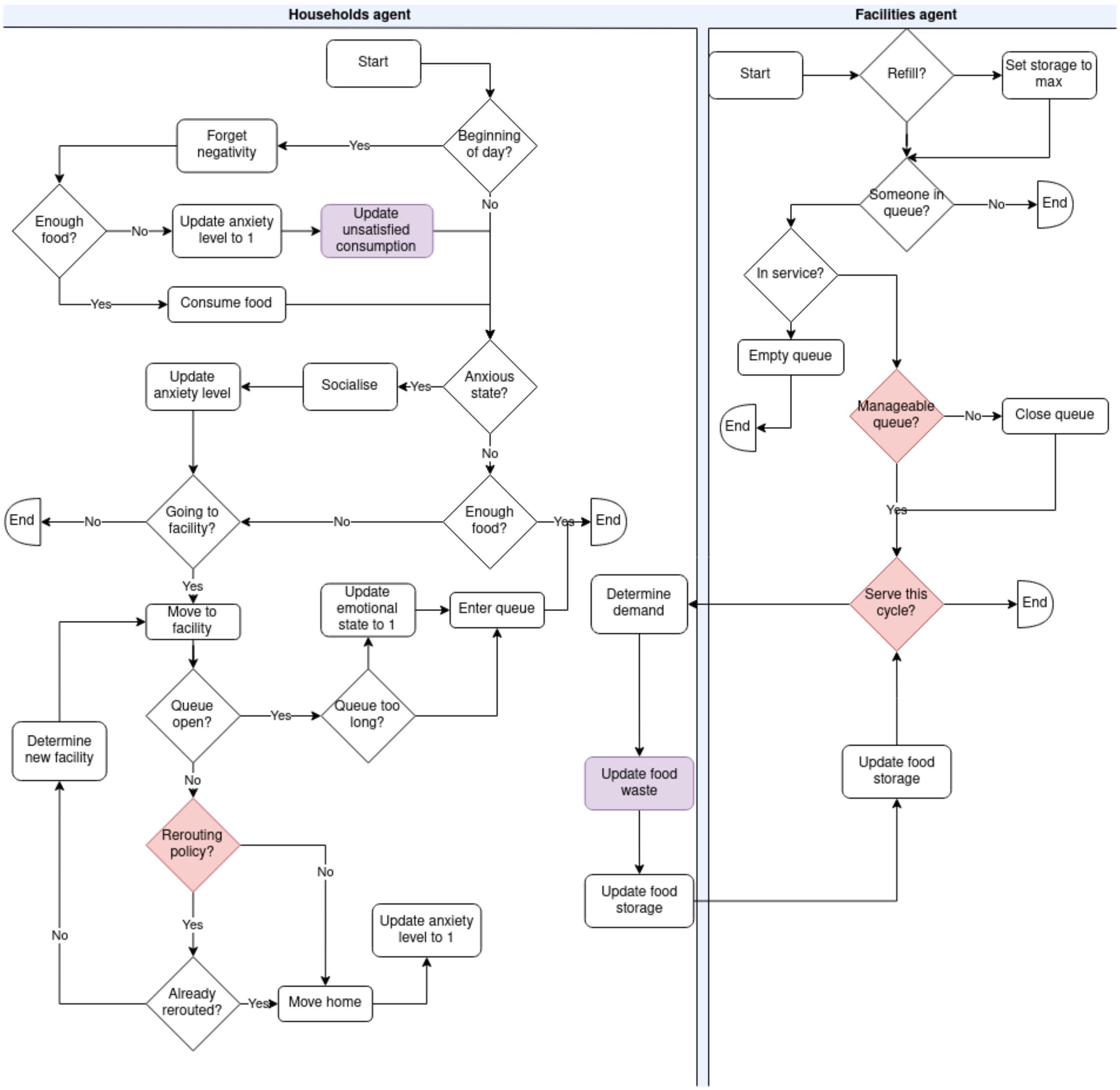


Figure 4.9: Flow chart of Facilities and Households agents and their interaction. Chart represents one cycle.

4.6 Model implementation

Having formalised the model in concrete steps as shown in figure 4.9, the model logic can be implemented in a software environment. In other words, a flowchart coneptually reduces system relations to shared variables and what-if logic allowing a translation in code. Before this translation can be done, one has to make a choice for a software tool.

The software infrastructure giving a place for the interactions as conceptualised is defined as the modelling environment (Van Dam et al., 2013). A great variety of packages exist for this purpose, many with different focal points. Recall how the interaction between model elements brought us to the choice for the Agent-Based Modelling (ABM) technique. Also, the interaction between the system elements partially depend on their location. Subsequently, it can be said that the model is approached as a geo-spatially explicit ABM. GAMA is a software package allowing for the incorporation of geography, with built-in functions for geo-spatial relations between agents (Taillandier et al., 2019). Such usually thoroughly tested functions allow for relative ease of implementation and thus an advantage over custom-built functions.

4.6.1 Parametrisation

For an agent-based model we are interested in three time-related dimensions important for model functionality and thus influencing its results. The first and foremost time-related element that has to be defined is the so-called 'tick'. The tick is a sequence between two events in which it is assumed that nothing happens. Hence, we have to make think about that *nothing of interest* occurs. The smallest time period between two relevant events is the estimated serving time for one household in a facility: 10 minutes. Thus, the 'real time' one tick represents is 10 minutes.

When determining the relevant runtime for the model, it is important to take a step back and remember one's focus: the improvement of a monthly organised food distribution system. The fact that the monthly character is the departing point one aims to improve, and arguably functions as a fallback option. In other words, the system is only relevant if it performs better over the course of one month. Thus, the considered runtime is 30 days.

4.7 Experimentation

(Van Dam et al., 2013) explains how experimentation with agent-based models can help us 1) to investigate the conditions under which a macroscopic regularity (in reality) occurs or 2) how emergent behaviours and regularities can be observed from this (virtual) agent-based model. The former tends to be applied in the context of an *existing* system in which, for example, the efficacy of interventions can be investigated. Investigating the possible adverse effects of human behaviour on a (non-existent) system of Food ATMs corresponds with the latter.

Van Dam et al. further states the impossibility to determine whether model results are "right" or "wrong", since results cannot be tested against a real scenario (2013). It is further stated that the validity of the observed behaviour can be tested by it 1) having a clear correlation with input variables and 2) emerging under reasonable conditions. It must be stressed that careful choice of experiments is paramount to the ability to consequently understand observed behaviour.

Limitations in the number of experiments that can be conducted due to the corresponding computational expense obliges us to approach experimentation incrementally. That is, experiments are designed with the goal of 1) finding relevant scenarios and 2) testing policies.

4.7.1 Key Performance Indicators

The performance of a system of Food ATMs is directly connected to stating the problems of the current way of distributing food. In other words, the Food ATM's added value is based on improving the current system: inability to get food, long queues and food loss are points of concern for current food distribution. Hence, the performance can be measured according to three KPIs:

- **Queuing load per facility**. In case the serving capacity is lower than the number of household agents joining the queue per unit of time, household agents wait before being served. For every tick, the number of people is summed, boiling down to computing the integral of the function of number of people in-queue over time.
- **Cumulative amount of unsatisfied consumption by households**. Unsatisfied consumption entails the gap in estimated consumption needs of a household and the amount of food in storage. In other words, when a household agent has enough food in storage, it will be consumed; if not, the shortage will be counted as unsatisfied consumption. See Figure 4.9 where this statistic is updated in the model cycle.
- **Food waste**. The idea of food waste is based on the assumption that larger amount of foods degrade due to inadequate storage facilities. In this case, it is assumed that all amounts exceeding a household's 15-day ration goes to waste.

4.7.2 Point-wise experiments: behavioural scenarios

Scenarios are a consequence of different combination of behavioural factors. The following four behavioural factors and their name in the model are considered. The total list of experiments are a permutation of the values of these factors.

- **Forgetting rate** (α) $\in$ [0,1]: Forgetting rate, reducing an agent's anxiety. A value of 0 means stable anxiety, a value of 1 halves anxiety levels daily.
- **Social interaction** (β) $\in$ [0,0.5,1]: Representing the rate of social interaction. A value of 0 means there is no social interaction between agents, whereas a value of 1 means social interaction with 1×20 people in an agent's social network.

Scenario #	Forgetting rate α	Social interaction β	Visiting frequency γ	System perception ϵ
1	High (1.0)	None (0.0)	Low (7.0)	Bad/Good (0.1/1.0)
2	High/Low (1.0/0.0)	High (1.0)	Low (7.0)	Bad (0.1)
3	High/Low (1.0/0.0)	High (1.0)	Low (7.0)	Good (1.0)
4	High/Low (1.0/0.0)	High (1.0)	High (3.0)	Bad (0.1)
5	High/Low (1.0/0.0)	None (0.0)	High (3.0)	Good (1.0)

Table 4.4: Comparison of scenarios by behavioural factors and indication of peak load per KPI

- **Visiting frequency** (γ) $\in$ [3,7]: represents the size of an agent's contingency food storage and consequently the base visiting frequency. A value of 3 means an agent keeps 3 day's food in storage, implying a base visiting frequency of a visit every three days.
- **System perception** (ϵ) $\in$ [0.1,0.5,1]: represents the a population's general tolerance to malperformance. Agents individually evaluate the performance of the system according to the length of the queue of the visited Food ATM. The threshold for triggering anxiety is then linearly dependent on the system perception: a value of 0 means a tolerance of 0, and 1 of the daily serving capacity of a Food ATM.

4.7.3 Point-wise experiments: policy analysis

The tested policies are:

1. No policy:
2. Rerouting: redirecting home
3. Rerouting: redirecting to closest facility
4. Rerouting: redirecting to random facility
5. Capacity: Food ATM size according to expected demand
6. Capacity: Assign beneficiaries to one Food ATM
7. 15-day ration:

Under various scenarios that have been selected in the scenario discovery:

Chapter 5

Model validation

Van Dam et al. states that the 'traditional' view on validation is whether we built an accurate representation of the real world (2013). However, the exact research problem is, to the best of knowledge, that a decentralised food distribution system taking into account potential risks of beneficiary behaviour has never been designed. Therefore, one should rather focus on the question whether the model is the right tool to answer the questions of the problem owner and whether these results are convincing.

Since this research is conducted in the context of designing operational policy for the Food ATM, expert consultation is the basis to illustrate the physical character and design boundaries thereof. It has been discussed whether the investigated policies are realistic and also the design goals of the Food ATM have been checked. For example, important properties such as the implementation of the Food ATM in the Bidi Bidi refugee camp and a design capacity of 2,500 households are the result of expert consultation.

Secondly, the notion that panic buying-like dynamics are a major risk to undermining the Food ATM's functioning led to borrowing concepts of research in this field. However, it is said that "research on understanding consumer panic buying is conducted by sociologists and psychologists but is mostly limited to statistical analysis" (Dulam et al., 2020). Such statistical analysis corresponds with Van Dam et al.'s historic validation, which is not possible. Consequently, in order to compare research on panic-buying dynamics, a translation will have to made by comparing various essential model elements.

Table 5.1 shows how similar model elements relate to the conceptualised system. This study and the Upton and Nuttall's conceptualisation of the relevant system is based on the idea that the system's performance either propagates adverse behaviour or stifles adverse behaviour. In both models, it is assumed that people naturally propagate calm, unless being anxious (or in Upton and Nuttall's terms: panicked) (2014).

A big difference in the models can be observed in what these models are said to describe. Upton and Nuttall's model describes a pre-panic situation in which panic is introduced, leading to panic buying. The moment the rumour stops spreading, it can be observed how the system returns to normalcy. Hence, the model is said to describe three phases: 1) pre-panic, 2) in-panic and 3) post-panic. This stands in stark contrast to what our model describes. Figure 5.1 shows how actual demand is a *composition* of

Study / Model elements	**This study**	**Upton and Nuttal (2014)**
Stabilising factors	Propagating calm; Forgetting rate	Propagating calm
Disruption	None	Rumour introduction
Environment	Bidi Bidi camp	UK Petrol stations
Agent's physical constraint	Rations	Agent's car petrol tanks

Table 5.1: Comparison of model elements between this study and Upton and Nuttall (2014)

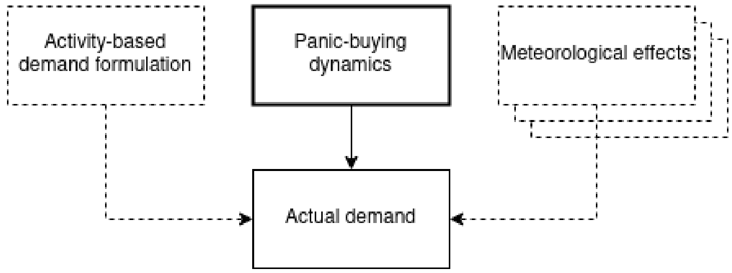


Figure 5.1: Relation demand-inducing dynamics to actual demand

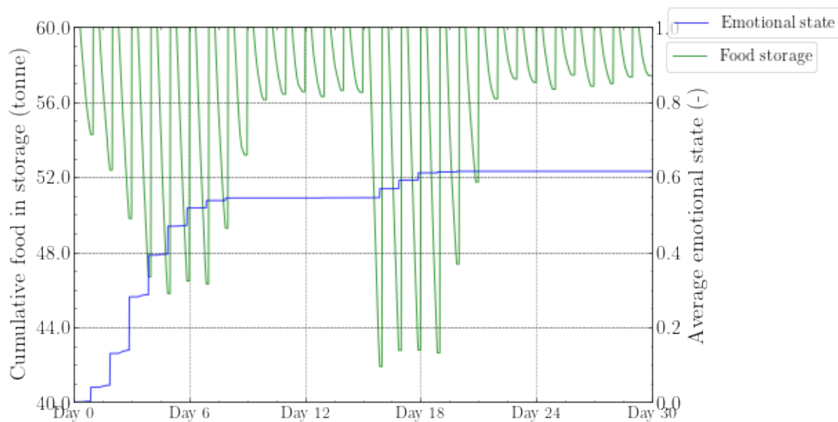


Figure 5.2: Emotional state versus food in storage for 15-day ration policy

multiple dynamics. In case of panic-buying dynamics, it is thought that only that one is *dominant*, compared to secondary examples such as events or weather.

Investigating the relation between the level of anxiety and cumulative food in storage in Food ATMs, it can be observed that our system does not know a stable pre-panic state, nor a stabilising post-panic state. Hence, correct interpretation of the results should thus *only consider an in-panic system state.* Notwithstanding this, increasing oscillations in the supply chain's capacity to deliver during the in-panic situation are also described by Upton and Nuttall's model. More precisely, the same behaviour can be observed when relating anxiety (or panic) to food storage (or petrol availability).

