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THESIS

AGENT-BASED MODEL AND SYSTEM DYNAMICS MODEL FOR PEACE-KEEPING OPERATIONS

by

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September 2014

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Military operations other than war (MOOTW) make up a large percentage of total military operations. Some common MOOTW operations are peacekeeping (PKO) and humanitarian assistance, and disaster relief (HADR). System dynamics (SD) uses a top-down approach that models high-level system behavior as compared to the use of agent-based modeling (ABM), which uses a bottom-up approach to generate system-level behavior through emergent behavior. In this work, SD and ABM were applied to model a food distribution scenario during the early phases of PK/HADR and the implementation process and results compared. The results were that large variations in food prices were observed as the time step and the integration technique were varied. Both SD and ABM, however, displayed similar emergent behavior in terms of crimes that occurred due to relative deprivation within the population. As an alternative to time step approximation, discrete event simulation (DES) may be used to implement the SD model through discretization of stocks or flows within the system and identifying events that change these quantities. The quantization of continuous variables in SD into discrete quantities may, however, introduce quantization errors. Emergent behavior seen in ABM can occur in SD through the interactions between equations. Due to the compactness of SD equations, it feels less intuitive to develop models using SD than it does to develop models using ABM.

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AGENT-BASED MODEL AND SYSTEM DYNAMICS MODEL FOR PEACE-KEEPING OPERATIONS

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ABSTRACT

Military operations other than war (MOOTW) make up a large percentage of total military operations. Some common MOOTW operations are peacekeeping (PKO) and humanitarian assistance, and disaster relief (HADR). System dynamics (SD) uses a top-down approach that models high-level system behavior as compared to the use of agent-based modeling (ABM), which uses a bottom-up approach to generate system-level behavior through emergent behavior. In this work, SD and ABM were applied to model a food distribution scenario during the early phases of PK/HADR and the implementation process and results compared. The results were that large variations in food prices were observed as the time step and the integration technique were varied. Both SD and ABM, however, displayed similar emergent behavior in terms of crimes that occurred due to relative deprivation within the population. As an alternative to time step approximation, discrete event simulation (DES) may be used to implement the SD model through discretization of stocks or flows within the system and identifying events that change these quantities. The quantization of continuous variables in SD into discrete quantities may, however, introduce quantization errors. Emergent behavior seen in ABM can occur in SD through the interactions between equations. Due to the compactness of SD equations, it feels less intuitive to develop models using SD than it does to develop models using ABM.

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List of Acronyms and Abbreviations

ABM agent-based model
BDI belief-desire-intention
CAS complex adaptive system
CLD causal loop diagram
DES discrete event simulation
EBM equation based models/modeling
FDP food distribution point
HADR humanitarian assistance/disaster relief
MOE Measure of Effectiveness
MOOTW military operations other than war
NPS Naval Postgraduate School
PK peacekeeping
PKO peacekeeping operations
SD system dynamics
SDM system dynamics models/modeling
SSTR stability, security, transition & reconstruction

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CHAPTER 1:
Introduction

Military operations other than war (MOOTW) makes up a large portion of the operations that the military participates in during peacetime. Some of the common operations for MOOTW are peacekeeping operations (PKO) and humanitarian assistance/disaster relief (HADR). Simulation, for analytical or training purposes of PKO/HADR is thus an area of interest. One key difference between modeling PKO/HADR and traditional military operations is that these operations rely on the cultural and social behavior aspects of the region they are carried-out in [1].

Given that one definition of a society is “a highly structured system of human organization for large-scale community living that normally furnishes protection, continuity, security, and a national identity for its members” [2], it implies that a society is a system that is confounded by certain structures and rules, one possible way to exploit that society is a system is confounded by certain structures and rules is to apply the principle of the law of large number to model groups within the system. Johnson explained that the law of large number works because “the average in each case is dictated by something structural and predetermined, while the spread in values around the average is due to environmental ad hoc reasons” [3]. An example of this is that, even though the height of a population may vary from 1.5 to 2 meters, there is an average height for human beings arising from our genetics, which dictates the general height of individuals within the population. The differences in height from individual to individual could be due to up-bringing.

Hence, it is hypothesized that it might be possible to study the effect of society at an aggregate level without looking at individual differences. This is the impetus for the author to look at the use of the agent-based model and system dynamics model as approaches for modeling peacekeeping operation.

1.1 System Dynamics Modeling

System dynamics (SD) is one of the approaches used in studying large-scale complex systems. According to [4]:

> The system dynamics approach emphasizes a continuous view. The continuous view strives to look beyond events to see the dynamic patterns underlying them. Moreover, the continuous view focuses not on discrete decisions, but on the policy structure underlying decisions. Events and decisions are seen as surface phenomena that ride on an underlying tide of system structure and behavior.

From a functional perspective [5]:

> System Dynamics is nothing more than a palatable front-end to a set of Differential-Algebraic Equations (DAEs): i.e., a set of differential equations, with a set of subsidiary algebraic equations for defining intermediate and rate quantities. Each compartment is a state variable, and each flow contributes to the rate-of-change expression for the associated state variable(s).

One of the tools in SD is the causal loop diagram (CLD). CLD is a thinking tool that can be used to document/visualize how factors within the system affect each other. Factors may have positive re-enforcing effects on another factor, e.g., increasing the price of items may lead to increase in profits, or negative re-enforcing effect, e.g., decreasing the cost of sales may lead to increase in profits. The rate at which one factor affects another factor is specified as "flows," which may be specified as equations. The impact of a change in one factor to another factor may be "delayed." For example, since it takes time for goods to be delivered, increasing orders for goods may not lead to an increase in inventory until after the goods are delivered.

As CLDs are fairly easy to understand, the author's opinion is that CLDs can be useful as a communication tool to elicit knowledge from stakeholders on what they consider to be important factors in PKO.

Since the rate of flows is usually specified as differential equations, the SD models are also known as equation based modeling (EBM). To compute the differential equations used in the stocks and flow, SD usually uses a time-step approximation such as Euler or Runge-Kutta.

In summary, SDMs are usually:

- Equation-based
- Continuous
- Deterministic

1.2 Discrete Event Simulation

Discrete event simulation (DES) describes an event-oriented methodology of simulation where events may happen at any time. The operation of the system is represented as a chronological sequence of events. Each event occurs at an instant in time and marks a change of state in the system [6].

A graphical method to represent this event-oriented methodology is through the use of event graphs [7]. Event graphs are comprised of:

- A set of states (i.e., variables that changes in accordance to events that happen within the model)
- A set of parameters (i.e., a set of design-time values used by the model for determining the model's behavior)
- A set of events the associated state changes that occur upon the occurrence of the event
- Scheduling and cancellation edges between events and their associated scheduling condition and the simulated time at which the event occurs

Figure 1.1 shows an example of an event graph. Events are represented as circles, with their state transition listed below them. The scheduling of events is shown using arrows with the required condition for the event to be scheduled specified in round brackets. Parameters for the events are enclosed in rectangles next to the scheduling arrow.

1.3 Agent-Based Modeling

According to Macal and North, "agent-based modeling and simulation (ABMS) is a new approach to modeling systems comprised of autonomous, interacting agents" [8]. An "agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators" [9]. An important characteristic of agent-

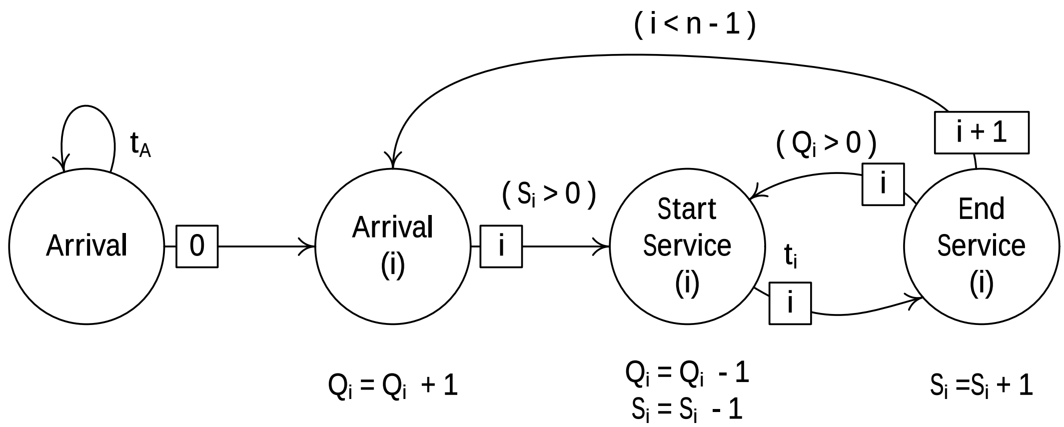

Figure 1.1: Example of an Event Graph (after [7])

based model (ABM) is that each individual agent is unique, which “implies agents usually are different from each other in such characteristics as size, location . . . ” [10]

Thus, ABM is a method for representing the world through modeling of the environment, and entities that interact with the environment as individualized autonomous software component with individual properties and characteristics, i.e., each entity is unique from one another.

The interest in ABM (for this thesis) is in the use of ABM for implementing complex adaptive systems (CAS). A CAS is a system that uses simple behaviors to generate complex behaviors through emergence behavior.

1.4 Complex Adaptive System

Mitchell defines a CAS as a “system that exhibits nontrivial emergence and self-organizing behaviors” [11], i.e., a system that uses interactions between agents to build complex behavior.

Johnson contributed seven characteristics that he considered CAS should have [3]:

- The system contains a collection of many interacting objects or “agents”
- These objects’ behavior is affected by memory or “feedback”

- The objects can adapt their strategies according to their history
- The system is typically "open" ... can be influenced by its environment
- The system appears to be "alive" ... evolves in highly non-trivial and often complicated ways
- The system exhibits emergent phenomena, which are generally surprising, and may be extreme
- The emergent phenomena typically arise in absence of any sort of "invisible hand" or central controller

1.5 Belief-Desire-Intention

The belief-desire-intention (BDI) model is a technique often used to model the behaviors of software agents in modeling CAS. BDI describes a high-level architecture in which an agent forms its intent (what it would like to do), based on its beliefs (what it understands of the environment) and desires (what it wants to do). The intention of the agent is translated into finer detailed steps that are linked together to form a plan for the agent to execute.

A basic algorithm for BDI is described below [12]:

BDI-Interpreter

```
initialize-state();
repeat
    options := option-generator(event-queue);
    selected-options := deliberate(options);
    update-intentions(selected-options);
    execute();
    get-new-external-events();
    drop-successful-attitudes();
    drop-unsuccessful-attitudes();
end repeat
```

Options, i.e., alternatives to accomplish the desires of the agent, are first generated based on the event queues, which contain a list of events from the external environment and execution of the intent by the agent. Not all options may be available due to the condition that agent is in. Options with preconditions that are not met are removed by the option generator process.

The *deliberate* process selects an option from the list of feasible options based on the agent's beliefs, desires, and current executing intention. Depending on the implementation, the selected option may cause new intentions for the agent to be added, or change the active intention of the agent.

In BDI, a desire is an objective that the agent wishes to carry out, while an intent is a selected desire chosen by the *deliberate* process that becomes the focus of the agent. From the intent, a path of execution by the agent is generated to achieve the intent.

To avoid confusion between beliefs, desires, and intention, a more instinctive approach to BDI would be to use the following notions [13], [14]:

- Events: stimuli that change the agent's beliefs
- Beliefs: represent information available to the agent (e.g., about the environment or other agents) and the preferred state of the world that the agent wishes to bring about
- Desires (i.e., Goals): states of affairs the agent wants to bring about; usually specified during design time
- Intentions: selected desires, i.e., one intention is selected from many possible options through the deliberation process
- Options: alternatives to accomplish the desires
- Plans: recipes for action, representing the agent's know-how towards achieving an intention

To illustrate the BDI model, consider an agent with the desire of getting to the office by 8 am. The agent may have more than one way to get to the office (i.e., options); it may choose to drive to the office, or take a bus. To drive to the office, the agent would need to:

- Find the car keys
- Get into the car
- Start the engine
- Drive to office

Alternatively, to take a bus to the office, the agent would need to:

- Walk to the bus stop
- Wait for the bus
- Board the bus
- Travel on board the bus for 10 minutes to reach the bus stop outside of the office

Both of these options comprise a set of actions that forms a plan based on the agent's knowledge base on how to get to the office. To decide which option to choose, the agent would rely on its knowledge base of beliefs, i.e., the agent may believe that:

- It is more efficient to drive
- The current time is 0740
- The car has sufficient gasoline and is serviceable
- The bus to the office will arrives at 0745 at the bus stop outside the house

Based on the two options, it may score the option to drive higher due to its efficiency, and decide to drive to the office. Once the agent decides that it would drive to the office, the decision becomes the intention of the agent, which causes the agent to execute the plan for driving to the office. The agent stops working on an intention when it achieves its goals, or when the intention can no longer be carried out. For example, if the agent found that the car is out of gas after deciding to drive to the office, the intention for the agent to drive to the office can no longer be executed. As the desire to get to the office still exists, the agent re-evaluates its options based on the new belief that the car is out of petrol and picks the only option available, which is to take a bus to the office. Figure 1.2 illustrates how the BDI structure for this example would look.

The difference between BDI and a decision tree is that options in BDI may be generated dynamically based on its current beliefs and intention (e.g., through inference). For example, in the case of driving to the office, the 'drive to the office' step may itself be a sub-goal and any plans that will eventually reach the office by driving may become valid options under the intention of 'drive to the office.'

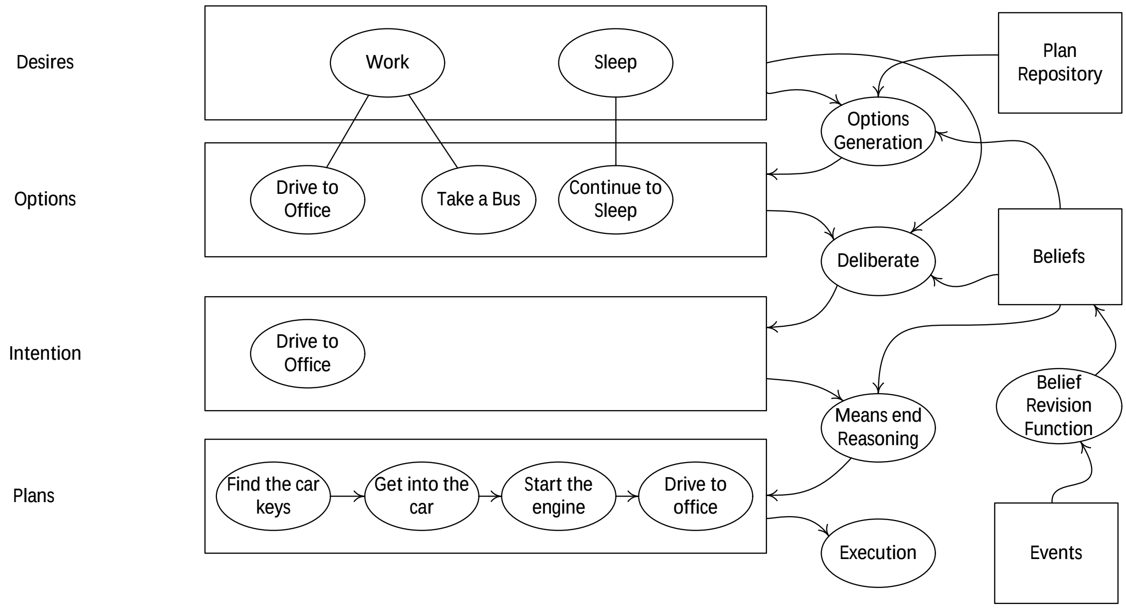

Figure 1.2: Example of BDI Structure for Getting to Work

1.6 Comparison of SD and ABM

Borschchev summarizes the comparison between DES, ABM and SD in Figure 1.3.

In summary, SD and ABM are two very different approaches to modeling, with SD adopting a top-down approach towards modeling the behavior of the system in contrast to ABM, which adopts a bottom-up approach of modeling individual behavior and attempts to generate the system-level behavior through emergence behaviors.

Borschchev characterized DES in terms of a process/resource "world view," which is substantially different from the Event Graph world view discussed in Section 1.2. The Event Graph world view overlaps 100% with Borschchev's characterization of ABM.

1.7 Stakeholder Analysis

The purpose of the task analysis is to identify the parties involved in a PKO/HADR operation and the likely task that they will need to be performing. The task that the users perform are used to understand what their needs might be for a PKO/HADR simulation. Three possible levels of peacekeepers include the following:

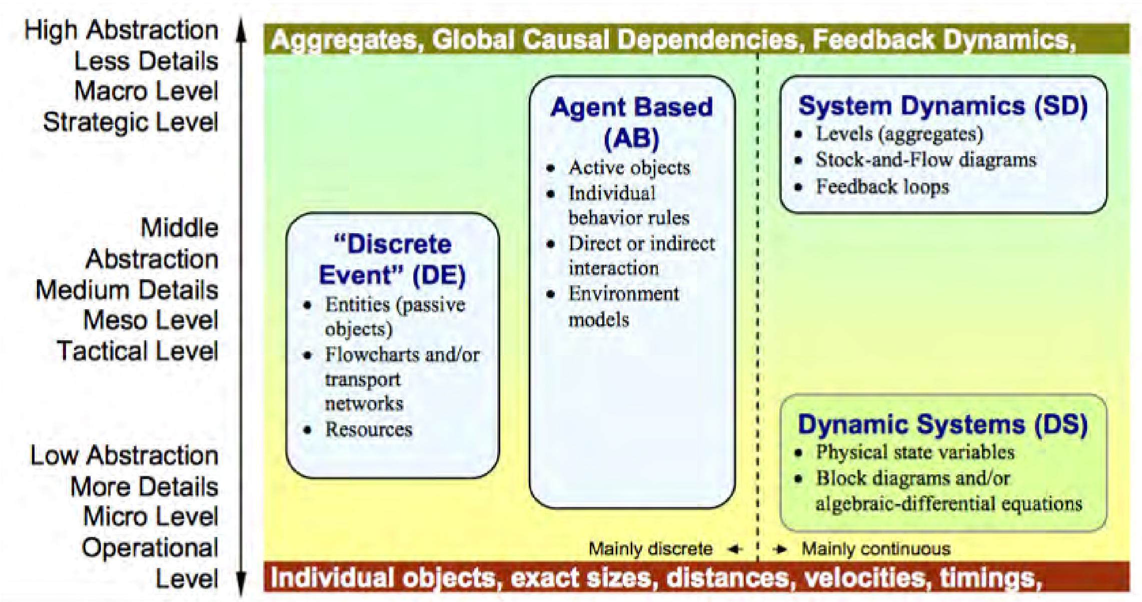

Figure 1.3: Abstraction Level and Scale of DES, ABM and SD (from [15])

1.7.1 Peacekeeping and HADR Personnel

For peacekeeping and HADR personnel that are tasked to carry out the peace-keeping or HADR operations, the essential skills required are individual proficiencies such as:

- The technical abilities to carry various military roles, such as patrolling, setting up of barricades, food distribution points
- Understanding their mission/role in the peacekeeping process
- Understanding the social and cultural differences of the host nations to be able to interact with the locals and make decisions during their operations

These personnel may also be required to know the doctrines and processes that they are required to follow in order to carry out their peace-keeping operations. For example, they may be required to assess the likelihood that the situation might escalate; they may be required to know what steps that they are to take to prevent the situation from escalating, i.e., negotiation, containment, and dispersion of a rioting crowd.

Based on these tasks, the simulation needs for peacekeeping personnel would probably be best served with cultural trainers and procedural trainers, where they can re-enact situations that they might encounter in the field [16].

1.7.2 Tactical Commanders

Tactical commanders are in charge of supervising operations, operation planning, and making tactical decisions for the conduct of peacekeeping operations, such as deciding the patrol routes, selecting the location of barricades, location of food distribution points.

Tactical commanders have to understand that their decisions could affect the success of the peacekeeping force. Hence, they need to be able to assess the situation for possible reactions of the civilian or hostile forces to their course of action. As a person on the ground, Tactical commanders are likely to be interested in the terrain and environment, which would affect how they plan their operations.

Therefore, for tactical commanders, their simulation needs would probably be best served with simulations where they can play out their plans and observe the effect of their decisions based on the terrain and the effective population.

1.7.3 Strategic Commanders

Strategic commanders are tasked to achieve the goals set out for the peacekeeping operation and determine the policies and strategic objectives of the peacekeeping force. Thus, strategic commanders are likely to be interested in understanding what are the factors that would affect the success of the peacekeeping operations. For example, they are likely to be interested in deciding the allocation of resources to mission objectives or deciding policies for the distribution of humanitarian aid (e.g., who gets humanitarian aid and who is provided with food coupons).

1.8 Previous Work

The following sections describe the work of three previous Naval Postgraduate School (NPS) theses relating to the topic of modeling peacekeeping operations:

1.8.1 Agent-Based Simulation of Military Operations Other Than War, Small Unit Combat

Woodaman's thesis, titled "Agent-based Simulation of Military Operations Other Than War, Small Unit Combat" [17] is probably one of the first attempts at building an agent-based simulation of peacekeeping. In his thesis, the effect that an agitator has on the crowd is modeled using thermodynamics law [17].

Three categories of agents were implemented: rioters, rioter leader, and peacekeepers. Each rioter and rioter leader has heat receptors and radiators with thermal falloff based on Stefan Law. Riot leaders try to maintain their heat at 500 and act as agitators in the crowd; rioters transit into aggressive mode once their temperature reaches 100, leading them to attack the peacekeepers. In response, peacekeepers may adopt a reactive or proactive approach towards the rioters. In the reactive approach, peacekeepers may fire non-lethal shots at their last detected attacker with a 50% targeting error applied. In the proactive approach, peacekeepers fire at any rioters that have a heat level that is above 100 and is within attack range [17].

The Measure of Effectiveness (MOE) used by Woodaman were the average number of hits taken by a peacekeeper and the expected number of hits taken by a rioter [17].

1.8.2 German Peacekeeping Operations for Units up to Platoon level

Erlenbruch's thesis, titled "German Peacekeeping Operations for Units up to Platoon Level," attempts to model the reaction of the peacekeepers to rioters using BDI. The MOEs used by him were to minimize [18]:

- Access to red objective (weight: 0 or 1)
- Number of peacekeepers killed (weight: 0.4)
- Number of peacekeepers injured (weight: 0.1)
- Number of protesters killed (weight: 0.45)
- Number of protesters injured (weight: 0.05)

One observation of these MOEs is that there was no consideration of blue force's movement towards the red force's objective, i.e., there is no need for the protesters to protect any locations, whereas the mission is considered to be a failure for the blue force if any protester is able to reach their objective. Given that the blue force's primary objective should be to defend their base from being invaded by the red force's agents, it is unclear why the behavior model of the peacekeeper should include goals that would steer the blue force agents towards their objective location when it does not count towards the MOE.