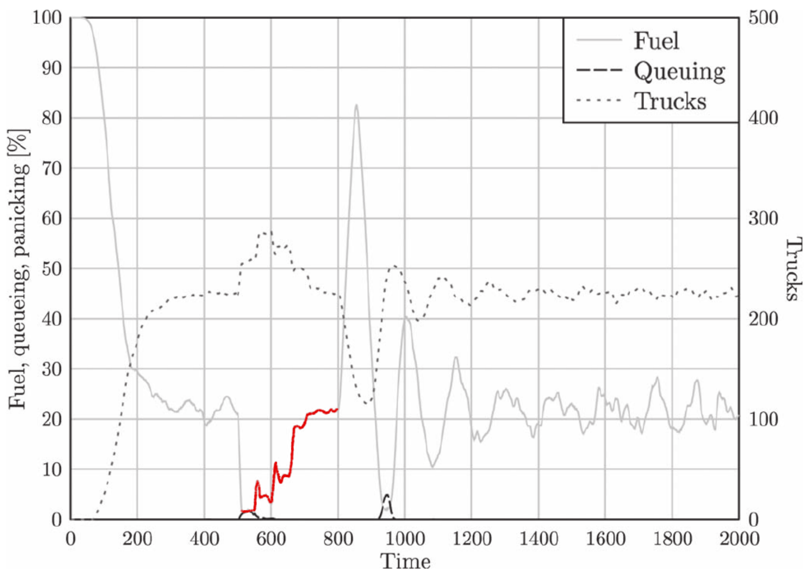


Figure 5.3: Fuel ownership over time, *in-panic* situation in red (% of max) (Upton and Nuttall, 2014)

Chapter 6

Results

In this section the output of the three modelling steps will be presented. Firstly, the output of the optimisation model is presented: a set of Pareto optimal locations for the locations of the proposed system of 12 Food ATMs. This knowledge on where to place the Food ATMs is used as input for the simulation model. Analysing the simulation model was done in two parts: *Scenario discovery* and *Policy analysis*. The first, scenario discovery, will present relevant scenarios under which proposed policies will be tested (also see the chapter 4.7 on experiment design). Secondly, policy analysis entails the investigation of the influence of the proposed policies under the identified relevant scenarios.

6.1 Optimisation

Recall the objectives of the optimisation: minimising the average distance between households and a facility, minimising the maximal distance between one household and a facility and minimising the 'penalty' for the absence of road access. Inherent to a multi-objective optimisation, a 'best' solution cannot be presented, but the results do provide insight in possible challenges in choosing locations for "a system of Food ATMs".

6.1.1 Outcome exploration

Firstly, the so-called *pairplot* is presented in figure 6.1. When using a complicated optimisation algorithm, one is obliged to verify whether the outcomes provided by the algorithm make sense. For example, the absence of a part of the outcome space (i.e. a combination of outcomes) might indicate that the algorithm presents a solution without having explored all possibilities.

Interestingly, it can be observed how a gap in the outcome space exists for maximal distance. Taking a look at figure 6.3, showing the locations of the buildings, we see that buildings are clustered. This implies a discontinuous maximal distance, explaining the gap in the outcome space.

A so-called *parallel-axis plot* allows us to gain insight in the trade-offs between the different KPIs. It can be observed how the placement within the clusters (low penalty) tends to result in a higher maximal distance than placement outside of these clusters (high penalty). This is a logical consequence of the fact that there are more clusters than facilities and subsequently it pays off to place facilities between clusters.

6.1.2 Locations and estimated demand

Recall that the penalty KPI represents road access. Although not the best performing policy in terms of average and maximal distance, policies with a penalty of 0 are the only ones deemed to be realistic.

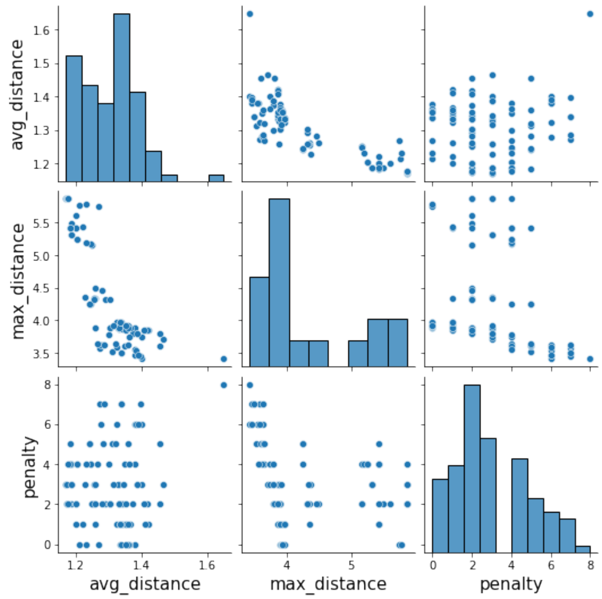


Figure 6.1: Pairplot pareto optimal results

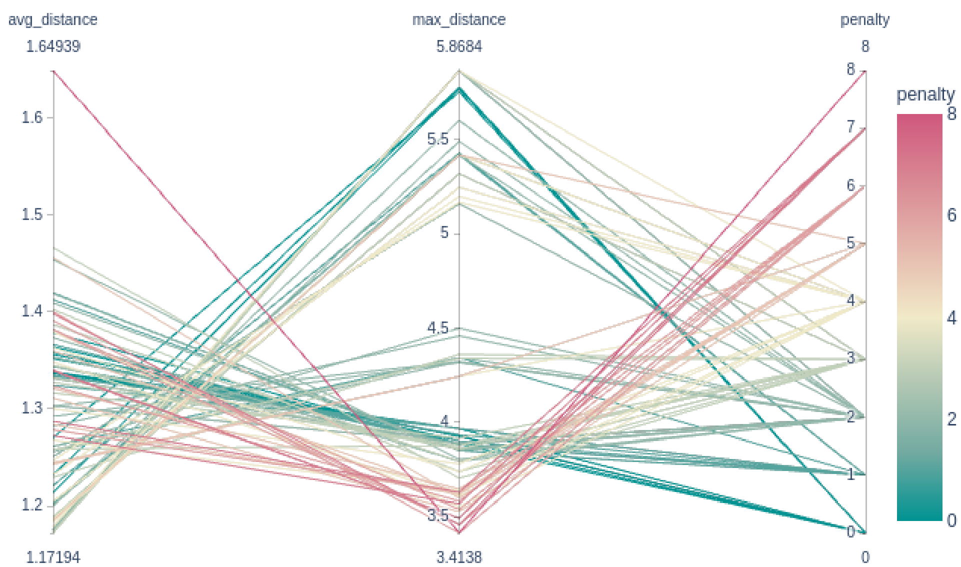
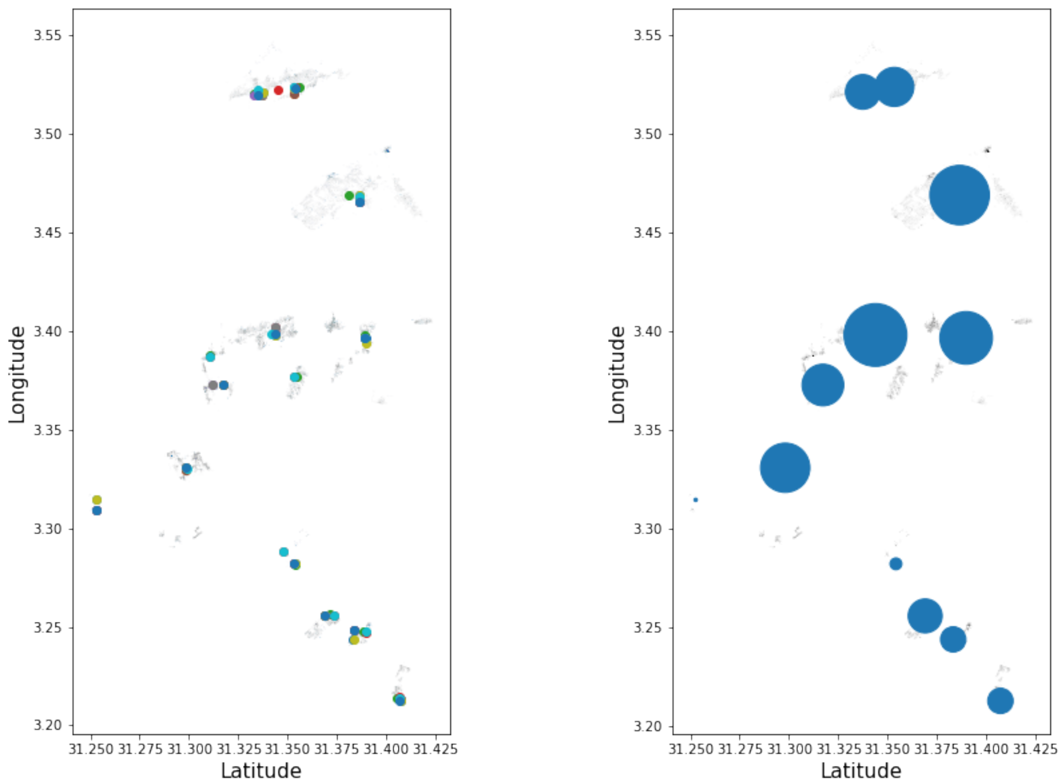


Figure 6.2: Parallel axis plot of Pareto optimal results



(a) All options, changing color per set

(b) Selected set, size as # closest buildings

Figure 6.3: Locations of facilities for penalty=0, a: all locations, b: size of one set

Consequently, the other location options are filtered out and only selecting the set of locations for which the penalty equals zero results in the map as shown in figure 9.2.a. Figure 6.2 also shows policy options with a high maximal distance. Looking at the map, this corresponds with the outlying cluster at (31.250, 3.31).

Section 4.7 elaborates on the design of experiments for the ABM. One of the investigated policy options is designing facilities capacitated or uncapacitated. This entails designing a system with fixed facility size or vary size based on estimated demand, respectively. Preference for a facility is solely driven by the its proximity to a beneficiary's home. Hence, the estimated necessary size of a facility is determined by the number of buildings closest to that particular facility. The facilities with corresponding markersizes is shown in figure 6.3.b.

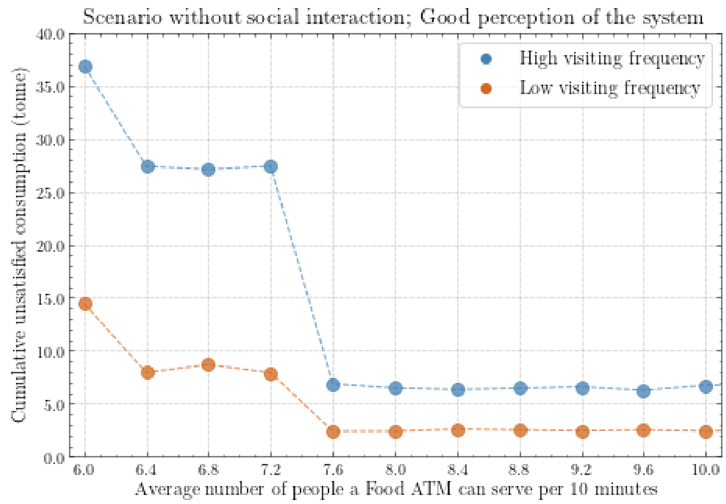


Figure 6.4: Cumulative unsatisfied consumption of all household agents under various serving capacities

6.2 Scenario discovery

Corresponding to the modelling step of *Data exploration* as described by 2013, the goal is to find, visualise and explain patterns in the data that was generated by the Agent-Based Model (Van Dam et al., 2013). 'Patterns' in terms of analysis of model-generated data essentially entails linking (combinations of) input parameters to values of Key Performance Indicators (KPI). Subsequently, a (combination of) input parameter(s) can be explained by a *narrative*: a textual explanation of what a relation between input and output *could* mean in reality.

Scenario discovery is in this case particularly useful because of two reasons. Firstly, it enables to quantify the effects of uncertain input parameters on model output, helping to understand the system better as well. It is thought that knowledge on model dynamics inherently improves the understanding of the performance of a policy. Secondly, the technical environment in which the model was implemented has its limitations in terms of computational expense and complex data analysis. Hence, scenario discovery in combination with separate policy analysis allows for manageable, step-wise data analysis and thereby reducing the number of model simulations (computational expense) compared to an automatic combination of the two.

Firstly, Sensitivity to key uncertainties will describe the influence of two key uncertainties on the main KPI: unsatisfied consumption. Resulting quantification will be use to subsequently discover scenarios per simulation KPI: unsatisfied consumption, queuing and food waste.

6.2.1 Sensitivity to key uncertainties

The experiments have been designed with the goal in mind to investigate the influence of (a combination of) behavioural factors on system behaviour. The idea is that knowledge on the effects of individual beneficiary behaviour, enables one to design effective policy. Besides these *behavioural* factors, it is thought that *environmental* uncertainties also influence system performance, such as 1) the location of Food ATMs, 2) serving capacity and 3) the average size of the social network. Whereas (1) can be seen as a choice, (2) and (3) are uncertainties regarded as providing relevant context to the behavioural factors. In other words, it is only relevant to investigate the behavioural factors *given* a particular range of these environmental uncertainties.

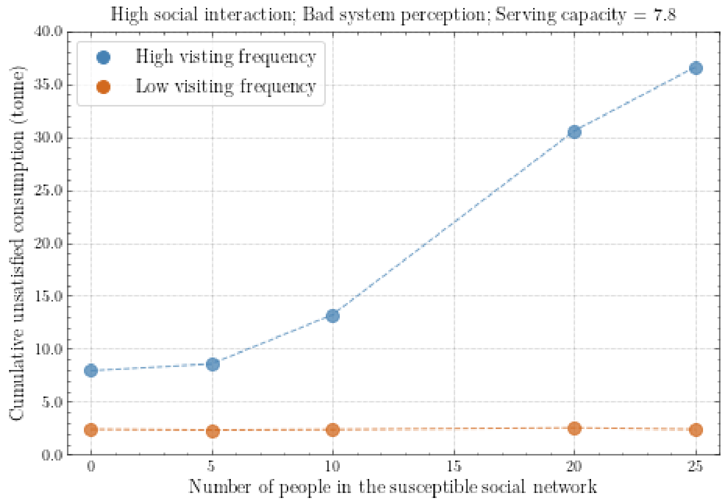


Figure 6.5: Cumulative unsatisfied consumption of all household agents under various social network sizes

Figure 6.4 shows the evolution of the main KPI *Unsatisfied consumption* as a function of the average number of people that are served per 10 minutes. It is important to note that no social interaction occurs in the population (in order to exclude (3), the social network size). For both a population with a high as well as a low visiting frequency, the same pattern occurs: a sharp increase at 7.2 and 6.0. Firstly, it can be concluded that the system reacts very abruptly to a low enough serving capacity. Secondly, due to the lack of any interaction between agents and exchange of beneficiaries between Food ATMs, this abruptness can be attributed to negative performance of *individual* Food ATMs.