Erlenbruch mentioned "the PKO agent's set of current options is modelled by seven different goals [18]. At all times, the agent tries to achieve one of them." The seven goals of the agents are shown in Table 1.1:

Table 1.1: Objectives and Consideration Used in Erlenbruch's Thesis (from [18])

Objectives	Consideration
AdvanceObjective	Inversely to distance from objective
CloseToFriendlies	When injured, or when the ratio of enemies is high
CloseToLeader	Agent will try to stay close to a leader unless itself is a leader or has an assigned task
AffinityToAction	Desire to move close to action
RiskAversion	Avoid enemy, inversely to distance from the base
ShockInfluence	Probability of getting hit and reaction time
Training	

Erlenbruch was able to synthesis the agent's behavior using these simple but conflicting objectives (e.g., staying alive, occupy enemy objective, protect own base). In his implementation, there does not appear to be any sub-goals within these seven initial goals. This means that the agent behavior that he implemented is likely to be somewhat reactive rather than deliberate.

Erlenbruch did not use a belief revision function in his implementation to determine a new set of beliefs [18]. Thus, the beliefs of the system are fixed and immutable.

1.8.3 An Upgradable Agent-based Model to Explore Non-Linearity and Intangibles in Peacekeeping Operations

Lehmann's thesis, titled "An Upgradeable Agent-Based Model to Explore Non-Linearity and Intangibles in Peacekeeping Operations," is an extension of Erlenbruch's thesis to focus on the effect that the personality factors of the agents have on the scenario outcome. Lehmann described his thesis as "analysis of encounters between peacekeepers and demonstrators," and "interactions of influence between personality factors and arousal of violence" [19]. This differs from Erlenbuch's objective, which is to minimize the number of casualties of both the peacekeepers and the protesters.

To explore the effect of the change in agent's personality, Lehmann used the following MOEs, which presumably act as a proxy for measuring the "arousal of violence" in the peacekeepers:

- *timeToFirstShot* - *timeToFirstDetection*
- *timeToFirstWounded* - *timeToFirstDetection*
- *timeToFirstKilled* - *timeToFirstDetection*

In Lehmann's design of experiments, two levels (high and low) and three factors (i.e., risk aversion, affinity to action and closeness to friendlies) were used, even though the actual number of possible variations in the system greatly exceeds the two levels and three factors approach that he uses in his design of experiment. For example, the training level of the peacekeepers was not considered. This could have an influence on the ability of the peacekeepers to shoot accurately to inflict injuries, but not to cause death, which would lead to a lower drop in utility due to the low weights assigned to the number of injured protesters.

Lehmann chose to omit the physical environment, citing "Simulating urban terrain consumes a tremendous amount of computing power without adding knowledge to the research questions explored in this thesis" [19]. Since Lehmann's focus was on the effect of the personality factors, this is probably a reasonable simplification. In the author's opinion, however, the effect of terrain could have an impact on the outcome of the scenario for situational analysis.

Another assumption that might have been made in Lehmann's thesis was that both peacekeepers and protesters use the same set of personality factors. The personalities of the bystanders were also not described.

Lehmann provided room for interpretation in his thesis as to what other events and their corresponding impact should be in changing the agent's personality. For example, Lehmann wrote that the agent's personality changes when it is injured, from which it is inferred that the agent is still capable of moving [19].

Another area in which Lehmann left room for interpretation is in the implementation of the *AgentAdjudicator* class [19]. The *AgentAdjudicator* holds the key to the evaluation of the effect of the events that has occurred, and how statistical data are computed. The *AgentAdjudicator* was also apparently responsible for the routing of events between the environment and the agent, e.g., the translation of *doFiringAir* into *doHearShooting(Agent)* [19].

Based on the information in Lehmann's thesis, the author could not decide how to re-implement Lehmann's model as there are several possible ways in which the model could have been implemented.

1.8.4 Discussion

Handling of riots is an operation that may be faced by a peacekeeping force. Several theses have been written to address this aspect of peacekeeping [17], [18], [19]. Handling of riots, however, does not constitute the whole mission of peacekeeping. The full process of peacekeeping goes beyond just stopping a riot; it "encompasses a broad range of activities spanning from repatriation of refugees and other displaced populations to revitalization of local economies to livelihood and employment creation to reconstruction of physical infrastructures to provision of political development assistance or human rights promotion, among others" [20].

One interesting observation from reviewing the previous work done in NPS is that most of these studies seem to focus on the behavior of the military but not on the behavior of the civilians. Hence, one of the motivations of the thesis would be to look at the modeling of PKO from the civilian's perspective.

1.9 Problem Statement

Railsback wrote that "Using ABM (Agent Based Modeling) lets us address problems that concern emergence: system dynamics that arise from how the system's individual components interact" [10]. Interestingly, in Railsback's use case for ABM, the desired outcome is to model the "system dynamics" of the system.

Since all models are simplifications of the real world, SD can help to reduce this complexity by creating simpler, easier to understand models that capture the essential characteristics of the model. Rather than using ABM, it would be interesting to see how SD could be used to model high-level behaviors of a system. Since SD utilizes temporal discretization for approximation of equations, another area of interest would be to look at how DES could be used as an alternative to temporal discretization. Thus, this thesis aims to answer the questions:

- Can we model the desired behavior directly using system dynamics instead of agent-based modeling?
- Can we take a simple causal loop diagram and build a discrete event simulation out of it?
- How does this compare to the agent-based model for the same problem?

1.10 Scope of Work

Based on the task analysis, likely needs of each category of peacekeeping personnel, the availability of time and data, the author has chosen to scope the simulation to focus on the possible behavior response by the civilians towards the actions of the peacekeepers.

Therefore, the scope for the thesis is to:

- Develop model of a PK/HADR environment
- Develop system dynamics or equation based model of the environment
- Develop agent based model of the environment
- Convert system dynamics model into discrete event simulation
- Output analysis

The use of SD and ABM approaches toward modeling Peacekeeping (PK)/HADR allows for the appreciation of the differences between using a top-down and bottom-up approach. The output analysis shall look at how the differences in the approaches might translate to differences in results. The comparison of the results from two different implementations also serves to cross-verify that the implementation is correct.

CHAPTER 2:
Background

As a start towards understanding the social behavior needed for modeling PK/HADR, background research on general social-behavior theories (i.e., Social Ecological Theory and Social Cognition Theory) and criminology was conducted. The following sections describe some of these theories/hypotheses.

2.1 Social Models

Many theories try to explain how human behavior in a social environment exists. These include theories such as Game Theory, Symbolic Interaction Theory, Conflict Theory, and Sociobiology. The following section reviews two such theories that more directly relate to social behaviors, i.e., Social Cognition Theory and Social Ecological Theory:

2.1.1 Social Cognition Theory

The Social Cognition Theory was developed based on Social Learning Theory by Bandura to explain how humans learn and act. The hypothesis of Social Cognition Theory is that human behavior both affects and is affected by personal and environmental factors (Figure 2.1).

Social Cognition Theory believes that the actions made by an individual could have an effect on the environment, which could in turn induce or reinforce behavioral changes in others [21]. The belief is that an individual learns from the environment and forms their expectations based on their abilities. The individuals then self-regulate (change) their actions based on observation of the outcome of other people's actions.

The hypothesis of Social Cognition Theory states that behaviors that are rewarded tend to be repeated, whereas behaviors that are punished tend not to be repeated. For example, if a person is surrounded by neighbors that appear to be anti-social, he/she will also have a tendency to react in the same way by not trying to socialize with them.

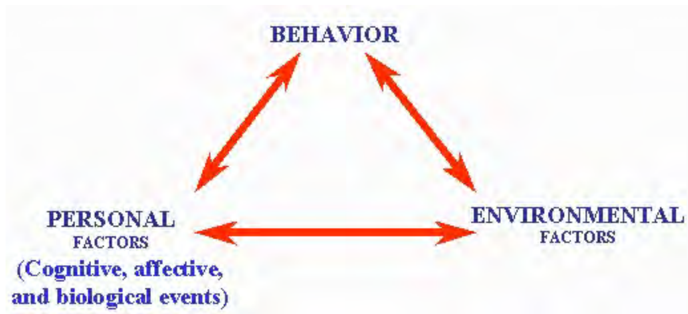

Figure 2.1: Interdependencies Between Behavior, Personal and Environmental Factors (from [21])

2.1.2 Social Ecological Theory

Ecology is essentially an understanding of how living systems interact with the environment. The Social Ecological Model [22], in a nutshell, suggests that a person's behavior is linked to his/her environment at different levels, ranging from the individual to the microsystem level. That is, from the individual's immediate surroundings to the macrosystem that is affected by factors such as attitudes and cultures. The different levels of interactions are shown in Figure 2.2.

The importance of Social Ecological Theory is that, when looking at the behavior, one needs to look beyond just the individual factors and at the entire ecosystem.

2.1.3 Discussion

The key takeaway from both theories is that social behaviors are influenced by the environment. Social Ecological Theory and Social Cognition Theory complement each other in that Social Ecological Theory expands upon the "environmental" factors of Social Cognition Theory. Social Ecological Theory helps to explain the effect (reinforcement or learning) that causes a person to adapt his/her behaviors based on the environment (i.e., it helps to explain the basis for the belief that the law of large numbers is applicable to social behavior of different groups within the society, as mentioned in Chapter 1).

2.2 Criminology

While the social models provide the basis for the applicability of the law of the large numbers to social behaviors, the two social theories in Section 2.1.1 and Section 2.1.2 do not provide much specificity as to why people may choose to adopt criminal behavior. To better

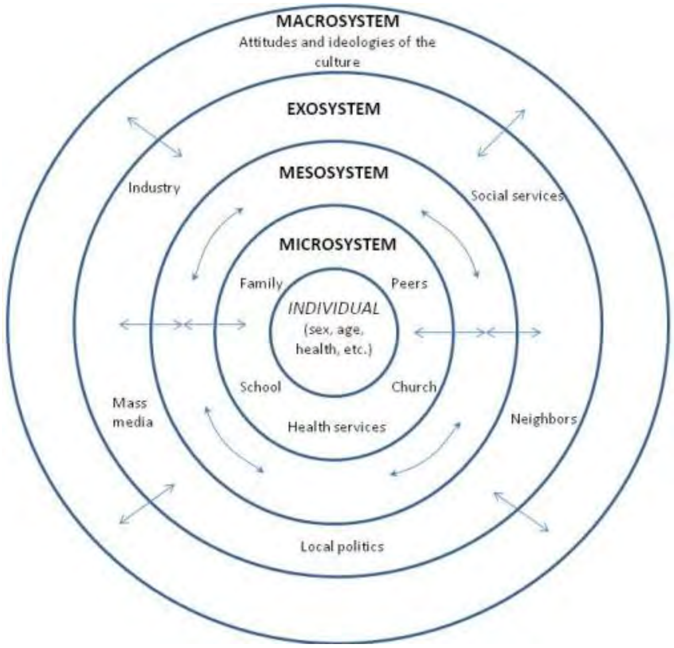

Figure 2.2: Bronfenbrenner's Ecological Theory of Development (from [23])

understand why crime may occur during PK/HADR, research on why crimes occur were conducted. A list of theories of crime can be found in Table 2.1. The following sections look at three theories from the three major theoretical schools for criminal behaviors.

2.2.1 Anomie Theory

In general, Anomie Theory (or Social Strain Theory) hypothesized that crime is the result of discrepancies between goals and a person's means to achieve their goals. The causes of strains arise from several possibilities ranging from the uneven distribution of resources to alienation by the society. Anomie Theory hypothesized that as a result of the mismatch expectations, a person may commit crime with the aim to "right the wrong" either to bring about change to the benefit of himself/herself, or to bring about change for the benefit of the society as a whole.

Durkheim explained Anomie Theory as a process whereby some members of the society revolt against obsolete structures, and proposed that the definition of "crime" is a way in which society differentiates between what is accepted and what is not accepted as social norms [25].

Table 2.1: Major Theoretical Approaches in Mainstream Criminology (Sociological) (from [24])

Theoretical School	Major Themes/Concepts	Major Theorists
Sociological Mainstream	Crime reflects consensus mode	
Anomie Theory	Anomie (normlessness) lessens social control	Durkheim
	Anomie (gap between goals and means) creates deviance	Merton
	Differential social opportunity	Cloward and Ohlin
	Lower-class reaction to middle-class values	
Social Process	Social disorganization and social conditions	Shaw and McKay
	Routine activities	Cohen and Felson
	Crime is learned behavior, culturally/sub-culturally transmitted	Sutherland
	Local concerns of lower class	Miller
	Subterranean values, drift techniques of neutralization	
Social Control	Containment theory	Reckless
	Social bonds weakened, reducing individual stakes in conformity	Hirschi
	Low self-control and self-interest	Gottfredson and Hirschi
Developmental/Life Course	Antisocial potential	Farrignton
	Longitudinal studies	Blumstein
	Life course criminality	Sampson and Laub

Smith suggested that "alienation" is a key concept for Anomie Theory because it is the social structural conditions that determine the attitudes and behaviors of the criminal [25]. Five common interpretations of alienation that were defined by Melvin Seelman:

- Powerlessness (Marx): expectancy or probability held by the individual that his own behavior cannot determine the occurrence of the outcomes he seeks
- Meaninglessness (Mannheim): low expectancy that satisfactory predictions about future outcomes of behavior can be made
- Normlessness (Durkheim-Merton): high expectancy that socially unapproved behaviors are required to achieve given goals
- Isolation (Nettler): low reward value assigned to goals or beliefs that

typically are highly valued in the given society

- Self-estrangement (Fromm): degree of dependence of the given behavior upon anticipated future rewards

2.2.2 Social Disorganization Theory

Another theory of crime is Social Disorganization Theory proposed by Shaw and McKay. Shaw and McKay noticed that "neighborhoods that have the highest rates of crime typically have at least three common problems (Figure 2.3): physical dilapidation, poverty, and heterogeneity." [26] That is, crimes are more likely to occur in places where the physical environment is rundown, poorer and comprised of a higher cultural mix.

Tibbets cited Miller in his explanation of Social Disorganization Theory on how different social classes have different beliefs and culture. Miller wrote that the lower class believed in and socialized the value of six focal concerns: fate, autonomy, trouble, toughness, excitement, and smartness. Miller explained that their belief in fate served as a way to disregard the responsibility and accountability for one's action. The belief of autonomy is the result of their value of independence from authority, and the belief of avoiding trouble is the mind-set of avoiding personal and legal issues. Hence, one possible reason for the differences between the set of beliefs and cultures of the lower social class and upper social class may be that the people from upper social class have the experiences and the knowledge to achieve their goals rather than to believe in fate.

Physical dilapidation was also explained as one of the factors in Social Disorganization Theory. Physical dilapidation is explained as the difference in the physical environment between neighborhoods. The services and amenities available are believed to be greatest at the city center, which drives the development of the land next to it. The process of development continues, which leads to an environment where the further the place is from the city, the fewer amenities and poorer living condition it is likely to have. Because of the differences in amenities, people who can afford to would choose to live nearer to the city, whereas those who choose to live at the edges of the city would probably care less for their environment as it is already run down.

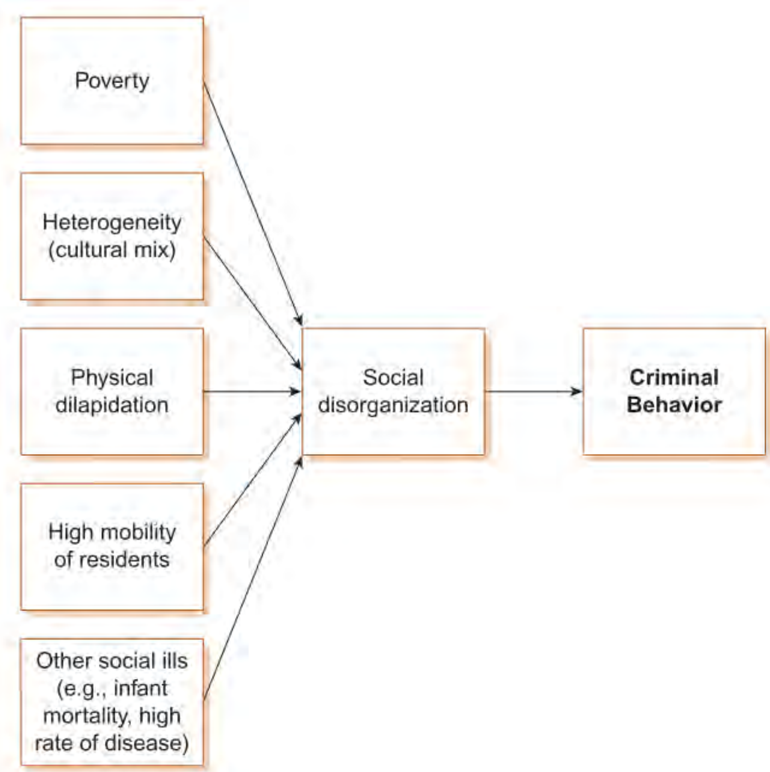

Figure 2.3: Model of Shaw and McKay's Theory of Social Disorganization (from [26])

2.2.3 Self-Control Theory

The Self-Control Theory of crime (also known as The General Theory of Crime) was proposed by Grottfredson and Hirschi to explain the occurrence of criminal behavior. Grottfredson and Hurschi believe that the people with lower self-control are more vulnerable to "acts of force or fraud undertaken in pursuit of self-interest" [27].

In their book, Grottfredson and Hirschi listed four personal traits that they believed put people with low self-control at risk for criminal offending:

- They are oriented to the present rather than to the future, and crime affords them immediate rather than delayed gratification.
- They are risk-taking and physical as opposed to cautious and cognitive, and crime provides them with exciting and risky adventures.
- They lack patience, persistence, and diligence, and crime provides them with quick

and easy ways to obtain money, sex, revenge, and so forth.

- They are self-centered and insensitive, so they can commit crimes without experiencing pangs of guilt for causing the suffering of others.

2.3 Effects of Crime

Some of the effects of crime on society include [28]:

- Loss of productivity
- Increase in health care
- Increase in security cost for businesses
- Direct costs

Loss of productivity is probably the main effect of crime on businesses. Loss of productivity occurs when businesses react to crime by staying open for a shorter period to reduce the risk of being targeted by criminals. Loss of productivity is also incurred when people channel their efforts into crimes rather than productive work. Loss of productivity may also occur due to the loss of manpower arising from injuries or deaths as a result of crimes.

Increased security costs for businesses occur when businesses invest in security systems to deter crime. Direct costs are incurred when businesses suffer monetary losses due to crime, such as the loss of goods due to fraud, theft, arson or looting. Firms that suffer significant losses may also be forced to close down when they are the victim of crime, which could lead to higher loss of productivity. Increases in health care cost occurs as a result of injuries that occur because of crime proceedings.

The loss of productivity and the higher direct and indirect business costs due to crime may translate into higher cost of goods and services, which could be passed down to customers, driving prices up.

2.4 Behavior during Disasters

With the basic understanding of criminology, the following sections look at how people behaved during crisis or disaster.

2.4.1 Violence

Slettebak wrote that disasters provide both push and pull factors that could affect conflict risks. Factors such as environmental stress that arises during disaster, which should lead to increase in violence, may in fact act in the opposite manner [29]:

> The common fate that is reported to unify disaster victims may be a double-edged sword: if disaster exposure follows social or ethnic divides, then this increased cohesion may contribute to exacerbating between-group conflicts. If all are affected equally, on the other hand, the opposite may happen.

Conversely, Slettebak also cited work from Drury and Olson, and Homer-Dixon and Wilkinson, that disasters may lead to an increase in violence as a result of the loss of the state's ability to enforce the rule of law:

> State capacity is perhaps the most important factor here: as disasters are likely to over strain authorities' ability to enforce rule of law and provide aid, actors that aim to strike a competing ethnic group or instigate an insurgency become more able to do so.

In his analysis of the data on Hindu-Muslim riots, however, Slettebak could not find conclusive evidence to support either of the approaches. He reported "finding of a weak tendency of more riots in the first months after climate-related natural disasters and then a drop in the rates in the longer term does not really support any of the two approaches."

2.4.2 Looting

Looting is an activity that is thought to occur during disasters. Bakonyi found, in her study on the looting that happened in the Somali wars, that looting consists of complex social activities that can be caused by motivations other than pure economic gains [30]. She summarizes her analysis of the types of looting, occurrence, motivation, actors and how looting is carried out during the Somali wars in Table 2.2.

Emergency Nutrition Network pointed out an interesting observation in their analysis of Bakonyi's paper [31] :

Table 2.2: Five Types of Looting and Racketeering (from [30])

Type	Objects	Main motivation	Actors	Performance
Strategic looting	Property of enemies	War strategy	Militias, government forces	Selective targeting, humiliation of enemies,
Protest looting	Public goods	Protest exclusion	Mobs, masses, gangs	Selective attacks on public facilities, often angry and aggressive
Leveling looting	Property of privileged groups	Protest social injustices	Mobs, masses	Urban riots with festive character
Poverty looting	Food, medicine	Survival	Gangs, urban masses, militias	Raids on food stores, markets, harvests
Organized looting	Exchangeable and sellable goods	Material benefit	Gangs, militias in cooperation with business persons	Goal oriented raids, strategic planning
Rackets	Sale of protection	Material benefit, power and domination	Violent organizations and business people	Vigilantism, police functions, cooperation with population/business people/NGOs

> If organized looting materializes, violent actors usually cooperate with business people and regularly with local or national authorities and international partners. However, widespread looting leads to exhaustion. Outside input is required to sustain looting economies, which in Somalia took the form of humanitarian aid.

Another interesting observation from Table 2.2 is that looting is often carried out in conjunction with some organizations, e.g., businesses, militias, government forces. From the paper, it can be derived that relationships exist between gangs, businesses and militias and that there needs to be a venue for the looted goods to be converted into economic value. Thus, an understanding of how the local government, businesses and militias might react to capitalize on the situation may be needed to model the social behaviors completely within the area of operations for a PK/HADR operation.

2.5 Military Perspective of Peacekeeping

From a military perspective, HADR operations are part of stabilization operations that are carried out to stabilize the region. The military classified HADR into three categories: emergency humanitarian and disaster assistance, shorter-term transition initiatives and longer-term development assistance. These three categories can be approximated as the initial response, transformation activities and activities that foster sustainability in the stabilization operation [32]. These three activities can be thought of as the prevention of the situation from worsening, resolving the situation and preventing the situation from re-occurring. The five core functions of stabilization operations are listed as:

- rebuilding infrastructure
- supporting economic development
- establishing rule of law
- building accountable governance
- establishing essential services
- building a capable host nation to build a foreign nation's (FN) internal capacity

The *Guiding Principles for Stabilization and Reconstruction* listed five end states and their necessary condition for a stable state in Figure 2.4. The definitions of these end states are [33]:

- Safe and secure environment: Ability of the people to conduct their daily lives without fear of systematic or large-scale violence.
- Sustainable economy: Ability of the people to pursue opportunities for livelihoods within a system of economic governance bound by law.
- Stable governance: Ability of the people to share, access or compete for power through nonviolent political processes and to enjoy the collective benefits and services of the state.
- Social well-being: Ability of the people to be free from want of basic needs and to coexist peacefully in communities with opportunities for advancement.
- Rule of law: Ability of the people to have equal access to just laws and a trusted system of justice that holds all persons accountable, protects their human rights and ensures their safety and security.