Suspecting that the existence of a social network contributes to the spread of anxiety in a population and consequently adverse behaviour, a system with a serving capacity of 7.8 is chosen. Figure 6.5 shows for 0, without social interaction, that this configuration coincides with stability as in figure 6.4. As a function of the number of people in the social network an exponential increase can be observed, till a number of 20.

In short, the exploration of the effects of quantifying serving capacity and the size of an average social network provided knowledge on two things. Firstly, the unequal spread in demand causes distinctive malperformance on individual facilities. Secondly, we know how to quantify serving capacity and social network size in order to generate behaviour-related dynamics with this particular model. Namely, the serving capacity will be **6.0 | 7.8** and agents will have an average of **20** people in their social network.

The size of the food storage of each Food ATM is determined by design specifications at roughly 5 storage silos of 15 metric tonnes each, totalling 75 tonnes. These silos are supposed to be filled on a regular basis. Depending on the frequency of these refills, an often visited Food ATM might run out of food, provoking worse system performance. Figure 6.6 shows the unsatisfied consumption with various refill frequencies. Per tick entails a refill every 10 minutes, ensuring permanent availability. Daily and every other day entail a *consistent refill* every 144 and 288 ticks of 10 minutes respectively. It can be observed how the system performs worse starting from a refill frequency of every other day. For the rest of the generated scenarios, a **daily refill frequency is used**.

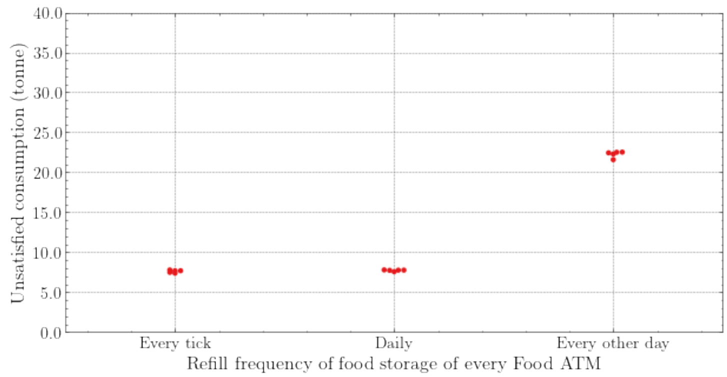


Figure 6.6: Cumulative unsatisfied consumption of all household agents under varying refill frequencies

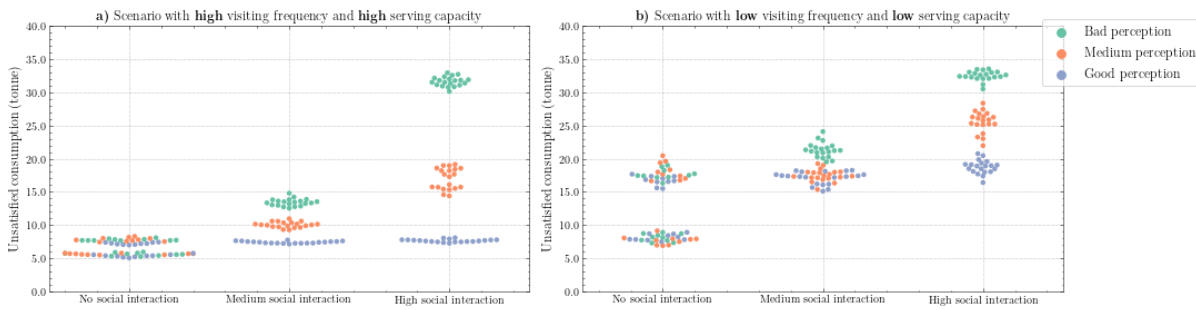


Figure 6.7: Cumulative unsatisfied consumption of all household agents at day 30 (kg)

6.2.2 Unsatisfied consumption

Ensuring the provision of sufficient food for consumption to beneficiaries is the main goal for the Food ATM. At the beginning of each day, the daily ration of 500 grammes per person is subtracted from the household's food storage. However, it might occur that no food is available: unsatisfied consumption. Hence, this metric shows to what extent households are prevented from accessing food. The model logic accounts for three reasons a household agent might not succeed in providing enough food: 1) insufficient amount of food in the Food ATM's storage, 2) a queue can be too long for the household to be served within the Food ATM's service hours and 3) a household agent can arrive at a Food ATM after closing.

Figure 6.4 showed how enlarging the service capacity (the number of persons served per unit of time) reaches a some minimum. The potential unsatisfied consumption shows to be significantly higher. This, together with the notion that the system is assumed not to find any hindrance from a badly performing upstream supply chain (inadequate food in storage in a Food ATM), queuing is the main cause of prohibiting access to food. In other words, the dynamics regarding queuing and perception thereof are the main drivers of unsatisfied consumption.

In figure 6.7 the end-of-simulation values (at the end of day 30) of unsatisfied consumption are represented as dots. Figure 6.7.a and b show results of a scenario with a high visiting frequency and high serving capacity (7.8 agents/10 min) and a scenario with low visiting frequency and low serving capacity (6.0 agents/10 min), respectively. The dots are coloured according to the population's general perception of the system: a 'good' perception means that the population is very tolerant with regards to the length of the queues.

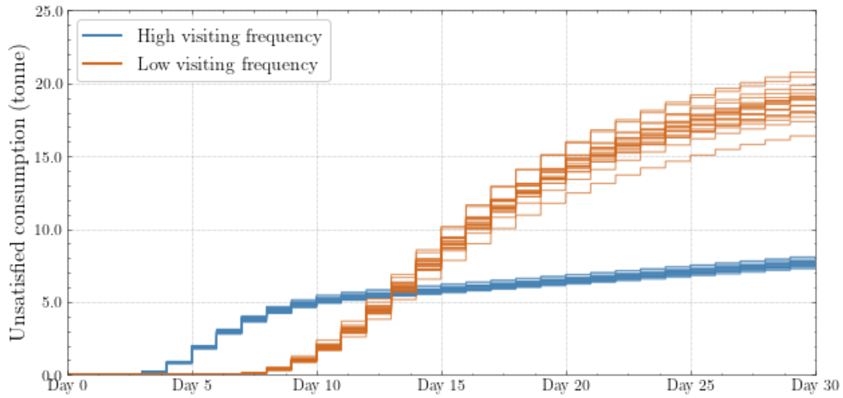


Figure 6.8: Cumulative unsatisfied consumption over time, selected for **good system perception**

On the horizontal axis a distinction between populations is made based on the population's social interaction. That is, to what extent negative emotions about the system of Food ATMs diffuses within the population. Differentiating for social interaction and colouring dots for system perception allows us to observe clear clusters in scenarios with social interaction. That is, high unsatisfied consumption can be observed for a social population with a bad perception of the system. General bad perception contributes to the existence and subsequently spread of negative emotions within a population, which is stimulated by high social interaction.

Secondly, it can be observed how a good system perception results in relatively good performance for a high serving capacity but shows significantly worse results for a low visiting frequency. One contributing factor is the higher serving capacity enabling a Food ATM to provide food to more people. The second contributing factor is a dynamic that can be later observed in queuing as well. Whereas a population's anxiety provoked by *individual perception* increases linearly (due to the temporally equal spread of demand), a population's anxiety provoked by social interaction increases exponentially.

As a consequence of this exponential increase, the negative emotion in the population can gain momentum, as figure 6.8 shows. Here, for both the 'Good perception' scenarios in a population with high social interaction are selected. The part of the population that is naturally more anxious consumes their ration *before* the effect of the diffusion of emotion actually occurs. Consequently, the sudden increase dies out, whereas the naturally anxious part of the population is triggered for a scenario with a low visiting frequency.

Figure 6.9.b sheds more light on the relatively high values for a scenario with a low visiting frequency without social interaction. In this case it can be observed how the main contributing factor to unsatisfied consumption is the forgetting factor. Although the value is significantly lower, a similar cluster can be observed figure a, the scenario with a high serving capacity.

Summarising, the analysis taught that the combination of high social interaction and bad system perception tends to lead to a relatively high value for unsatisfied consumption. Where a bad perception provokes negative emotions in the population, social interaction facilitates diffusion. A good perception of the system however, only depends on the situation to have a beneficial result: low visiting frequency leaves room for rapid diffusion through the social network. In a population without social interaction, the forgetting rate is determining for performance.

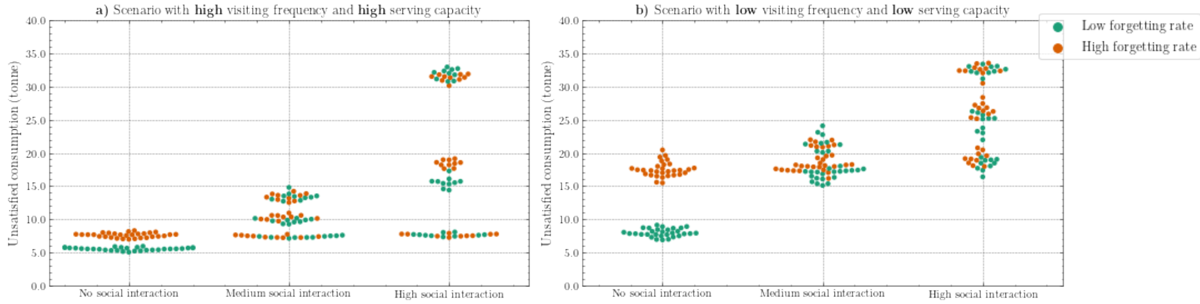


Figure 6.9: Cumulative unsatisfied consumption of all household agents at day 30 (kg)

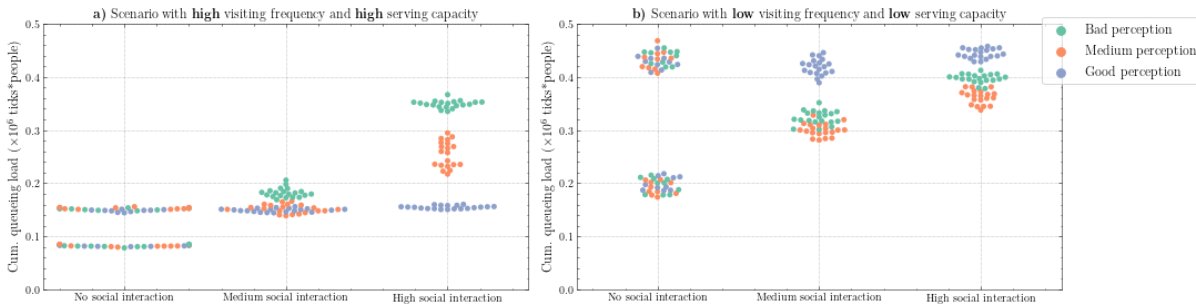


Figure 6.10: Cumulative queuing load in ticks*people, for facility #5 (busiest)

6.2.3 Queuing

When the serving capacity of a Food ATM (that is, the number of people that can withdraw their food per unit of time) is lower than the number of people that would like to be served, a queue emerges. As illustrated in the introduction, huge queues tend to form at food distribution points putting people in dangerous positions. Queues are evaluated by computing the total queuing load (ticks×people). Recall the abrupt increases in figure 6.4, suggesting inadequate serving capacity for *individual* Food ATMs. Hence, the queuing load is evaluated for the system as a whole, as well as for the busiest facility.

Similar to the visualisation of Unsatisfied consumption in the previous section, figure 6.10 shows the cumulative queuing load represented as dots. Figure 6.10.a and b show results of a scenario with a high visiting frequency and high serving capacity (7.8 agents/10 min) and a scenario with low visiting frequency and low serving capacity (6.0 agents/10 min), respectively. The dots are coloured according to the population's general perception of the system: a 'good' perception means that the population is very tolerant with regards to the length of the queues.

It can be observed how factors contributing to negative performance change significantly as a function of visiting frequency and/or serving capacity. Analogous to bad performance for unsatisfied consumption, a scenario with high visiting frequency shows worst results for a population with high social interaction and bad system perception. However, the previously described dynamic of the combination of diffusion of anxiety and low visiting frequency (also see figure 6.8) tends to be dominant for populations with social interaction.

Figure 24.b sheds more light on the relatively high values for a scenario with a low visiting frequency without social interaction. In this case it can be observed how the main contributing factor to cumulative queuing load is the forgetting factor. Although the value is significantly lower, a similar cluster can be observed figure a, the scenario with combining a high visiting frequency and a high serving capacity.

Investigating the cumulative queuing load of all Food ATMs combined, the same relations are found. In this base case, it seems that the busiest Food ATM contributes for almost 30% to the total.

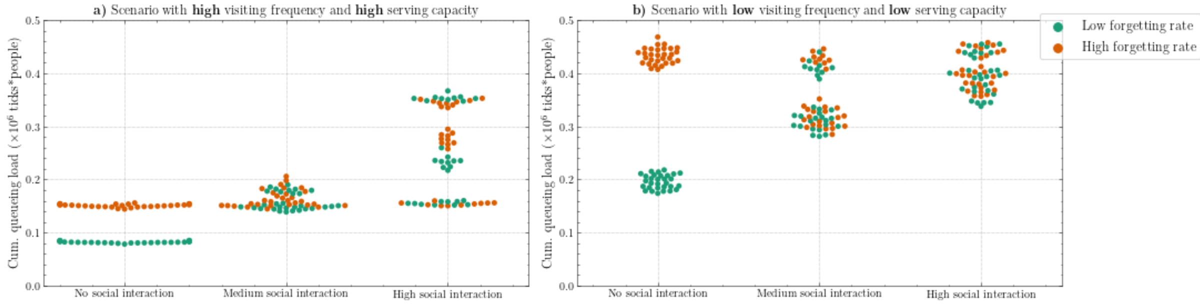


Figure 6.11: Cumulative queuing load in ticks*people, for facility #5 (busiest)

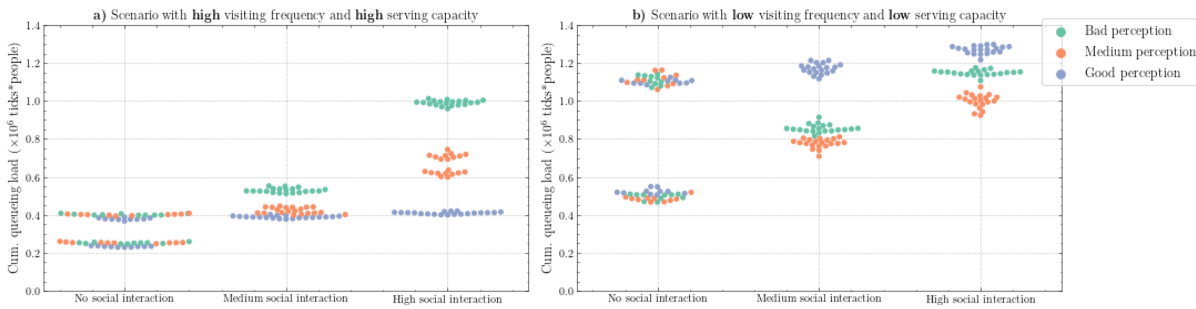


Figure 6.12: Cumulative queuing load in ticks*people, for all Food ATMs combined

The analysis taught that in a population with social interaction, the importance of behavioural factors change per scenario.

6.2.4 Food waste

An important goal for the Food ATM is the reduction of food waste. It is thought that up to a third of distributed food goes to waste, due to inadequate storage of sizeable amounts of food. Although continuous food supply by means of the Food ATM in principle means that beneficiaries *are able* to reduce the amount of food in storage, but uncertainty on the availability of food might provoke people to increase the size of their 'security stock'. Consequently, a bigger security stock is associated with degradation due to inadequate storage facilities in refugees' homes. In this case, it is assumed that if a household's food storage exceeds the estimated two-week amount, food is 'wasted'.

In order to understand the pattern with regards to food waste, one has to take note of the roughly

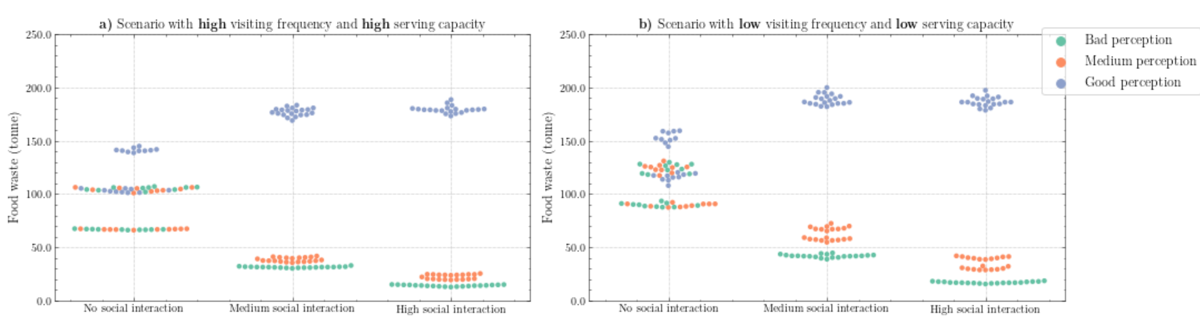


Figure 6.13: Cumulative food waste at day 30 (end of simulation); Differentiated for system perception

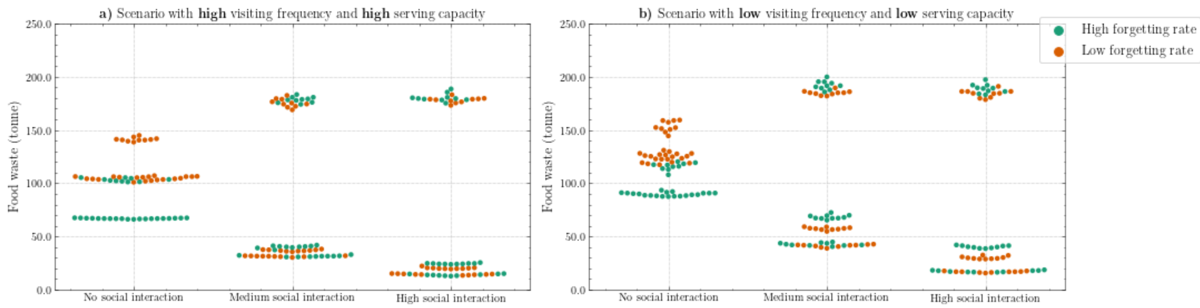


Figure 6.14: Cumulative food waste at day 30 (end of simulation); Differentiated for forgetting rate

three situations: 1) small load on the system, low anxiety in the population, 2) medium load on the system, high anxiety in the population and 3) high load on the system, high anxiety in the population. Respectively, these scenarios coincide with 1) medium food waste, 2) high food waste and 3) low food waste. Investigating the cumulative amount of food waste in tonnes presented in figure 6.13 that in both a system with high and low serving capacity food waste is minimal. Recall how this combination of behavioural factors provoked the highest value for Unsatisfied consumption (Figure 6.7, suggesting high load and anxiety).

On the other hand, a good system perception can consistently be associated with high food waste in populations with medium or high social interaction, in contrast with varying queuing load (figure 6.12) and relatively low unsatisfied consumption (figure 6.7). Figure 6.14 shows how a high forgetting rate in a population without social interaction results in low food waste, being consistent with favourable values for unsatisfied consumption and queuing load.

Summarising, it can be said that food waste as a metric should be interpreted with caution. That is, although a low value might suggest favourable system performance, in reality this is highly dependent on the system state. For example, a low value for food waste in combination with a high value for unsatisfied consumption (scenarios with bad system perception and high social interaction) suggests that beneficiaries are prevented from enlarging their ‘security’ stock by an overloaded system.

6.2.5 Summary

Scenario discovery for has served three purposes: 1) finding the parameter range of the key system uncertainties for which the model yields relevant behaviour, 2) better understanding for which combinations of behavioural factors contribute to a system state in which policy intervention might be beneficial and 3) the exact specification of scenarios that are relevant for analysis of policy which is conducted in the next chapter.

1) The key system uncertainties have been determined to be:

- Serving capacity: 6.0, 7.8
- Refill frequency: daily
- Social network size: 20 persons

2) Better system understanding entails that the analysis shows how a multiplicity of behavioural factors can provoke undesirable system state. This means that behind the same observation according to the identified KPIs can lie a contribution of different behavioural factors. Hence, *not all panic buying loops are equal.* Consequently, the effectiveness of policy might vary per scenario.

In order to further investigate the suspicion of varying performance of policies per scenario, 3) a specification of scenarios in which different factors contribute to weak system performance has been

Scen #	Forgetting rate	Social int. act.	Visiting freq	System perc	Peak for KPI
1	High	None	Low	Bad/Good	Queuing, Uns. Cons.
2	High/Low	High	Low	Bad	Uns. Cons.
3	High/Low	High	Low	Good	Queuing
4	High/Low	High	High	Bad	Queuing, Uns. Cons.
5	High/Low	None	High	Good	*Policy analysis*

Table 6.1: Comparison of scenarios by behavioural factors and indication of peak load per KPI

made. Note that scenario # 5 does not contribute to weak system performance under the base case, but rather under certain policy implementations.

6.3 Policy analysis

Policy analysis can be seen as a second data analysis, after manual scenario discovery.

The scenario discovery taught us that a particular combination of behavioural factors result in a(n) (un)favourable system state. Policy intervention aims to improve the system state. Hence, policies are investigated in the following scenarios:

- **Scenario 1** is characterised by a population with a preference for a relatively high contingency food storage and consequently a low visiting frequency. Low trust in the food distribution and peers result in a bad system perception and no social interaction with the rest of the population.
- **Scenario 2** is characterised by a population with a preference for a relatively high contingency food storage and consequently a low visiting frequency. Lack of trust in responsible authorities and reliance on the community result in a population with high social interaction and bad system perception.
- **Scenario 3** is characterised by a population with relatively high trust in the system as well as the rest of the population resulting in good system perception and high social interaction. However, the population does have a preference for a relatively high contingency food stock resulting in low visiting frequency.
- **Scenario 4** is characterised by a population with a preference for a relatively low contingency food storage and consequently a high visiting frequency. Lack of trust in responsible authorities and reliance on the community result in a population with high social interaction and bad system perception.
- **Scenario 5** is characterised by a population with low contingency food storage and trust in the responsible authority resulting in a high visiting frequency and good system performance. Information on food distribution is not part of social interaction, hence begin absent.

6.3.1 Food waste and ration sizing

As elaborated upon in the previous section on scenario discovery, we found how the prevention of food waste does not necessarily coincide with a desirable system state. In other words, if the system performs badly according to the other KPIs, food waste is reduced. On the other hand, a well functioning system reduces the population's anxiety, indeed reducing the size of withdrawals people make and subsequently the amount of food that goes to waste. In short, one could say that food waste reaches its maximum for a situation in which the naturally anxious part of the population is triggered, whereas the system hasn't collapsed due to mass anxiety yet.

A peak in food waste with different contributing factors can be observed in both a highly communicative population as well as a population without communication whatsoever. Scenario discovery taught us that the contributing factors are the same both a scenario with a high visiting frequency as a low visiting frequency. That is, the population has a favourable perception of the Food ATM. Figure 6.15 shows for scenario a and b *base case* reference point. It can be observed how rerouting (in all its variants) only lowers given a population without social interaction.

In the scenario discovery chapter, the dynamics causing food waste in this case was discussed: anxiety. The population is assumed to be linearly heterogeneous in terms of anxious reaction: this causes a significant part of the population to react anxiously in almost all situations. Since the 'rerouting' and 'capacity' policies aim to provide access in case of overload and this part of the population already reacts anxiously such policies are unlikely to have an effect.

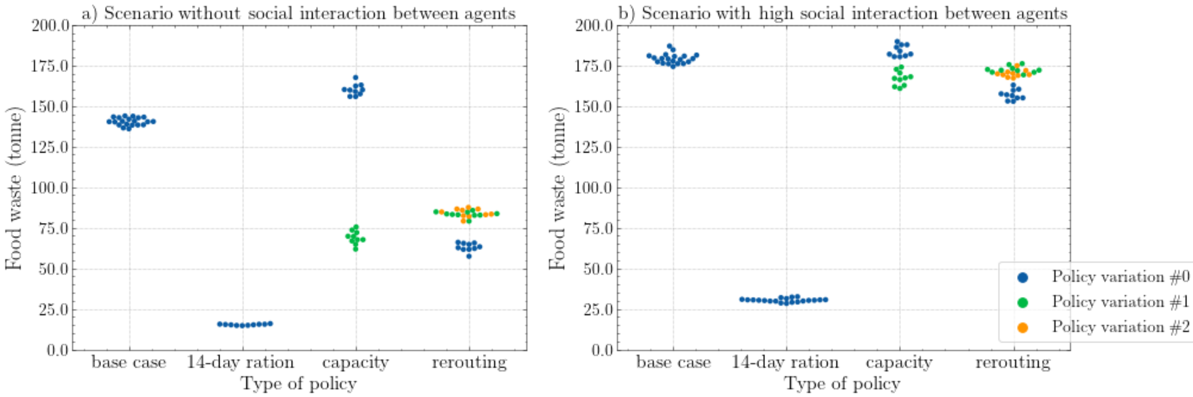


Figure 6.15: Food waste under four policies in two scenarios

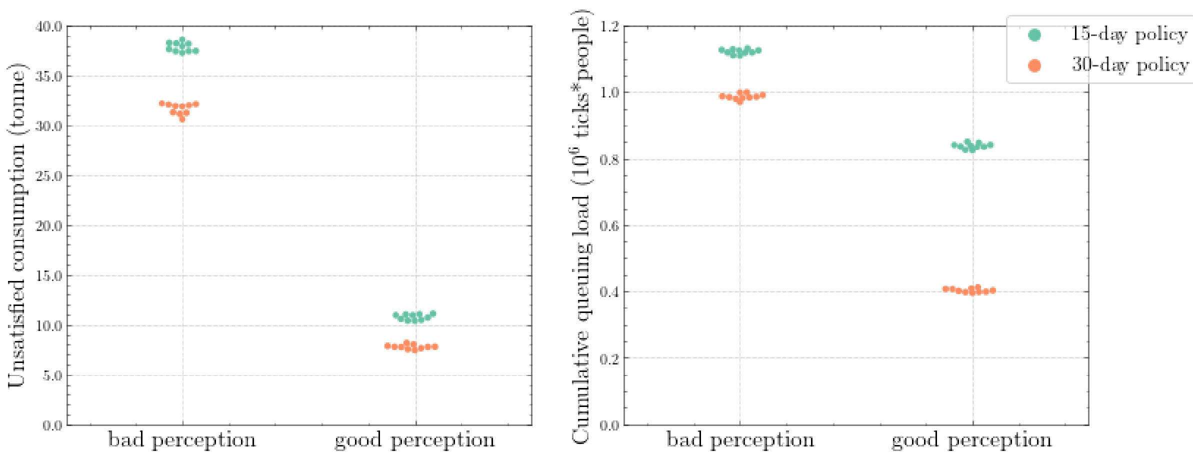


Figure 6.16: Influence of implementing a 15-day ration on highly social population for good and bad perception of the system

The *15-day ration* policy does seem to be an effective method of reducing food waste. This policy goes back to the cause of food waste: inadequate storage of relatively big amounts of food. Subsequently reducing the amount people can withdraw inherently reduces the amount of food that degrades.

Notwithstanding the desirability thereof, it can be observed in figure 6.16 how reducing the amount of people are allowed to withdraw can increase the pressure on the system. In a case of overload triggering anxiety in the population, the withdrawals are bigger as well. Limiting the size of the withdrawals will make people come back, causing even more load on the system.

6.3.2 Increasing capacity or spread demand

Enabling beneficiaries to freely 'choose' their Food ATM leads to an unequal spread in demand. In this case the optimisation of the locations of the twelve Food ATMs aimed to reduce the average and maximal distance between beneficiaries and Food ATMs. Although this can be solved by *equally* positioning Food ATMs, *realistic preference* is multi-dimensional and set in uncertainty. Therefore, unequal spread in demand as a consequence of free choice is likely to be a given reality.