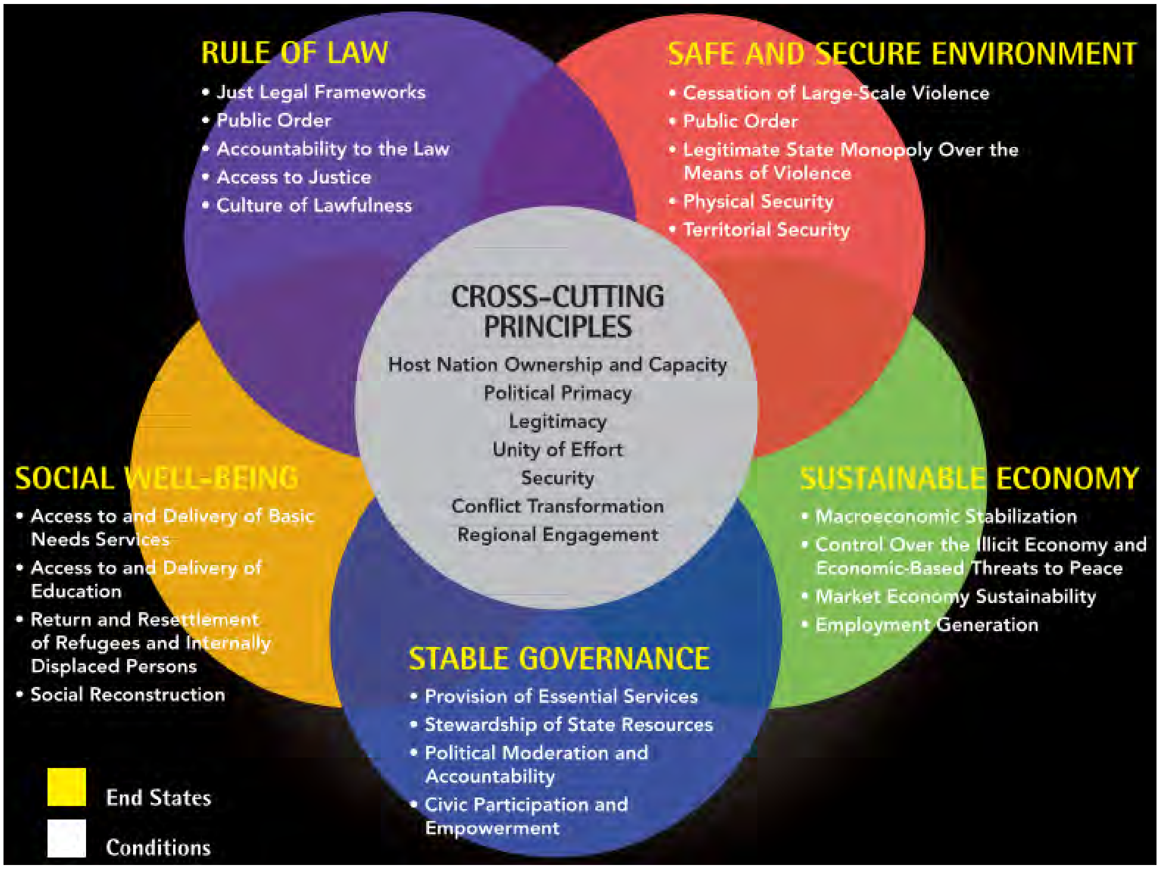

Figure 2.4: Strategic Framework for Stabilization and Reconstruction (from [33])

2.6 Discussion

The General Theory of Crime focuses on personal factors that are believed to lead to low self-control, which is responsible for crime. In contrast, the Anomie Theory and Social Disorganization Theory focused on environmental conditions that resulted in crimes.

It is easy to see that the Social Disorganization Theory is a good fit to the concepts from the Social Ecological Theory based on the explanation of how life experiences of people from different social classes may have different cultures and beliefs. While the General Theory of Crime focuses on personal factors that lead to crime, the Social Ecological Theory could be used to brainstorm possible causes for why people could have developed behaviors of low self-control that is believed to cause crimes. The Anomie Theory is interesting in that it explains crime as a revolutionary process used for breaking the social norms that were imposed upon specific groups of the population. The alienation topology provides a useful breakdown of measures that might be useful for developing models to estimate the likelihood of crime.

An important takeaway from the Social Disorganization Theory, and in some way, the Anomie Theory, is the idea that crime occurs because of heterogeneous groups due to differences within the society.

The concept of system boundaries and influences can also be observed from the different types of looting and the different actors involved in looting. Hence, it is important to view society not as a homogeneous group but as a heterogeneous system, and to clearly identify the boundaries within the modeled system.

CHAPTER 3:
Conceptual Model

To develop the model, a fictional situation is created to provide the background and use case for the simulation. The purpose of the model, potential MOEs, and considerations and assumptions for the model are described in the following sections.

3.1 Scenario Description

The scenario chosen for the thesis is a fictional situation that covers both the need to maintain peace/establish stability and to provide humanitarian aid.

In the scenario, a natural disaster has struck a South-Asian town. Food has become scarce, and food prices have risen drastically. Many of the civilians have very little food left. Following the disaster, the local authority has not been helpful in providing aid or in maintaining peace and order. As a result, some residents have started looting.

As part of humanitarian aid, a small peacekeeping force is to be deployed to the town with humanitarian aid to be distributed to the needy civilians and to restore public order.

3.2 Purpose of Model

The purpose of developing a model for the food distribution process during the early phases of the HADR operation would be to gain insight into the effect that various factors have on HADR, such as:

- What impact does the amount of the initial food supply have?
- What impact does the setup time of the food distribution point have?
- What impact does the amount of food aid have?
- What impact does the number of patrols have on crime?

The possible use of the model could be to provide an understanding of what should be the appropriate course of action to be taken under different HADR environments.

3.3 Measure of Effectiveness

The MOE for the system would be the reciprocal of the time taken for the population to return to steady state and the amount of food and personnel that were used, measured in 1/meal-day, i.e.,

$$\frac{1}{duration \times resources}$$

This MOE that was chosen as the objective of an HADR operation is to stabilize and bring back the area to its original pre-crisis state. The amount of resources used is taken into consideration as there is a probable positive correlation between the amount of time taken to stabilize the system and the amount of resources put into the system, i.e., having massive amounts of humanitarian aid would probably make it easier to conduct the HADR.

3.4 System Boundaries

To analyze the system to be modeled, the scenario is analyzed using the PESTLE (political, economical, social, technological, legal and environment) perspectives. The PESTLE technique is a generic-thinking tool that has been used for business and strategic planning that facilitates the identification of system boundaries [34]. The purpose of identifying system boundaries is to identify what components fall within and outside of the system, and how they might influence each others. A common addition when applying the PESTLE technique is to include an additional "time and timing" perspective to take into account the time-related factors such as the time frame of the system, delays, and opportunity windows.

Some boundaries and factors that influences these boundaries are listed in Table 3.1. The list of influences is useful for identifying considerations needed for modeling the PK/HADR operation for the thesis.

The political boundaries identified that the model may be influenced by the local authority and the peacekeepers. One of the guiding principles for stability, security, transition and reconstruction (SSTR) is for the host nation to own the reconstruction operation [33]; as the model focuses on the initial response phase of the SSTR, the transition between the host nation and the peacekeepers shall not be modeled.

The economic boundary identified considerations on factors such as the supply and demand

Table 3.1: Boundaries for PK/HADR

Boundary	Included Influences	Excluded Influences
Political	Peacekeeper	Local authority
Economic	Supply and demand of food, Price of food	Financing
Social	Social groups	Businesses and criminals.
Technological		Equipments, Means of transportation
Legal		Existing laws
Environment		Location of FDP, location of businesses, external towns/cities.
Time & Timing	Initial response	Transformation and stabilization phase

of food and the impact of price of food. Elaboration of these economic factors is discussed in Section 3.7.1 and Section 3.7.2.

The social boundaries identified that there might be differences between the population in terms of social groups (e.g., high vs. low income), businesses and criminal groups. These social boundaries are important in that one of the factors that the Social Disorganization Theory used for identifying regions with higher crime rates is the presence of different social groups. Discussion of social groups, businesses and criminal groups can be found in Section 4.3.2, Section 3.5.2, and Section 3.5.3.

The technological boundaries identified that the availability and technological differences in the equipment used by the PK/HADR could affect the way the operations are conducted. The means of transportation, e.g., via planes or ship, could affect the amount and time required to response to the disaster. Since the model focuses on the initial response of the PK/HADR operation to return of the town to a stable state, however, these factors are generalized using factors such as the initial setup time of the food distribution point (FDP) and the amount of food aid available rather than modeling the influence technology has on the operation.

The environmental boundaries identified the issues of FDP, businesses, and existence of external towns/states. Due to time constraint, these factors shall not be considered in the modeling process.

3.5 Social

The Anomie Theory explained that one reason conflicts arise is because of differences in what is deemed acceptable within a society. Hence, while society is supposed to be made up of a group of people sharing common values, it is never truly a homogeneous entity. Differences within a group can exist due to cultural, physical, monetary or functional factors. The following sections look at the different groups that exist based on these differences.

3.5.1 Income Groups

Section 2.2.2 explains the physical differences that can exist within a town or city. Neighborhoods within a town or city usually follow outward expanding rings, such that the richer areas that are closer to the center contain more services, and the poorer suburbs are farther away from the center of town. The current model does not assume geographical regions.

Monetary disparity within the society is modeled by having two different income groups: high- and low-income groups. Both household income groups will have a mean income and standard deviation of income that is $\frac{1}{2}$ of the mean income.

3.5.2 Businesses

Consumers and producers (i.e., businesses) are groups that have conflicting functions in society; businesses aim to generate profit while consumers are aiming to reduce spending. During a disaster, businesses might attempt to take advantage of the disaster situation by stocking, restricting the availability of goods or even hiring criminal groups to illegally obtain goods. These behaviors could have an impact on the PK/HADR process and might be important if the model calls for accurate modeling of the goods market.

Besides stocking and restricting the availability of goods, the ability of the businesses to maximize their profit is also affected by the businesses' ability to obtain market information and to segment their markets. These strategies are complex processes that are not easily modeled. As the focus is on the food distribution rather than the actual market economy, businesses shall not be explicitly modeled in the thesis.

3.5.3 Criminal Groups

In addition to different income groups and businesses, a society may also contain several criminal groups. The impact of criminal groups would be on security and, as explained in Section 2.3, economy. Proper modeling of criminal groups would require understanding the organization of criminal groups, as well as details on how they operate.

For example, different types of criminal groups may operate differently. The context of how the group came to exist has an impact on the leadership style and modus operandi of the groups within the system. Some groups may adopt a central authority who dictates the course of action for the gangs, while other gangs may adopt a more democratic method of deciding who to rob. The course of action and logic used for determining where and when crimes are committed would affect the fidelity of the security operations in the model.

People join or form criminal groups because of the benefits that the criminal group bestows upon its members. The benefits may be in terms of intangible benefits like protection to more tangible benefits like food or money. It is reasonable to assume that the greater the benefits, the more likely people would be attracted to join the group. An increase in membership may also mean that the criminal group needs to deal with the organizational issues and secure more benefits for its increased membership base.

There are several considerations to the modeling of the criminal group, from the context of the group formation to the selection of the course of action for the group to take. If this information is not available, especially on how criminal groups make decisions of what crime to commit and when, then arguably there is no benefit to to classifying them as anything more granular than a single criminal group. Hence, the model for the thesis models criminals as individual entities with the intent to commit crimes for their personal benefit (Section 3.6.1).