Two types of operational policy targeting the demand-side has been formulated: 1) adjusting capacity

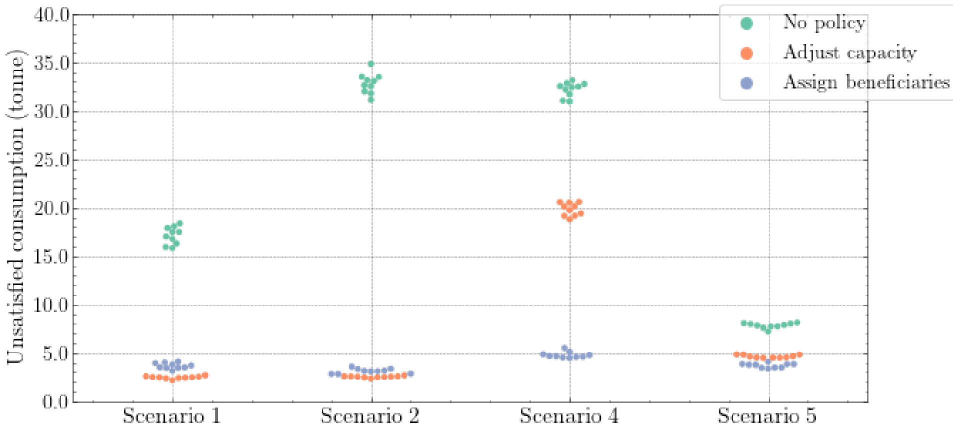


Figure 6.17: Influence of implementing a capacity-related policies on the cumulative unsatisfied consumption

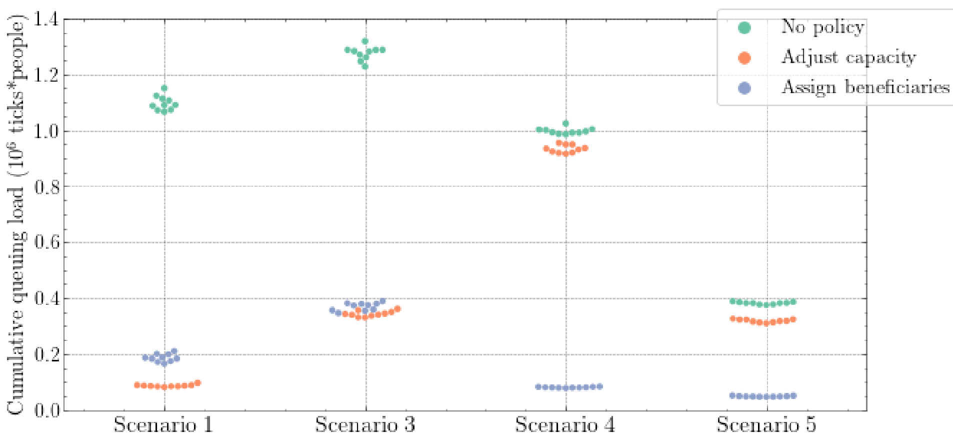


Figure 6.18: Influence of implementing a capacity-related policies on the cumulative queuing load of all Food ATMs

and 2) assigning beneficiaries to a Food ATM. By implementing 1) adjusting capacity one assumes to know the preference of beneficiaries. Consequently, the serving capacity is adjusted according to the expected demand. 2) Assigning beneficiaries to Food ATMs entails taking away the free choice element and thus equally spreading demand over the twelve facilities.

Recall that scenarios 1, 2 and 4 are associated a relatively unfavourable result with regards to unsatisfied consumption, as can also be seen in figure 6.17 when comparing to scenario 5. Both policies push the system in a significantly more favourable state in scenarios 1 and 2, regardless of the difference in social interaction (no vs. high social interaction, respectively).

Scenario 4 does show a significant difference between adjusting capacity and assigning beneficiaries. Adjusting capacity causes Food ATMs with less expected demand to have a lower serving capacity, ultimately resulting in relatively longer queues. Scenario 4 has a high visiting frequency, meaning a higher influence of individual system perception.

Investigating the policies' effects on cumulative queuing of all facilities combined, similar tendencies can be observed. Scenario 1 and 3 with low visiting frequencies show improved results for both policies, whereas scenario 4 and 5 with high visiting frequencies show relatively low improvement.

Although assigning beneficiaries to Food ATMs consistently shows positive results, enacting this

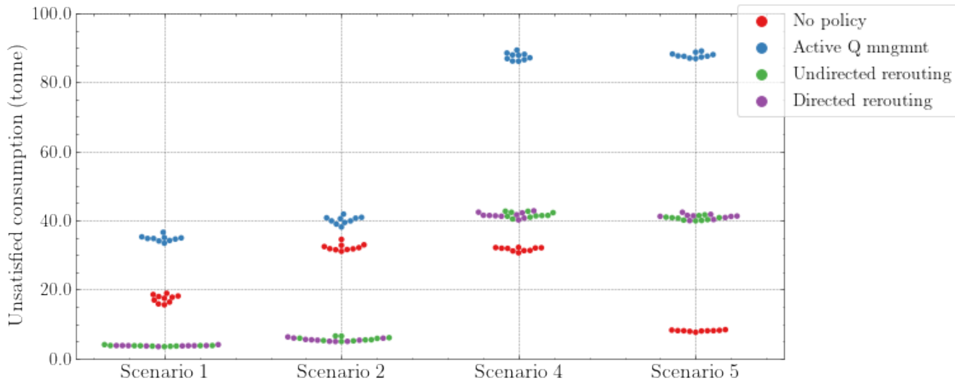


Figure 6.19: Influence of implementing a capacity-related policies on the cumulative queuing load of all Food ATMs

policy has an important side-note. The optimal placement of the Food ATMs aimed to reduce the distance that beneficiaries have to cover, improving accessibility. By assigning beneficiaries to Food ATMs and disregarding their location, the distance covered will also increase.

Adjusting capacity firstly assumes knowledge about beneficiaries's preferences *and* how that coincides with their location. Consequently, supply-side adjustments can be made and we do not observe the same problem regarding covered distance as with assigning beneficiaries. However, scenarios in which *individual evaluation* of the system plays an important role (that is, high visiting frequency and bad perception) the performance of this policy is significantly worse than assigning beneficiaries.

6.3.3 Rerouting

Again, in the context of unequally spread demand as a consequence of free choice by beneficiaries, rerouting policies aim to reduce the effects thereof. Rerouting is in principle based on actively directing visitors based on the state of the Food ATM that is visited: empty storage or a too long queue. Recall how empty facility storage is assumed to be caused by a supply chain disruption, which is not considered. Hence, the decision to reroute a visitor is based on the length of the queue. Active queue management entails sending people home when the queue is too long, reducing average queue lengths. (Un)directed rerouting takes advantage of the decentralised character of a system of Food ATMs. In other words, multiple Food ATMs can 'collaborate' to improve the system as a whole. Undirected rerouting entails that beneficiaries are free in their choice which other Food ATM to visit, whereas Directed rerouting entails a visiting a specific Food ATM.

Investigating the influence of the three policies on the Unsatisfied consumption KPI in figure 6.19, greatly varying results can be observed. Whereas scenario 2 and 4 without policy give the worst results, coinciding with high social interaction and bad perception of the system, with rerouting policy, scenario 4 and 5 give worst results. This coincides with a high visiting frequency and thus relative importance of individual evaluation of the system.

Evaluating the system for total queuing load in figure 6.20 very different tendencies can be observed. First of all, active queue management in whatever form reduces queuing time significantly. The slightly worse performance of rerouting versus active queue management in scenarios 4 and 5 suggest the importance of visiting frequency, consistent with the results of Unsatisfied consumption.

Lastly, by opting for directed or undirected rerouting, the total covered distance by people will increase as well due to visiting multiple Food ATMs. Recall how randomly assigning beneficiaries to Food ATMs provokes a significant increase in the distance people cover. Directed rerouting tends to cause significant distances as well.

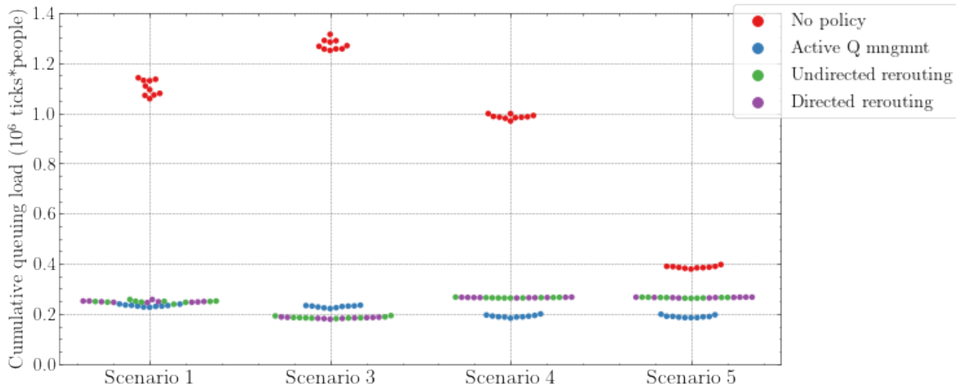


Figure 6.20: Influence of implementing a capacity-related policies on the cumulative queuing load of all Food ATMs

6.3.4 Summary

Most importantly the results show that the performance of policy intervention in a scenario directly depends on the myriad drivers of the undesirable system state in which one is intervening. In other words, depending on 'which' panic buying loop (see section 6.2.5) one aims to tackle, implementation of policy might work effectively or even counter-productively. Thereupon, we observe effects that also vary per investigated KPI.

Scenario discovery already taught us that food waste has a non-linear relation to the desirability of the system state. That is, a low value food waste does not necessarily relate to a favourable system state: low food waste might also indicate weak access to food. Based on this understanding, the effect of policy was approached differently. It shows that food waste can robustly be reduced by enacting a *15-day ration*: by not allowing beneficiaries to withdraw a 30-day ration the total amount of food inadequately stored is thought to reduce as well. On the downside, this policy worsens results significantly with regards to queuing and unsatisfied consumption.

The improvement of the system state as a consequence of adjusting capacity to the expected demand is highly dependent on the population's general perception of the system. Although queues are generally smaller for the busiest Food ATMs, adjusting capacity also entails relatively bigger queues for less frequented Food ATMs. On the other hand, assigning beneficiaries gives a consistently good result for all scenarios. However, it must be said that this policy results in a significantly higher distance covered by beneficiaries. This is due to not making use of the optimal placement of facilities.

With regards to the queuing load is rerouting a consistently well performing policy, but in scenarios with bad system perception the cumulative unsatisfied consumption shows differently. Upon rerouting beneficiaries to other Food ATMs, anxiety is spread as well.

Chapter 7

Discussion

The previous chapter discussed the results in a quantitative manner. This chapter builds on the results and will relate the findings to the bigger picture. Firstly, by means of critical assessment of the limitations of the study, it will be illustrated how the policy recommendations should be seen with respect to possible scenarios and the timeframe of the Food ATM's functioning. Secondly, it will be discussed what the findings imply for the *current* development of the Food ATM, being in a pilot-programme phase. Lastly, the research methods will be reflected upon.

7.1 Applicability of the study

This chapter describes the context in which the insights resulting from this study should be seen. It covers the scope of the research and subsequently its applicability in terms of time and system state. When researching complex systems it is important to determine beforehand what one exactly wants to research. Well-defined problems are not only more likely to yield insights (Van Dam et al., 2013), but are also thought to avoid confusion about the message a research aims to convey. Figure 7.1 will help us to understand the contribution of this particular research by stating its limitations.

On the x-axis we find an indication of time. *Grosso modo*, there are three phases: 1) adoption phase, 2) normal system usage and 3) re-adoption phase. In the case of our research, the adoption phase is assumed to be successfully completed. That is, beneficiaries seem to have found their way into proper usage. Going further in time leads us to a situation where it is likely that panic-buying dynamics exist. However, by no means it is certain how these dynamics influence the system *relative to other behavioural dynamics*.

Uncertainty about the relative importance of panic-buying dynamics brings us to the alleged stability of the system (see y-axis). It is very well possible that the system will perform according to expectations regardless of the identified behavioural factors. Also, a collapse of the system regardless of behavioural factors or implemented policy is possible. Notwithstanding this, there is a grey area, between certain collapse and full stability. Exactly in this area, the policy proposals are aimed to prove their added value. Essentially, policy proposals aim to **enlarge the acceptable outcome space**.

7.2 Implications of findings

If the system shows collapse (i.e. in a tipped state), the distribution of food is severely limited by very long queues. It is therefore essential to understand *why* these people are queuing. In a normal situation,

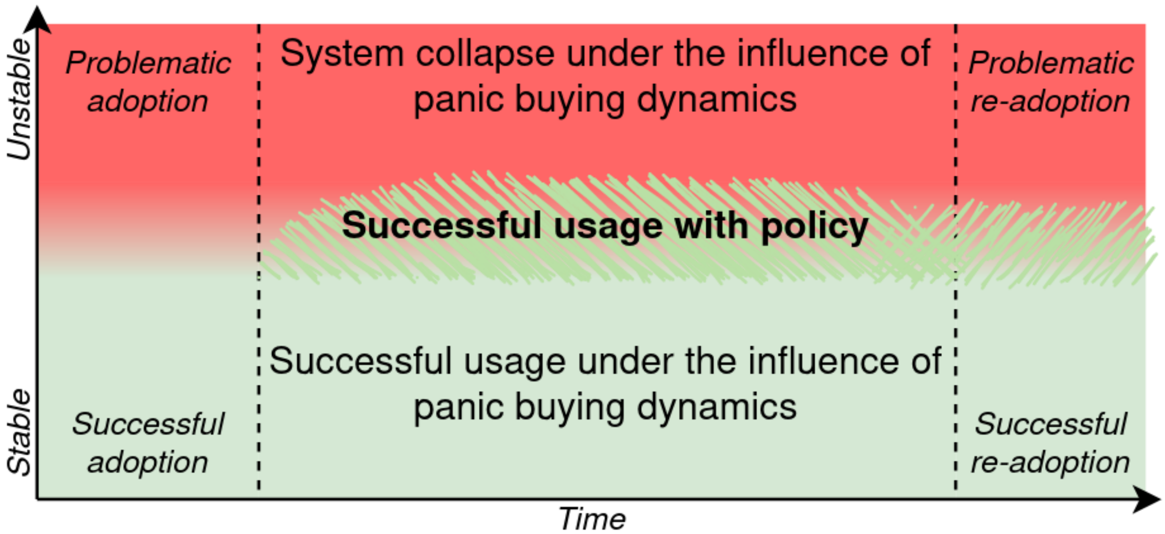


Figure 7.1: Qualitative illustration of the stability of the Food ATM in different phases over time

people would visit and queue because they need food. But, with the population reaching a high state of anxiety, people who are not short of food are visiting the Food ATM as well. This consequently results in people in need becoming deprived of access to food.

The current method of food distribution in large refugee camps does not meet the standards that are set by many international organisations and NGOs. Hence, it is safe to say that the Food ATM has at least the potential to bring an important improvement, regarding both accessibility and reducing the negative side-effects such as big queues.

Nevertheless, a collapsing system of Food ATMs has also the potential to relatively *worsen* the performance of the food distribution system. It is thought that the system could exceed its tipping point fairly quickly and the effects of any subsequent action might be severely limited. As a result, the sheer *unexpectedness* of a collapsing system has the potential to create a situation more dire than the system that was meant to be improved. Logically, the possibility thereof undermines the efforts with regards to improving food distribution by means of the Food ATM.

A common challenge in the field simulation modelling is the application of results by responsible stakeholders in the actual policy design process (Harper et al., 2021). However, expert consultation taught us that risks persist in usage and implementation of the Food ATM. With the current envisaged pilot programme in mind, new knowledge about the Food ATM's functioning will be gathered. Notwithstanding this, a trial tells us what "that actual intervention does in a *particular* population, in a *particular* context. You have to continue the science so you can understand how it's going to work in a different place, in a different context, in a different population, and have the same effect" (Dubner et al., 2020). A simulation model of this sort represents a first step in order to understand the potential effects of beneficiary behaviour on the performance of proposed policies. Moreover, it provides an opportunity for the responsible authority to expand the knowledge, increasing the chance on successful implementation.

7.3 Developing the Food ATM

Because the regarded situation in this research is only a conceptual version of a future system of Food

ATMs, translating lessons to currently relevant real choices and/or policy advice is a challenge. Conducting computational research on a conceptual problem like this obliges one to crystallise policies and come up with scenarios significantly more concrete than they currently are. As a result, one gains not only insight by interpreting results, but also by its limitations.

For example, pivotal for the model's behaviour is the location of households. Merely their locations are the driver for the spatial distribution of demand. Having conducted a literature research, it is known that activity-based analyses are made e.g. in the placement of retail. Thus, if the wish exists to fit facility capacity to estimated demand, research on how this behaviour takes place in the context of a refugee will have to be conducted before moving forward on this design aspect.

It is very challenging to argue that any system aiming to improve current food distribution would not be of added value. However, trying to add too much value and design principles to an already very challenging situation can undermine fulfilling the basic goals on which the legitimacy of the system's existence is founded. In other words, potential risks as a (partial) result of a free-choice system might prohibit taking advantage of any potential advantages the Food ATM has potentially to offer. Thus, a balance will have to be struck between resorting to access restriction to minimise risk and fulfilling design principles.

Chapter 8

Conclusion

This chapter covers the conclusion of this study. First, the sub-research questions introduced in chapter 3 are answered. Secondly, the findings are presented and used to answer the main research question. Thirdly, a set of concrete policy recommendations for the Food ATM is formulated, based on the answer of the research question. Fourthly, the model is critically analysed resulting in a list of the model's limitations and possible implications thereof. Lastly, inspired by the limitations, a direction for future research is suggested.

8.1 Research questions

The sub-research questions will be answered point-wise.

1. What Key Performance Indicators can be identified to evaluate the performance of a system of Food ATMs?

The analysis of a system always starts with the question what exactly one wants to analyse, rather according to which *metrics* one can determine the performance of a system. In this case, the modelling process and thus the definitions of KPIs were formulated in two phases. Firstly, in the optimisation we aimed to find an optimal placement *solely* based on spatial relations. The spatial relations translated in two KPIs: 1) average and 2) maximal distance between (a) household(s) and Food ATMs.

Phase two of the modelling approach entailed the conceptualisation of beneficiary behaviour vis-á-vis the Food ATM and subsequently its effects. Recall how the justification for a better food distribution system is partly based on the current bad performance regarding food waste and queuing. With regards to the choice-based Food ATM, the risk has been identified that collective behaviour could prevent people from getting food. Hence, three KPIs were formulated, one based on implementation risk (*Unsatisfied consumption*) and two based on the goals for better functioning of a food distribution system (*queuing* and *food waste*).

2. How can a system of Food ATMs be defined given the physical environment provided by the case study?
Firstly, the functioning of the Food ATM was to be determined. Considering that the Food ATM is a pilot programme, a lot of fundamental design options have not been crystallised yet. For example, neither the characteristics of the upstream supply chain (how food is delivered *to* a Food ATM) nor the types of food (staple, pulses, cooking oil, etc.) are determined. On top of that, the Food ATM being a versatile tool that is supposed to be usable in various circumstances, the type of food is thought to be highly dependent on the specific location. Hence, for the sake of simplicity and given the scope of this research (the impact of the behavioural dynamics in the implementation of policies), the upstream supply chain and different food types were not considered in this study. Subsequently, the model can be

'populated' on the locations that resulted from the optimisation model with Food ATM *agents* (model entities representing one Food ATM).

3. What factors of beneficiary behaviour affect, or are affected by, a system of Food ATMs in a semi-sustained refugee settlement?

As can be observed in the causal loop diagram in the introduction (Figure 2.1), (negative) emotion and thus perception of the Food ATM as a reliable (or not) system to distribute food is thought to be at the root of potential adverse collective behaviour. As a result, the four behavioural factors all show a direct relation hereto, representing the influence of any environmental factor hereon. The four factors are:

1. Forgetting rate of anxious emotions - a value of 0 means stable anxiety, a value of 1 results in halving anxiety every day.
2. Rate of social interaction within an agent's social network resulting in the diffusion of anxious emotions - a value of 0 means anxiety is not transmitted, a value of 1 means anxiety is transmitted to 20 other agents.
3. Preferred size of contingency food storage - a value of 0 means that a household is never incentivised to visit a Food ATM, a value of 30 means that when the food storage is lower than a 30 day stock, the agent will visit a Food ATM.
4. Perception of the system and subsequent tolerance to malperformance - a value of 0 means that a queue longer than 0 causes anxiety, a value of 1 means that the queue has to be longer than the maximal daily serving capacity in order to cause anxiety.

4. How can the effects of this interaction on system performance be investigated by means of an ABM?

The identified behavioural factors are formalised in a household *agent*, representing the household as a uniformly behaving entity. In other words, the household members are aggregated into one element. Together with the Food ATM *agents*, the model is 'populated' given the locations provided by the cleaned data file containing information about the location of buildings (in which a building represents a household).

As a next step, we have to design experiments. Essentially, designing experiments follows the notion that we want to investigate the system's performance under different behaviours, resulting from the four behavioural factors. Consequently, the behavioural factors have been initialised with a broad range of values, with the goal to yield a broad range of behaviours as a result.

5. Based on the ABM, what are the effects of various policies under relevant scenarios?

Most importantly the results show that the performance of policy intervention in a scenario directly depends on the myriad drivers of the undesirable system state in which one is intervening. In other words, depending on 'which' panic buying loop (see section 5.2) one aims to tackle, implementation of policy might work effectively or even counter-productively. The capacity-related policies do very in effectiveness, but never create adverse results. This in stark contrast to rerouting policies, which do create adverse effects under scenarios where the population generally has a negative perception of the system.

6. How can the model results be translated into an advice for decision-making?

First the model results. The model results can essentially be interpreted as follows: for change of factor, the performance according to one of the KPIs is evaluated. Then, the results are traced back to their respective input values. Hence, we know (to a certain extent) which combinations of input parameters cause either desirable or undesirable results.

Knowing the (combination of) input parameters for which adverse effects of collective behaviour has been observed, policy can be design qualitatively. That is, operational policy, such as rerouting policies aiming to spread demand, aiming to target scenarios with a capacity problems as an example.

8.2 Findings

In the introduction it explained how the choice-based nature of the Food ATM is expected to yield benefits as well as risks for the stability of food supply. These risks are a direct consequence of the unpredictability of human behaviour, more specifically the interaction between Food ATMs and its beneficiaries. In order to analyse the potential effects thereof an agent-based model was built. Previous section elaborated on this model's results and so how various behavioural elements influence food distribution by means of a system of Food ATMs. Knowledge on the type of behaviour helps to formulate effective policy for the Food ATM. Thus, this section will provide an answer to the main research question:
What operational policies show robust performance incorporating the influence of beneficiary behaviour on the performance of a system of Food ATMs in the context of a semi-sustained refugee settlement?

The over-arching lesson that should be drawn from the modelling process and subsequent results is the multiplicity of scenarios that are associated with an unfavourable performance of the food distribution system. Consequently, we encountered complexity yielding sometimes counter-intuitive results. Although this is not a novelty in the field of complex systems, it does show to which extent rethinking food distribution is needed when opting for behavioural freedom.

An important contributing factor to the system's problems is the unequal spread in demand. Food ATMs' locations are the only consideration agents make when determining a Food ATM of choice. Given the model, it show that an optimal in terms of reducing the average and maximal distance between agents and Food ATMs results does not necessarily mean better system performance. Whereas the conceptualised system only takes location into account, *realistic* choice is a highly uncertain factor. Notwithstanding this, placement of system should take equal spread of demand into account.

One of the most important targets of the Food ATM is reducing food waste due to inadequate storage of large quantities of food. When hoarding, the quantity of food that is inadequately stored increases and hence the food that goes to waste with it. Given the model we found that food waste is not a good indicator of the system performance under panic buying dynamics: a population without food has nothing to waste. Rather, the reduction of food waste is thought to be a inherent *consequence* of a well performing system.

Although rerouting entails spreading risk in a decentralised system we found that the unequal spread in demand might provoke adverse effects in some scenarios. Given a scenario in which people have a bad perception of the system, meaning that with relative little change in perceived performance (e.g. length of queues) people become anxious. Rerouting lets surplus demand spill over to other Food ATMs, causing anxiety among people who otherwise would not have a worse experience. Especially in a scenario where diffusion of information is relatively limited, the potential adverse effects of rerouting can be observed. In these cases, the physical 'diffusion' of people *acts as* the diffusion of information.

Adjust the size of Food ATMs as a function of the expected number of beneficiaries that will prefer that particular Food ATM tends to have significant positive effect under the assumption that the target population has a good perception of the system. The fact that this policy is implemented with the assumption that the system's *total* capacity remains constant, results in longer queues for less frequently visited Food ATMs. Hence, benefits in a scenario with a population with bad system perception yields limited positive results.

Restricting the preference of beneficiaries by 'assigning' them to a single Food ATM yields most robust results. Although we found that the covered distance is significantly higher due to the lack of individual preference, problematic scenarios do not seem to occur.

Restricting food withdrawal by doubling the ration frequency from 30 days to 15 days causes is an effective policy against food waste in case of system malperformance. However, by doubling the rationing frequency one eliminates the stabilising factor of finished rations. Subsequently, the increasing oscillations which are characteristic for a panic buying dynamic (see section 5 on model validation) double in frequency as well. Consequently, this tends to worsen the system state with regards to other KPIs.

8.3 Scientific contribution

Reviewing the state of the art literature has taught us that the necessary concepts for adequately evaluating risks for a well functioning continuous food supply are not covered by current Operations Research studies. Aid distribution in the humanitarian field are described stochastically. In order to describe the formulation of demand for continuous food supply by means of the Food ATM, a bottom-up agent-based model approach is proposed instead. In contrast to top-down stochastic formulation, an agent-based approach allows for demand formulation incorporating *interaction* between the food distribution system and the with beneficiaries of aid.

In order to investigate the effects of individual behavioural factors in the realistic context of food distribution in the Bidi Bidi refugee settlement, a multi-model framework was presented. This framework enables lending concrete examples from the real world.

Related to future work, the implementation of the model in the GAMA platform has been done in such a way that it facilitates expanding the model with upstream supply chain elements. For example, refill logic is described but is limited to numerical description due to the scope of this study.

Lastly, tools have been developed to address software-related limitations of the GAMA platform regarding efficient storage of model results and Python-based experiment definition. The functioning hereof is elaborated upon in section 4.4, *Computational Framework.*

8.4 Policy recommendations

The previous section on the findings describes which model-based insights we gained by interpreting the results. The section on policy recommendations provides in a translation of model results in concrete results. Thereby the requirements for successful implementation in terms of scenario-wise context and to be gathered knowledge are described.

8.4.1 Adjusting capacity to demand

The fact that people are enabled to act upon their preference for one Food ATM over the other as a consequence of free choice, is likely to create disparity in demand. However, the design capacity of all Food ATMs in the system is the same: circa 2,500 households per Food ATM resulting in unequal pressure on Food ATMs.

In this model, beneficiary preference is a function of the distance between a beneficiary location and a Food ATM. Research on people's preference for a location shows that such preference is a result of a multiplicity of pull and push factors (Baviera-Puig et al., 2016). Given one develops a method to gain knowledge pull and push factors that could adequately describe the distribution of preference in a population, adjusting demand according to expected demand is thought to have beneficial effects.

8.4.2 Rerouting

The implementation of a decentralised food distribution system allows for spreading the risk of an individual facility's failure. In the model, failure of an individual facility occurs when a queue is longer than the number of people that can be served until closing time. Subsequently, opting for rerouting policy allows beneficiaries to visit other facilities instead and so spreading demand.

Besides dealing with a surplus in demand, rerouting can benefit system performance in the case of facility breakdown. In such a case, the possibility of beneficiaries being rerouted to other distribution points functions as risk spreading. Recall how varying the size of facilities as a function of estimated demand is thought to be a beneficial policy. Especially in the light of a situation where such bigger Food ATM breaks down, adequate back up is essential which can be provided hereby.

Next to technical requirements that should work reliably, best results from rerouting can firstly be expected with a rerouted population that is willing to visit another Food ATM. In other words, the option for rerouting should result in less anxiety than being (temporally) denied access. Secondly, the secondary Food ATMs should be adequately equipped to deal with a possibly sudden increase in demand. That is, the interference with regular visitors by extra pressure should be limited to prevent adverse effects.

8.4.3 15-day ration

One of the pivotal goals of the Food ATM is the reduction of food waste, by means of enabling people to withdraw smaller quantities than their 30-day rations. As a function of the anxiety levels in a population, it is thought that people withdraw bigger quantities and consequently undermine this goal.

In scenarios where a population is very susceptible to the spread of anxiety, with regards to other Key Performance Indicators effective policies seem to have relatively limited effect on the amount of food that goes to waste. Limiting the maximal quantity people can withdraw by making rations based on a two-week cycle instead of the current monthly cycle, is thought to have significant positive effect on food waste.

8.4.4 Access restriction

This proposed policy entails strictly assigning beneficiaries to Food ATMs. Although this policy is more invasive in the freedom of choice it is a consequence of a trade-off that some scenarios oblige to make. In other words, naturally anxious populations with bad system perception in which rumours tend to spread quickly render other policy options relatively ineffective.

8.5 Future work

Modelling practice, and especially conceptualising a complex system for the purpose of simulation is often an act that raises additional questions about the system, based on what we learnt. Consequently, these new insights give direction to relevant topics for future research.

8.5.1 Agent demand formulation

Firstly, the factors standing at the base of decision-making of beneficiaries and hence the formulation of demand on system-level is thought to be dependent on a variety of factors that have not been considered in this model. That is, in a susceptible state (see section 4.5.1) the household agent only considers the amount of food in storage as the driver for demand, without any variation over time. In other words, the demand is unrealistically constant over time due to not incorporating other drivers. It is suspected that expanding demand formulation with secondary drivers such as activity-based demand formulation might yield insights in the effects thereof.