3.6 Security

Security in the scenario is modeled through the occurrence of crime and the effort by the peacekeepers to maintain public order, i.e., through patrolling and the arresting of criminals. The following sections describe the model for crime and public order.

3.6.1 Crime

As discussed in Section 3.5.3, one crime-modeling consideration is the benefit that the criminal gains from the crime. In Section 2.4.2, it was suggested that looting behavior occurs for many different reasons, and that looting is often carried out in conjunction with organizations. In addition to the economic benefits that are achieved (including self-consumption of food obtained through the crime), there must be a means through which the gains of the crime can be converted into economic benefits. Businesses, militias, and the government often provide the economic benefits for the criminal. Beyond the economic benefits of crime, there is also a need for self survival.

In modeling crime, a household may turn to criminal acts when it is unable to obtain enough food through the market or FDP, or when there are anomalies in the distribution of food. The second part of the condition is to address the observation that "if disaster exposure follows social or ethnic divides, then this increased cohesion may contribute to exacerbating between-group conflicts. If all are affected equally, on the other hand, the opposite may happen" [29]. Another rationale for this consideration is that, if all the neighbors are in the same state (i.e., no food), there is little that can be obtained by robbing the neighbors. Such an assumption is also consistent with the explanation of crime being an expression of alienation (Section 2.2.1).

Once a household turns to crime, it is assumed that it will consider crimes as an easy way to obtain food and hence, continue to commit them (reinforcing behavior proposed by Social Cognition Theory and discussed in Section 2.1.1). The household will continue to commit crimes until it is "re-integrated" as a law-abiding member through its arrest by the peacekeepers. Reintegration of criminals is a step towards stabilization of the town and improves the productivity of the town (since once reintegrated, the former criminal will start to produce food again).

3.6.2 Public Order

In the model, safe and secure environment is considered to be a region with absence of crimes (i.e., public order) because it is assumed that there are no other sources of violence (e.g., conflicting factions of power, militias, territorial securities). Thus, to return the region back to its stable state, the peacekeepers would need to eradicate the criminals and turn them back to being productive members of the society. This is needed to sustain the region because each household consumes one food unit and each productive household, i.e., households not involved in crime or are searching for food, produces one food unit towards sustaining the food supply within the region. Hence, the process of arresting and returning the criminals back into normal households contributes towards an important role of returning the region back to a self-sustaining state.

Monopoly of violence refers to the legitimate use of physical force within the area. Monopolizing violence means that no other party (i.e., criminals) may commit acts of violence without being prosecuted by the monopolizing party (i.e., peacekeepers). It is assumed that the peacekeepers seek to obtain monopoly over the means of violence and play the role in enforcing "law and order" by patrolling and arresting criminals. Patrols by peacekeepers are assumed to start off from an FDP and take on random paths within the operation area. Criminals shall be caught if they committed a crime within the effective arrest area of a peacekeeper. The effective arrest area is assumed to be the area in which a peacekeeper can respond fast enough to make an arrest.

The "re-integration process" is assumed to be effective and that criminals arrested would eventually be converted into normal members of the population, i.e., they would no longer be motivated to continue to commit crime as their preferred way to obtain food. They may become criminals again due to circumstances within the environment, however, as per the behavior of a normal household.

3.7 Economy

The price of food is an important consideration in the model and is used a mechanism to decouple the population's dependency on food aids. The price of food also serves as a way to distribute the local food supplies. For example, if instead of a free market economy, food supply is solely controlled and distributed free by the peacekeepers, there would not be a reason for the population to work, and the amount of food in the system would simply be the amount of food made available by the peacekeepers. Hence, by modeling price of food based on supply and demand and assuming food can be purchased easily, the model become less dependent on the peacekeepers for food. The following sections look at how economy is modeled:

3.7.1 Price Mechanism

In economics, the price mechanism serves three functions: signaling, rationing and incentive to producers [35]. The signaling function acts as an indicator for more suppliers to enter the market when price increases, and for more consumers to enter the market when price decreases. The rationing mechanism serves to allocate scarce resources to those who desire and can pay for it. Finally, the price mechanism acts as an incentive to producers to supply more goods when the demand for the goods is high.

The first two functions are modeled through the market mechanism (Section 3.7.2) via the supply and demand of food as a function of price. The model does not rely on the third function of price mechanism, which is to incentivize producers to supply more goods when prices increase. This is because it assumes that there are no other external venues in which to obtain more food (e.g., from nearby towns or cities), which is the basis for why HADR is required.

The change in price of food is based on the ratio between the difference of the supply and demand and the current supply. To provide an acceleration of the price, the lower of the demand and supply is used as the divisor. That is, if the demand is greater than supply, the new price will be calculated as:

$$price = price + \frac{(Demand - Supply)}{Supply}$$

If the supply is lower than the demand, the new price will be calculated as:

$$price = price + \frac{(Demand - Supply)}{Demand}$$

3.7.2 Market Mechanism

Supply and demand influence the price of food in the model, which in turn influences who can afford food. The supply and demand are also influenced by the initial condition of the town, i.e., how much initial food supply is available. If the town has zero food supply and is incapable of generating or trading for food, it essentially means that the peacekeepers would have to feed the whole population at the start, which is much more difficult compared to a town with some initial capabilities.

One desire for the system is to be capable of self-sustenance, i.e., if the appropriate amount of food aid is provided and the crime is under control, the town should return to its stable state and be able to self-generate enough food to meet its demand. Prices of the food should return to the normal level (i.e., an arbitrary \$1.00 was used as the price for each food unit, i.e., meal).

To allow for self-sustenance, the supply of food is organically generated by the town. It is assumed that each household that is not hungry is capable of generating one meal per day, which is equal to the minimum amount of food required for a household to not become hungry. If the household diverts effort away from producing food, however, the supply generated per day for the household should drop below one meal per day.

Demand for food is based on price. Households capable of affording at least one meal per day will buy one meal and households that are unable to afford at least one meal per day will buy as much as they can.

Thus, the demand of food is approximated as:

$$m + \frac{1}{2}(n - m)$$

where :

- n is the total number of households, and
- m is the number of households with income $>$ price of food

A triangle approximation of the residual demand for food is used, as at the boundary, i.e., the $m+1$ household, the amount of food that the household can afford should be approximate equal to one meal a day, which gradually reduces to zero meals per day for the poorest household.

3.8 Assumptions

The following is the list of assumptions for the model:

- The town is unable to trade or obtain food through external sources, i.e., the only external source of food is from the HADR. The rationale for this assumption is that if food is readily available from external sources, there will not be a need for HADR.

- The local authority is not doing anything to help the population. This assumption is based on the scenario description.
- The population comprises households of the high- or low-income group.
- Businesses are not explicitly modeled, but households are assumed to be able to buy food from businesses, which have perfect market information, and are assumed to sell food fairly based on price.
- Each household has a fixed income per day, which is the maximum amount that they can spend to purchase food. This difference in income disparity is assumed to have occurred due to differences in cultural or environmental factors.
- Each household consumes one meal per day; households that are unable to consume at least one meal per day suffer from hunger.
- Each household will buy food for one meal, or as much food as they can if they are unable even to afford at least one meal a day.
- Each household that is not suffering from hunger will contribute towards the production of food equivalent to one meal per day. The rationale is that people who are hungry may try to conserve energy or invest their energy in finding ways to obtain food.
- Households that suffer from hunger will try to obtain food from the nearest FDP that has food available.
- A household may attempt crime when it believes that it is unable to obtain enough food from the market and the FDP and that there are anomalies in the distribution of food (Section 3.6.1).
- Criminals continue to consume food, but do not contribute to the food supply as their effort is directed toward committing crimes (Section 2.3).
- Once a household turns to crime, it will continue to commit crimes until it is "re-integrated" as a law-abiding member of the society through its arrest by the peacekeepers.

3.9 Discussion

During the analysis of the scenario, several factors were found that could have influenced the model but may not be well understood. Considering that one of the aim of this thesis is to experiment with building model that provide high-level insights into how various factors in HADR affect the HADR operations, however, the author felt that, based on the various considerations listed in the chapter, the key desired characteristics of the model should be:

- Food pricing based on food supply and demand
- Food demand based on food pricing
- Food supply decreases as crime increases
- Crime rate dependent on discord of the population
- Should be self-sustaining when system is stabilized

The rationale for these characteristics is to have a stable town at the end of the scenario, which is the objective of the PK/HADR. That is, if the households are not diverted from doing productive work due to the lack of food, the town should be capable of generating enough food supply to meet its own demand for food.

In comparison with the Strategic Framework for Stabilization and Reconstruction [33], the desired characteristics of the model aim to achieve three of the end states: *Sustainable Economy*, *Safe and Secure Environment* and, to some extend, *Social Well-Being*. The end state for *Safe and Secure Environment* is achieved through the peacekeeping effort in Section 3.6.2 and driving down the need for people to commit crimes. The end state of *Social Well-Being*, i.e., the necessary condition of *Access to and Delivery of Basic Needs Services*, is addressed through the provision of humanitarian aid to drive down food prices, making them affordable to the majority of the households. The end state of *Sustainable Economy* is achieved when the town can largely self-sustain supply and demand for food (i.e., prices of food go back to normal).

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CHAPTER 4:
System Dynamics Model

As discussed in Chapter 4, SD is one of the approaches used in the studying of large-scale complex systems. Unlike ABM, SD models the system using a top-down approach that captures the high-level system characteristics rather than building "emergent behaviors" through the modeling of behaviors of individual agents. To develop the model for the PK/ HADR scenario, a high-level CLD was developed and then expanded to include stocks and flows. The following sections describe the SD model.

4.1 Conceptual Causal Loop Diagram

Based on the factors and decisions in Chapter 3, Figure 4.1 shows the conceptual CLD for the system:

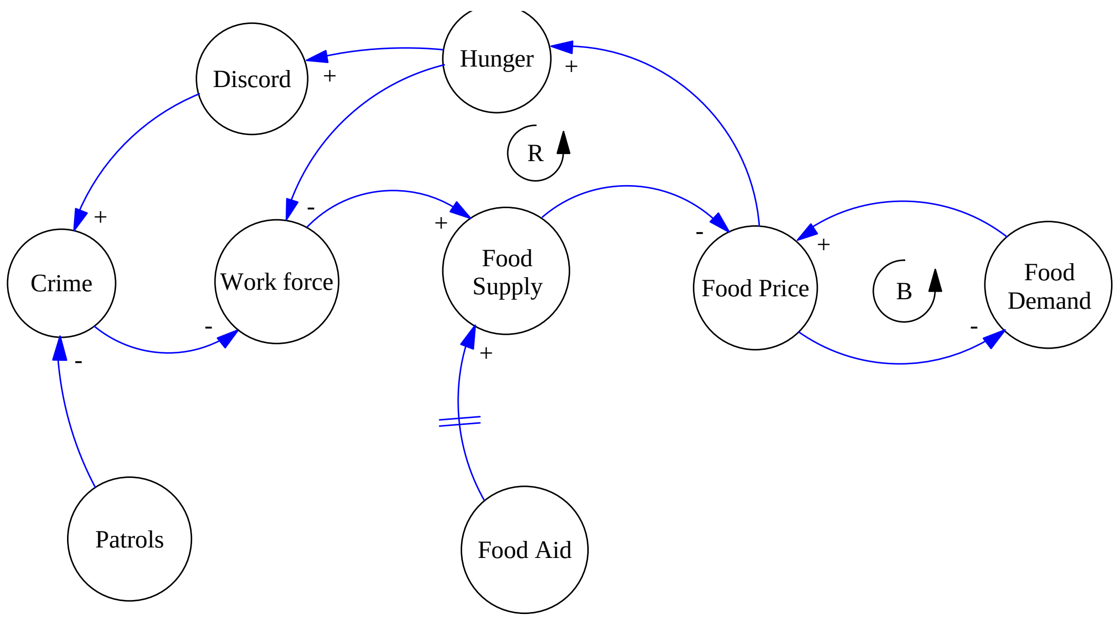

Figure 4.1: Conceptual Causal Loop Diagram

From the diagram, a balancing relationship exists between food price and food demand, and a reinforcing relationship exists between food price and food supply. That is, increasing the price of food would lead to a corresponding drop in food demand; increasing the price of food would also lead to fewer people being able to afford food, which causes more people to become hungry. There is no feedback loop between food price and food supply because the incentive component of the price mechanism is not used Section 3.7.1.