Moreover, the formulation of much of the potential complexity of the system is a direct consequence of design options. For example, whereas the formulation of demand is currently only based on staple foods, the Food ATM is supposed to offer multiple types of food. Also environmental factors incorporating behaviour that falls outside of this research's scope such as bad weather, are thought to have a significant influence on the actual demand.

Such considerations link to essential decisions. For example, are beneficiaries allowed to withdraw food types separately, or think of placement in the proximity of a church. For a system whose behaviour is thought to be so dependent on feedback loops, a small change might have very significant consequences.

8.5.2 Information diffusion

Secondly, the spread of information being an important element of the system and at the same time an extremely complex subject makes it an important limitation to identify. The social network is modelled being a random set of other household agents. Hence, the spread of negative emotion throughout a population affects Food ATMs evenly. In reality, the relative density of social networks can coincide with cultural or ethnic groups of its members. Subsequently, there is a risk of tensions between groups that could arise from any any *perceived* inequality in performance (Athumani, 2020).

The potential influence of spread of information, or rumours more specifically, are touched upon in many researches. However, the exact characteristics of the spread of information within (social) networks in the humaniatarian are only described qualitatively. This stands in stark contrast to the number of researches that have been conducted on exact characteristics in other networks, such as online social networks (Mazzoli et al., 2018; Zhu et al., 2019; Zhang et al., 2011). Especially in the light of potential implementation in societies known for divisive social tensions, it is important to understand how information spreads in a community, for example according to linguistic lines. Given certain system conditions, this could mean variation in performance according to these exact lines.

8.5.3 Environmental uncertainty

Lastly, the modelling approach does not contain any approach to account for uncertainties in the input data. Although we do understand that the data on the Bidi Bidi refugee camp only serves as a provider for concrete examples, rather than a basis for decision-making, how any variation might be observed as a function of a varying modelled environment is thought to be a useful contribution.

8.5.4 Adoption

Again touching upon the contribution of this research, as shown in figure 7.1, especially with respect to other phases of usage of the Food ATM. In particular, the adoption phase is pivotal for arriving at a point where the Food ATMs function as a stable food supply system. Many of the identified limitations and policy recommendations relate directly to a system that shows stability in some fashion. For example, employing authority figures to communicate the functioning of a system is questionable in case the system is not fully adopted. Therefore, research on the adoption of the Food ATM is thought to be essential to eventually create a situation in which this research finds its direct applicability.

8.5.5 Upstream supply chain

In the scenario discovery, the refill capacity has been touched upon as a key system uncertainty. For this research, the refill frequency was assumed to be a fixed daily refill of all facilities. However it has been observed that the model is quite sensitive to changes in this variable.

Extrapolating the refill frequency to the performance of the upstream supply chain, it is safe to say that the malfunctioning of the upstream supply chain has a potentially significant effect on the system performance. Therefore, it is thought to be an relevant topic for future research.

Chapter 9

Appendix

9.1 Verification optimisation

The necessity of verification is centred around the question whether the optimisation result is indeed the relevant result we attempted to find. Recall the nature of the optimisation problem: for 24 variables multiple objectives will have to be satisfied. The sheer size of the problem makes it too computationally expensive to analyse the entire outcome space. Making use of intelligent algorithms opens up the possibility to find relevant outcomes.

In order to verify a proposed solution, one can make use of the Hypervolume metric. This metric shows the "the dominated portion of the objective space as a measure for the quality of Pareto set approximations" (Zitzler et al., 2007). Recall section 4.2.2's description of two optimisation algorithms (NSGA-II and ε-MOEA). Solutions (and the Hypervolume performance metric|) for the same problem will be computed 10 times for both algorithms.

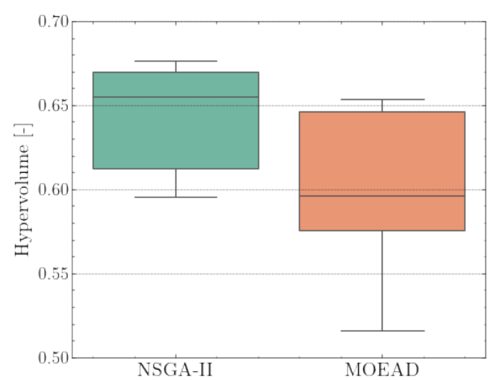


Figure 9.1: Hypervolumes

9.2 Verification ABM

Similarly to the optimisation, the modelling process of the ABM model should also go through a verification before using its results. This was done along the process of building the model through several ways such as testing extreme values for different valuables. By identifying errors in the behaviour during these tests, the model was accordingly fixed. This was done iteratively until the model passed the tests and could be considered verified.

9.2.1 Multi-agent testing: scaling

Essentially, scaling can be applied in this model in three relevant ways: aggregating agents, reducing the number of agents and reducing the temporal resolution. The first is essentially being done by aggregating individual beneficiaries into a single Household agent. Due to the big share of single-parent households it is assumed that strong hierarchy results in the virtual exclusion of other household members' considerations.

Reducing the temporal resolution entails reducing the period of time one tick is represents. This has to do with discrete handling of time in an ABM: between two events 'nothing happens' and computations are executed at certain events. For example, a 30-day runtime with a ticksize of one hour requires $24 \times 30 = 720$ ticks. That is, 720 computational events for one model run. Hence, decreasing the temporal resolution (i.e. tick size) linearly decreases the number of computation events.

"The resolution of that time step—whether it models a second, a season, a year, a generation, or even if it represents any real unit of time at all—is an important structural feature of the model and one that provides opportunities and constraints for calibration"

The current tick size is chosen to be 10 minutes, the minimal serving time of one beneficiary in a Food ATM. In order to prevent an unreasonably large runtime for the model, we have the option to reduce the number of ticks. However, it is important to think of the possible implications for the accuracy of the assumptions made in the model.

Queuing logic: people join the queue upon arrival, but the arrival time has only a resolution equal to the tick time. The 10th percentile distances of buildings to the closest facility equals ca. 0.65 km, thus with a walking speed of 4km/h the closest 10 percent of people arrive at the same tick. Subsequently, they will perceive the queue in the same way. The perception of the queue is conceptualised to be a singiicant contribution to the overall anxiety and thus total behaviour of the system.

The number of agents and the number of interactions between the agents is $a = n \times log(b)$ with a being the number of agents and b the number of resulting interactions and n some constant. Hence, it can be said that reducing the number of agents is a relatively effective method to reduce the computational expense of a model.

Reducing the number of agents is subject to a three-fold challenge:

1. Maintaining the spatial distribution of agents
2. Maintaining the characteristics of the social behaviour
3. Maintaining the representativeness of the Food ATMs

With the available computational capacity, we found that reducing the agents to a number of 3k reduces the needed computational expense to an acceptable level, with one model run accounting for some minutes. The scaling down is conducted in a step-wise manner: the original number of 33k is reduced with a factor 5 and 11. In order to verify model functioning the following steps are undertaken:

1. Design a framework to analyse, and analyse the spatial distribution of agents.
2. Appropriately change model parametrisation to fit the scaled-down version.

3. Run the scaled-down model to find a variation of model behaviour.

4. Run the ‘original’ model size with parameters resulting in ‘varying’ model behaviour.

5. Analyse the runs in order to find the influence of reducing the number of agents.

Designing a framework: select all zones, count the number of buildings that fall within a zone for 73k 33k 7k and 3k and compare them relatively.

Changing model parametrisation: Introducing a scaling factor. Since we still want to research 12 facilities, and there is an iomportance is queueing and the influence of queuing we have to change model parametrisation in: 1) amount of food in a facility 2) serving capacity to ”ensure” formation of queues 3) the perception of queues has to change. Subsequently also the outputs

Name	# buildings (original)	share	# buildings (scaled)	share	# households (pop data)	share
Zone 1	13,134	0.179	427	0.185	7,399	0.172
Zone 2	10,148	0.139	295	0.128	8,420	0.197
Zone 3	25,096	0.343	826	0.358	11,254	0.263
Zone 4	8,276	0.113	248	0.107	6,067	0.142
Zone 5	16,538	0.226	509	0.221	9,601	0.225
Total	73,192	1.000	**2,305**	1.000	42,741	1.000

Table 9.1: Number of buildings on map and number of households in population data (UNHCR and Government of Uganda, 2020)

fatm_id	latitude	longitude
0	31.29808896116017	3.330721824166764
1	31.36900873950802	3.255576462801982
2	31.38977206889771	3.396560239249954
3	31.31719299109965	3.372688531581409
4	31.33741198449811	3.521324337318772
5	31.34380669377194	3.398040032737117
6	31.35337220882557	3.523837703938518
7	31.40715457288425	3.212475435879833
8	31.38647411802192	3.468988134568133
9	31.25272920168192	3.314425756123745
10	31.35419169150111	3.281981179016886
11	31.38322008894195	3.243666523777996

Table 9.2: Location of facilities

9.3 Parametrisation ABM

The parametrisation, in other words assigning values to model variables was done by two methods: 1) automatic, data-driven intalisation and 2) assigning plausible ranges based on literature and expert judgement. The exact code regarding treament of data prior to initalisation can be found on this research's Github page and a brief discussion thereof in chapter 4.1.

9.3.1 Generalities

The table below is a numerical summary of the treatment of population data. In order to make the model less computationally expensive, the number of buildings has been scaled down upon which the spatial distribution of the remaining buildings has been tested (relative number of buildings per zone). The scaled-down number of buildings **2,305** is used as the number of household agents that will be initialised.

All 12 Food ATM agents will be initialised with a selected policy resulting from the optimisation.

Type	Name	Type	Value*
Policies			
Constant	capacity_policy	int	[0,1]
Constant	minfood_access_policy	int	[0]
Constant	ration_size_policy	int	[15,30]
Constant	day_access_policy	int	[0]
Constant	rerouting_policy	int	[0,1,2,3]
Policies			
Constant	scaling_factor	int	15
Constant	default_nb_households	int	2500
Constant	avg_hh_size	int	7
Constant	avg_food_consumption	float	0.5
Constant	food_preservation_days	int	14
Constant	avg_degradation_portion	float	1.0
System behaviour			
Constant	parallel_served_full	int	range(6,10)
Constant	avg_interactions	int	range(0,25)
Constant	alpha	float	range(0,1)
Constant	beta	float	range(0,1)
Constant	gamma	int	range(3,14)
Constant	epsilon	float	range(0,1)
Time			
Constant	step	float	10.0
Constant	cycles_in_day	int	144
Constant	opening_hour	int	8
Constant	closing_hour	int	20
Constant	wake_up	int	6
Constant	go_sleep	int	23

Table 9.3: Global agent's characteristic variables

9.3.2 Global agent

The *Global agent* is the GAMA-specific representation of the environment. This agent takes care of the intialisation of prepared data and the conversion into model agents. Besides that, system structure (e.g. policies) and uncertainties (e.g. behavioural factors) are defined in this Global agent by means of assigning values to variables.

Type	Name	Type	Value
Constant	ration	float	0.5
	home_location	point	n.a.
	infected_threshold	float	0.5
	nb_members	int	[1,5]
	pc	float	[0,1]
	social_network	list <households>	n.a.
State	incentive_to_facility	bool	n.a.
State	incentive_to_home	bool	n.a.
var	facility_of_choice	facilities agent	n.a.
var	food_storage	float	n.a.
var	unsatisfied_consumption	Float	n.a.
var	unsatisfied_demand	Float	n.a.

Table 9.4: Households agent's characteristic variables

Type	Name	Type	Value
const	location	point	X
const	facility_food_storage_size	int	X
const	nb_beneficiaries	int	X
state	queue_open	bool	n.a.
var	queue	list<households>	n.a.
var	facility_food_storage	float	X

Table 9.5: Facilities agent's characteristic variables

9.3.3 Household agent

2. Households agent. This agent is initialised by means of the map as shown in Figure 4.1: every polygon is counted and its location is interpreted as a Households agent's location (*home_location*).

9.3.4 FATM agent

3. Facilities agent. This agent represents the facilities. These are initialised based on the results from the optimisation model: optimal locations and corresponding size of the facility is loaded into GAMA in order run the simulation. The resulting locations as shown in Figure 6.3 correspond with the location parameter *location*.

9.4 Experiment design

Essentially, 'experimentation' covers the modelling step to explore model results given the possible range in values for the input parameters as defined in the Parametrisation, chapter 9.3. In order to know which values for the input parameters are of interest, one first has to determine to goal of experimentation. According to Van Dam et al., experiments can mainly serve two goals: 1) replicating a recurrence in the real world and 2) determining a connection between the input value and emergent behaviour shown by the model. The first, replication a recurrence in the real world, can be tested by means of comparing model results with a real-world scenario. For example, data produced by the model can be compared to data from measurements.

In the context of the Food ATM, a system that does not exist (yet), experimentation will have goal number 2: determining a connection between the input values and the emergent behaviour. In other words, we want to *understand* how the uncertain factors (behaviour, serving speed of a Food ATM, etc.) relate to the identified KPIs. In contrast to testing model results with for example historic data, open *understanding* of a system prohibits the possibility of a clear right/wrong judgement (Van Dam et al., 2013). In its place, the quality of model results can be determined in terms of their *plausibility* and their potential contribution to knowledge about the system.

Concretely, the plan to increase 'knowledge about the system' can be subdivided into three parts. Firstly, the identification of the KPIs: three metrics that give an indication of the state of the system. Secondly, scenario generation. A scenario entails the combination of values of the input variables, representing a possible state of the system. It is thought that scenarios have varying relevance with regards to the problem statement. That is, one should be looking for a combination of values that might suggest a scenario of interest. For example, in a scenario with Food ATMs having significant overcapacity queuing problems are likely to be absent and consequently not a good scenario to test the effectiveness of policy targeting queuing problems. Lastly, in order to answer the main research question about policy mitigating the effects of behavioural factors, we define a set of operational policy that will be tested under identified, relevant scenarios.

9.4.1 Key Performance Indicators

Judgement of the performance of the model. The starting point is the optimisation model; as close as possible, hardcoded in agent behaviour.

Operational policy can have other goals;

- **Queuing load per facility**. In case the serving capacity is lower than the number of household agents joining the queue per unit of time, household agents wait before being served. For every tick, the number of people is summed, boiling down to computing the integral of the function of number of people in-queue over time.
- **Cumulative amount of unsatisfied consumption by households**. Unsatisfied consumption entails the gap in estimated consumption needs of a household and the amount of food in storage. In other words, when a household agent has enough food in storage, it will be consumed; if not, the shortage will be counted as unsatisfied consumption. See Figure 4.9 where this statistic is updated in the model cycle.
- **Food waste**. The idea of food waste is based on the assumption that larger amount of foods degrade due to inadequate storage facilities. In this case, it is assumed that all amounts exceeding a household's 15-day ration goes to waste.