The most direct effect of the increase in hunger is that people who are hungry do not work. This leads to a decrease in workforce, which results in lower food supply/production. Thus, an increase in food price would lead to a decrease in food supply, which would further drive up prices of food.

A secondary effect resulting from the increase in the food price is that, due to the increase in the number of people who are hungry, there would be an increase in tension and discord within the population. That is, there would be a divide between those that can afford food and those that cannot. The discord or unhappiness caused by people who cannot afford food (which constitutes basic survival needs) would lead to an increase in crime. This leads to a decrease in the production of food supply as efforts are diverted into crime.

The number of patrols is a control variable that has a negative impact on the number of crimes, i.e., the more patrols there are, the less crime there should be. Likewise, the amount of food aid and the delay in food aid (denoted by the parallel lines on the arrow between *Food aid* and *Food supply*) are control variables that would affect the food supply.

4.2 Simplified Causal Loop Diagram

The simplified CLD shown in Figure 4.2 is the translation of the Conceptual CLD into stocks and flows but without detailed modeling of the various parameters. The model was built as a quick prototype towards looking at how the various factors interact with each other.

The stocks and flow rates in the simplified CLD are modeled with a value of 0 to 1 to represent the ratio of the quantity of stocks, instead of the actual units. For example, the value of one would represent the entire population for both food supply and demand. Other than units, the model also uses user-specified parameters instead of computing the actual rate of change. For example, to model the change in food demand due to an increase in food price, the model uses a *demand per dollar* parameter to estimate that change in demand with respect to price instead of computing the number of households that can no

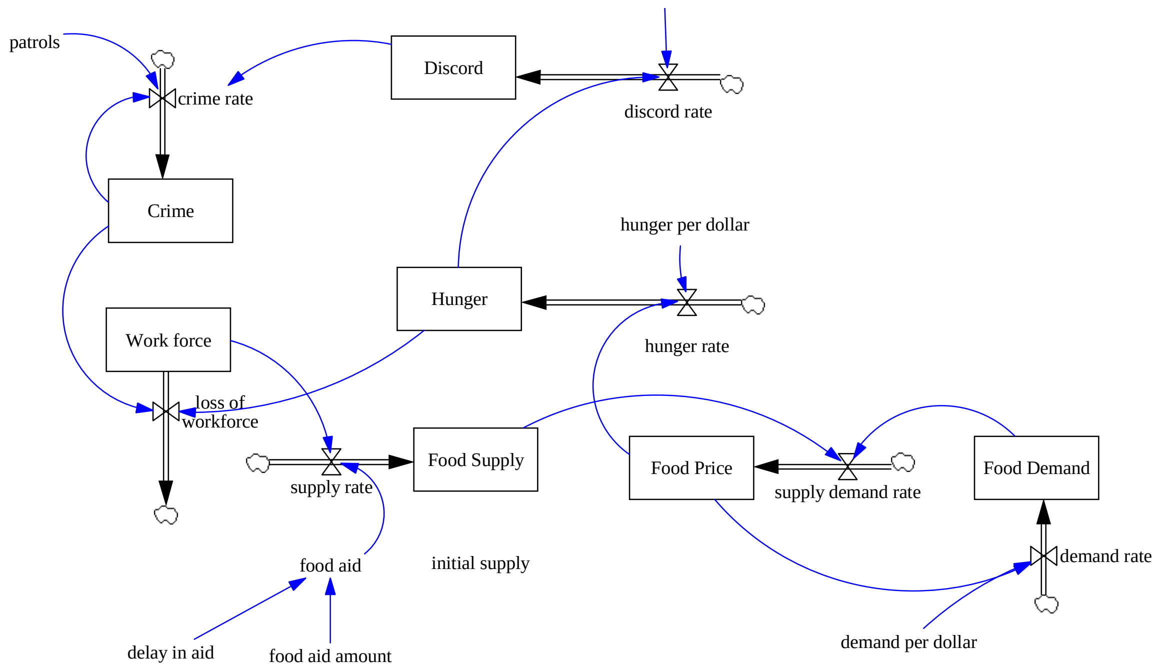

Figure 4.2: Simplified Level Causal Loop Diagram

longer afford to purchase food.

4.3 Causal Loop Diagram

The final CLD is an expanded version of the simplified CLD, which replaces the user-specified parameters that control flow rate based on the conceptual model described in Chapter 3. The following sections describe how those characteristics are implemented using SD. Appendix A. contains the equations for implementing the SD model in the following sections using Vensim: a software used for modeling SD models [36].

4.3.1 Parameters

Figure 4.3 shows the parameters for the CLD. The *area of ops* for the PK/HADR is assumed to be a circular area with *ops radius*, in which the operations are carried out. In the scenario described in Section 3.1, this would be the area of the town.

The *coverage per patrol* is the area within the radius of *response range*. This is the area in which a peacekeeper can respond in time to call for help in the event of a crime. For example, peacekeepers on foot may have a response range of 1/2 mile, whereas peacekeepers

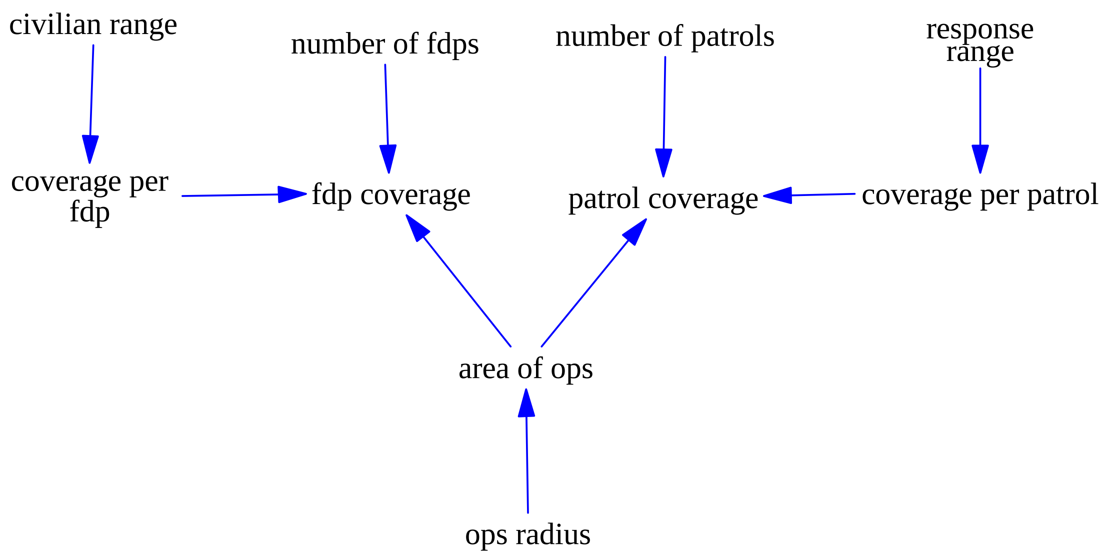

Figure 4.3: Parameters for System Dynamics

riding in a patrol car may have a response range of 2–3 miles. The patrol coverage is the percentage of *area of ops* that are covered, i.e.,

$$patrol\,coverage = \frac{number\,of\,patrols \times coverage\,per\,patrol}{area\,of\,ops}$$

The *civilian range* is the effective reach of the FDP, or the recommended maximum distance that a person should travel to a FDP for food. A distribution site within walking distance of 5 kilometers is recommended by the Norwegian Refugee Council [37]. The *fdp coverage* is the percentage of area within the *area of ops* that is covered by an FDP that is accessible to a civilian within *civilian range*, i.e.,

$$fdp\,coverage = \frac{civilian\,range \times number\,of\,fdp}{area\,of\,ops}$$

4.3.2 Social Groups

The model divides the society into a high- and a low-income group. The parameters *number of high income* and *number of low income* may be changed to reflect the number of households in the high-income and low-income group respectively.

As mentioned in Section 3.5.1, both household income groups will have a mean income and standard deviation of income that is $\frac{1}{2}$ of the mean income. The mean income of the high- and low-income group may be changed via the *high-income amount* and *low-income amount* parameter.

For simplicity, the distribution of household is approximated using a triangle distribution instead of a normal distribution. The distribution mean is the mean income of the income group, and the maximum income of the group is assumed to be twice the mean income. Assuming a standard distribution of 1/2 of the mean income, the percentage of households covered within one standard deviation based on the triangle distribution is 75% and 100% for two standard deviations (as compared to 68.27% and 95.45% for the normal distribution).

4.3.3 Markets

The main system dynamic for the system is the causal loop for the Food Market (Figure 4.4), which is affected by *Food Supply*, *Food Demand* and *Food Price*.

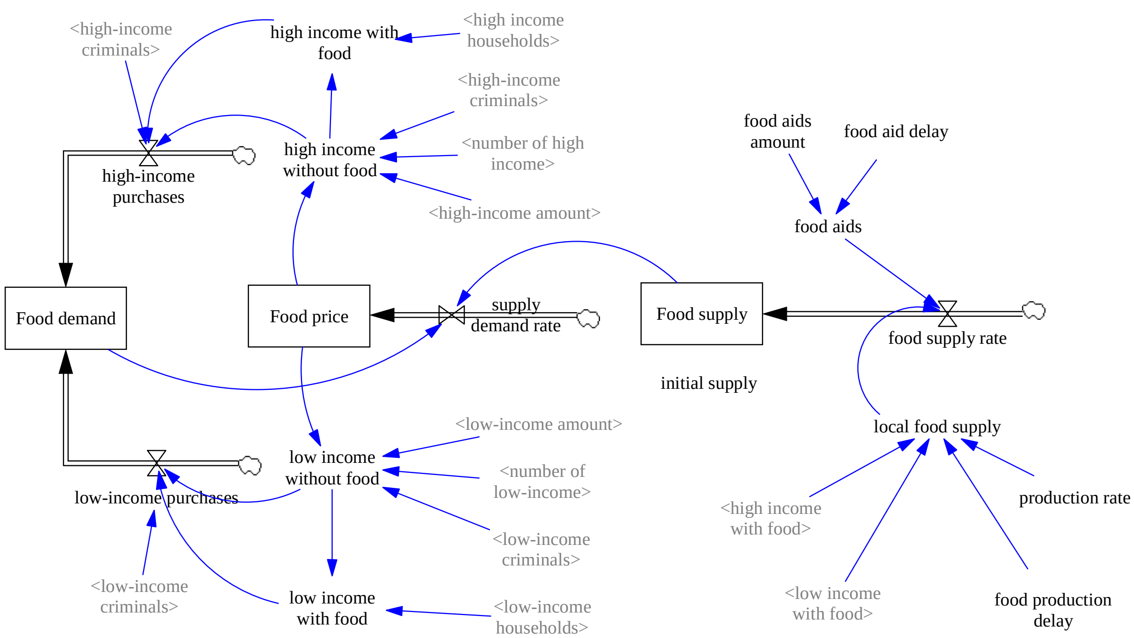

Figure 4.4: Causal Loop Diagram for Food Market (Supply, Demand and Price)

Food price is changed by the *supply demand rate*, which is determined by the difference between supply and demand (Section 3.7.1). To make the rate of change faster, the divisor for the *supply demand rate* uses the existing food supply when the demand is greater than supply and food demand when supply is greater than demand.