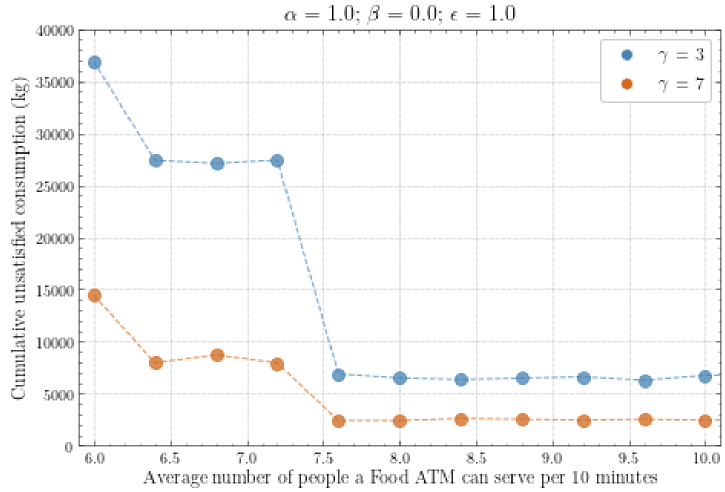


Figure 9.2: Exploring serving capacity size for epsilon=1.0; beta=0.0;

9.4.2 Scenario Generation

Recall the Causal Loop Diagram from the introduction. The two feedback loops as identified in this diagram form the basis of the potential existence of a feedback loop as observed literature on panic-buying dynamics. The diagram mentions 1) Other beneficiaries and 2) Pressure on the system as variables being pivotal to the system. Regarding the parametrisation of the model, these reflect the size of a beneficiary's social network and the number of people that can be served per unit of time.

Firstly the pressure on the system and the corresponding variable number of people served per unit of time (from now on referred to as *Serving capacity*). In order to investigate the influence of this variable of, the model has been initialised with variables INSERT VARIABLES and a broad range of values for the serving capacity. Especially for a lower value of gamma it can be observed how the model result for the KPI of unsatisfied consumption is very sensitive to the input for value of this particular parameter.

The significant sensitivity of the model to this parameter does not necessarily influence on the validity of the model, nor does it correctly represent a realistic situation. In other words, this particular sensitivity can be explained by the way demand and subsequent queuing is developed by the model. Demand is fully stable over time, being randomly generated by the agents. Hence, when the average serving capacity dips below a certain threshold, queues will start to emerge resulting in a reaction by the population.

In reality, such a small variation of the serving capacity is unlikely to have such a significant (and stable) effect on queuing. Notwithstanding this, one can imagine that designing a system with significant over-capacity is also unlikely to be subject to a panic-buying dynamic. All in all, this evaluation allows us to choose a parameter allowing us to observe changing model behaviour as a consequence of the identified *behavioural* parameters.

Secondly, the the size of social network has been sampled. For the sampled set, only for a low value of gamma, the model results vary significantly.

As a result we have a set of numbers for the uncertainties (serving capacity and social network size) and a set of interesting behavioural factors under which we can test policies.

We can conclude that if beta>0.0, the influence of alpha $\rightarrow$ 0. Hence, combining beta and alpha is of limited interest. Epsilon seems to be influential in both cases. Hence the scenarios can be defined as follows:

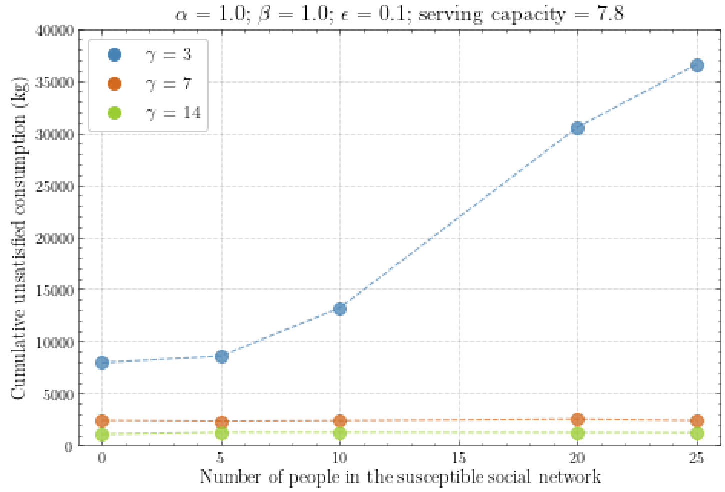


Figure 9.3: Exploring social network size for epsilon=0.1; beta=1.0; sc=7.8

Scenario #	**Forgetting rate α**	**Social interaction β**	**Visiting frequency γ**	**System perception ϵ**
1	High (1.0)	None (0.0)	Low (7.0)	Bad/Good (0.1/1.0)
2	High/Low (1.0/0.0)	High (1.0)	Low (7.0)	Bad (0.1)
3	High/Low (1.0/0.0)	High (1.0)	Low (7.0)	Good (1.0)
4	High/Low (1.0/0.0)	High (1.0)	High (3.0)	Bad (0.1)
5	High/Low (1.0/0.0)	None (0.0)	High (3.0)	Good (1.0)

Table 9.6: Comparison of scenarios by behavioural factors and indication of peak load per KPI

$$\{S_0..S_n\} = P(\alpha, \beta, \gamma, \epsilon, sc) = [0.0, 1.0], [0.0], [0.1, 1.0], [6.0, 7.8]) \tag{9.1}$$

$$\{S_0..S_m\} = P(\alpha, \beta, \gamma, \epsilon, sc) = P([1.0], [0.0, 1.0], [0.1, 1.0], [6.0, 7.8]) \tag{9.2}$$

9.4.3 Policy design

The tested policies are:

1. No policy:
2. Rerouting: redirecting home
3. Rerouting: redirecting to closest facility
4. Rerouting: redirecting to random facility
5. Capacity: Food ATM size according to expected demand
6. Capacity: Assign beneficiaries to one Food ATM
7. 15-day ration:

Under various scenarios that have been selected in the scenario discovery:

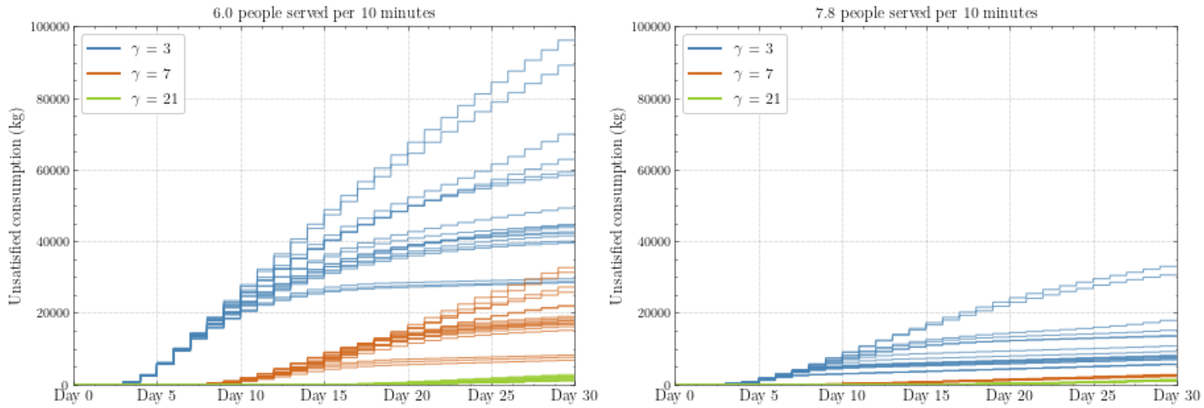


Figure 9.4: Unsatisfied consumption over time, day 1 to 30

9.5 Manual scenario discovery

Due to the computational expense of the model the random sampling required for automatic open exploration of the model is not possible. Also, limitations inb software tools prohibits the use thereof.

By means of heuristics there is a limited number of input variables that can be linked to model behaviour. In other words, with too many input variables one simply loses oversight which variable contributes to observed behaviour.

Hence, one has to be selective in terms of the sampling space and subsequent analysis. Recall the Parametrisation chapter in the appendix (chapter 9.3.2). In order not to lose track of things, as described in previous paragraph, a distinction is made between 1) quantitative uncertainties, 2) system-level uncertainties and 3) behavioural uncertainties.

9.5.1 Visualisation strategy

Manual discovery of scenarios was conducted by means of visual analysis. Thus, the observation of relevant outcomes is thus thought to affect the scenarios that one will find and therefore it is important to ensure to be transparent on the approach.

The over arching selection in the output data is the exclusion of the dimension of time. In other words, the time series output was converted to a single data point allowing for visual inspection.

Figure 9.4 shows a spaghetti plot of the unsatisfied consumption KPI over time. It is imaginable how the sheer number of lines prohibits solid visual inspection. The similarity in behaviour, that is, the sole increase over time allows for filtering the data. Only the last data point, at the end of Day 30 is taken for evaluation.

Queuing goes up and down over time. The total queuing time in ticks times the number of people in the queue gives a good indication of not only peak load but also the duration of peak load.

9.5.2 Key system uncertainties

Exploring the outcome space for key system uncertainties is analogous to the description of a system in which one is able to change the sytem state by means of the idnetified operational policies. In other words, a system of Food ATMs will have to 'meet' certain conditions to firstly be problematic and secondly susceptible to policy intervention. For example, a system with significant overcapacity is very

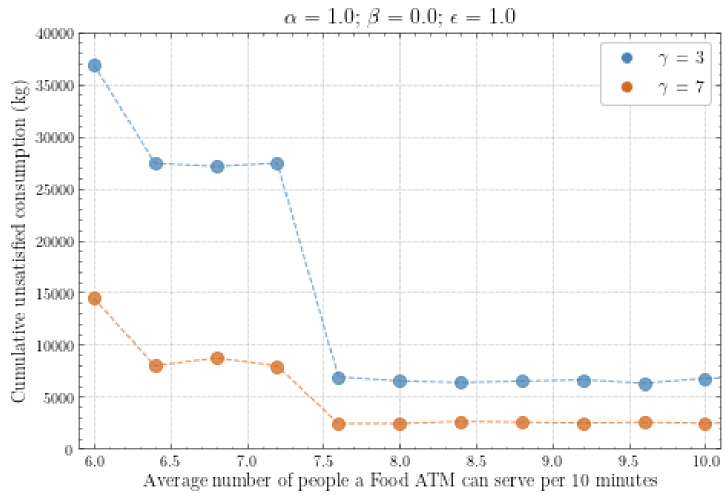


Figure 9.5: Exploring service capacity

unlikely to develop a queuing problem and thus evaluating such a scenario would be of limited value. The two system uncertainties that will be investigated are the size of the susceptible social network of household agents and the serving capacity (number of people served per 10 minutes).

The value for the serving capacity of a Food ATM has been determined by means of sampling for a quickly forgetting ($\alpha = 1$), non-interacting ($\alpha = 1$) and very unreactive ($\alpha = 1$) population. The base case does not allow rerouting between facilities and thus the facilities function fully independently of each other. Also, note that the size of the social network (the other *key system uncertainty* does not have any influence due to the social interactions set to 0.

Lowering the average number of people that a Food ATM can serve per unit of time (SC), a sharp increase can be observed at SC=7.2 and SC=6.0. The sharp increase is due to the emergence of a queue. Due to the demand being stable over time queues only emerge when the capacity is below a certain threshold, for one particular facility. The second increase corresponds with the emergence of a queue at a second facility.

The size of the susceptible social network of a household agent is evaluated by looking at the cumulative unsatisfied consumption, indicating how system under-delivery prevents people from getting food. A population is created with a high forgetting rate ($\alpha = 1$), high information diffusion rate ($\alpha = 1$), a high reactivity to the system ($\alpha = 1$) and a serving capacity of 7.8 people per 10 minutes. Figure 9.6 shows how system performance performs worse as a function of the size of the social network.

Relating this back to figure 9.5 it can be observed how an increasing number of social interactions has an influence on the system state on the condition of a relatively small size of the standard security stock ($\gamma = 3$).

9.5.3 Behavioural uncertainties

The search for relevant scenarios by sampling values for the behavioural uncertainties follows up on the investigation of the *system* uncertainties. It is thought to be important to analyse the contribution of different values for the system uncertainties in order to investigate their relative effect. Recall that the number of interactions is defined as:

$$NumberOfInteractions = \beta \times SizeOfSocialNetwork \tag{9.3}$$

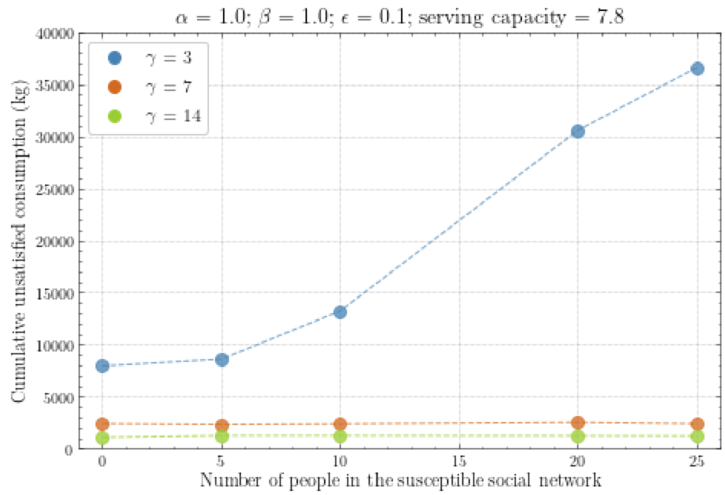


Figure 9.6: Exploring social network size

Hence, by sampling multiple values for β, the *effective* size of the social network changes. Subsequently, the sampling set for system uncertainties is determined to be:

- Size of social network = 20
- Serving capacity = [6.0, 7.8]

The behavioural uncertainties are parametrised at:

- α: [0.0 , 1.0]
- β: [0.0 , 0.5 , 1.0]
- γ: [3.0 , 7.0]
- ϵ: [0.1 , 1.0]

The temporal aspect of the outcomes (that is, the evolution over time) is not regarded. For Unsatisfied consumption and Food waste, the final value at the end of Day 30 is taken. For queuing, the total queuing time times the number of beneficiaries is evaluated. This allows better visual inspection of the outcomes.

By trial and error, visual analysis has been made possible by organising the outcomes in the following way. The outcomes are clustered for epsilon and alpha respectively. The value for the end results do very significantly, hence the choice for a varying y-axis and thus four plots each.

9.5.4 Policy analysis

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