Food supply is determined by the number of households that have food, which is the sum of the *local food supply* and *food aids*. The *local food supply* is determined by the number of low-income households and high-income households that have food. The *production rate* determines the number of meals that each household produces each day.

Food demand is determined by the amount of food that households purchase, which is limited to one meal per day for households that can afford to purchase food at the current market price, and proportions of a meal for those that cannot afford at least one meal Market Mechanism (Section 3.7.2). Criminals are assumed to rob and obtain food from those that can afford food; hence they contribute towards food demand as if they can afford to purchase food (Figure 4.5).

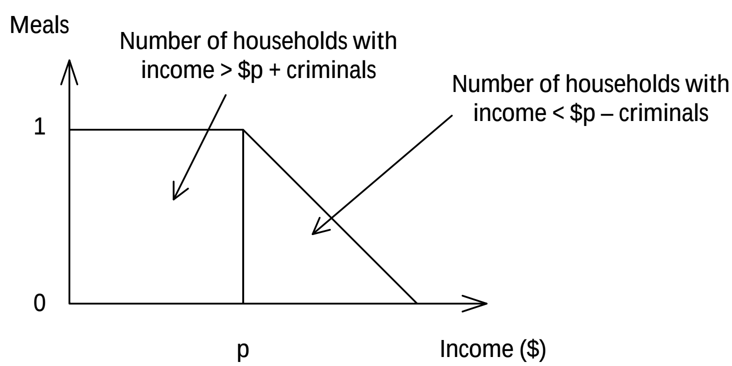

Figure 4.5: Approximation of Household Food Demand

Food aid is the (re-)supply rate in the number of meals per day that is supplied by the HADR. The availability of the food aid may be delayed by *food aid delay* days to mimic delay in the setup process.

The proportion of the households without food is estimated using the number of households with income lower than the price of food (p). When the *food price* is above the maximum income of the population (i.e., $2m$), the cost of food is too high for anyone in the population to afford food.

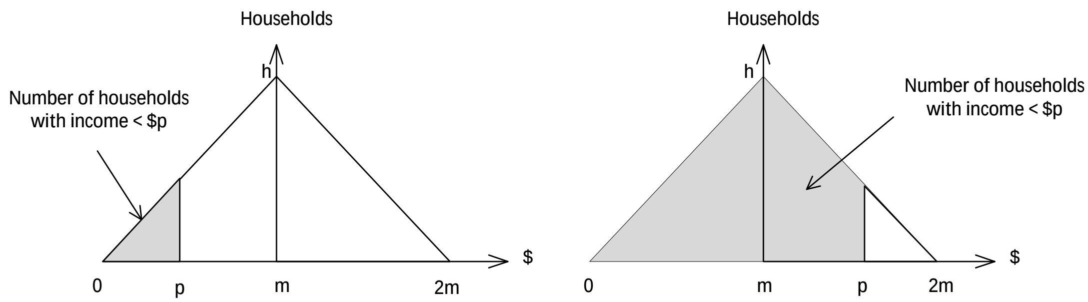

Figure 4.6: Approximation of Households With Income $<$ \$p (Left: \$p Less than Mean Income, Right: \$p More than Mean Income)

When the *food price* is below the mean income (m) of the income group, the number of households with income less than \$p is the area of the triangle shared gray (Figure 4.6.

The total area of the population is $2 \times \frac{1}{2} \times m \times h$. When the population is normalized to 1, the peak households is $h = \frac{1}{m}$.

If the price is less than the mean income, the number of households without food, w, (i.e., the area of the triangle) is:

$$y = \frac{p}{m} \times \frac{1}{m}$$

$$w = \frac{1}{2}(p \times y) = \frac{1}{2}(\frac{p}{m})^2$$

Likewise, if the price is above the mean income, the number of households without food, w, is:

$$y = \frac{2m - p}{2m - m} \times \frac{1}{m}$$

$$w = 1 - \frac{1}{2}((2m - p) \times y) = 1 - \frac{1}{2}(\frac{2m - p}{m})^2$$

The number of criminals is subtracted from the number of *households without food*, because a primary condition that leads to crime is often a household without food.

4.3.4 Crime

Crime is modeled as the transition of households into criminals (Figure 4.7). The *crime rate* is computed based on the *discord percentile* and *confidence in food aid*.

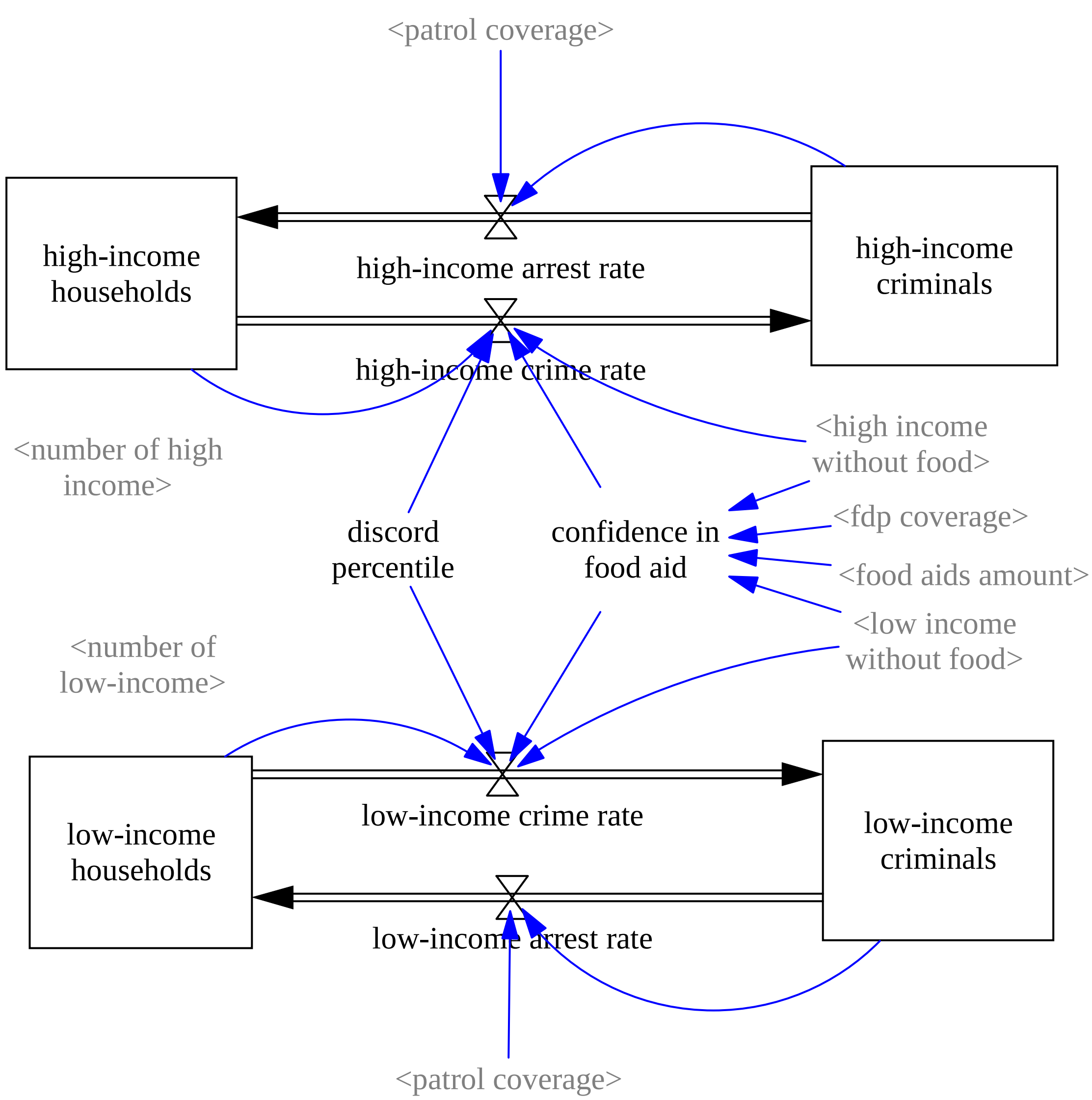

Figure 4.7: Causal Loop Diagram for Crime

The discord percentile (d) is set as the percentage of the lower k percentile of the population (N) that is among the population that do not have access to food. Discord is zero when there are fewer hungry households than the number of households that make up the k percentile of households. For example, if k is 0.1 (assume that k = 0.1 translates to 100 households) and that there are 200 households without food; the discord would be 100/200 or 0.5. Therefore, the discord percentile will be smaller when the population is more uniformly hungry and higher when only a small percentage of the population is hungry. The calculation for the percentage of households without food is explained in Section 4.3.3. Therefore, the discord percentile is simply:

$$d = \frac{k}{w}$$

The *confidence in food aid*, c, is the *amount of food aid* divided by the demand for food (which is assumed to be the total number of households without food). To consider the dispersion of FDP, the confidence in food aid may be multiplied by the *fdp coverage*.

The crime rate is affected by the confidence in food aid, and is the rate at which households within the discord group $(d \times N)$ turn to crime. Therefore, the number of households turning to crime is:

$$d \times c \times kN = \frac{k^2 cN}{w}$$

The arrest rate is modeled using the probability of arrest. Locations of crimes are assumed to be uniformly distributed, as are the patrols by the peacekeepers. Hence, the probability of arrest by the peacekeepers at any one time is the *patrol coverage*, which is determined by the *number of patrols* and the *coverage per patrol*. Since more criminals mean more likelihood of crimes being committed, the arrest rate for C criminals is:

$$C \times \frac{patrol\,coverage}{area\,of\,ops}$$

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CHAPTER 5:
Agent-Based Model

The ABM approach to modeling of the system is through the modeling of individual agents' behaviors. To build the ABM behaviors, experiences and insights from the SD model were expanded, and additional assumptions added. The ABM was built as both as time-stepped model using NetLogo, and as a DES using Simkit. The source code for the NetLogo version of the ABM can be found in Appendix B.

The following sections describe the ABM using Simkit, a Java package for development of DES models:

5.1 Software Architecture

Simkit provides software components that are useful for development of DES models. *Simkit* includes components such as the event list, statistical packages [38] and a "Simple movement and detection" (smd) package [39]. The *smd* package provides support for implementing *Mover* and *Sensor*, which are entities capable of movement, and the capability to detect entities entering or leaving within a certain range from the entity.

Figure 5.1 shows the class diagram for the ABM implementation using DES. The organization of the ABM consists of four Java packages: the main *agents* package, the *agents.ui* package, the *agents.bdi* package and the *bdi* package. The *agents* package contains the event graphs used for implementing the DES model for households, the peacekeepers, the food distribution points and the environment. The *agent.bdi* package consists of thirteen *intents* that are used for the implementation of the behavior model of the *household* agent. The *agents.ui* package consists of classes to support visualization of the model's behavior.

The implementation of the *Household* and *Peacekeeper* models uses movers and sensors from *Simkit* to provide the agent with situational awareness of its environment. Once a household is within the *Peacekeeper* response range, i.e., it gets detected by the sensor of the *Peacekeeper*, the peacekeeper will subscribe to the events of the *Household* agent. The *Peacekeeper* class also detects and stores presence information about nearby *Peacekeeper*

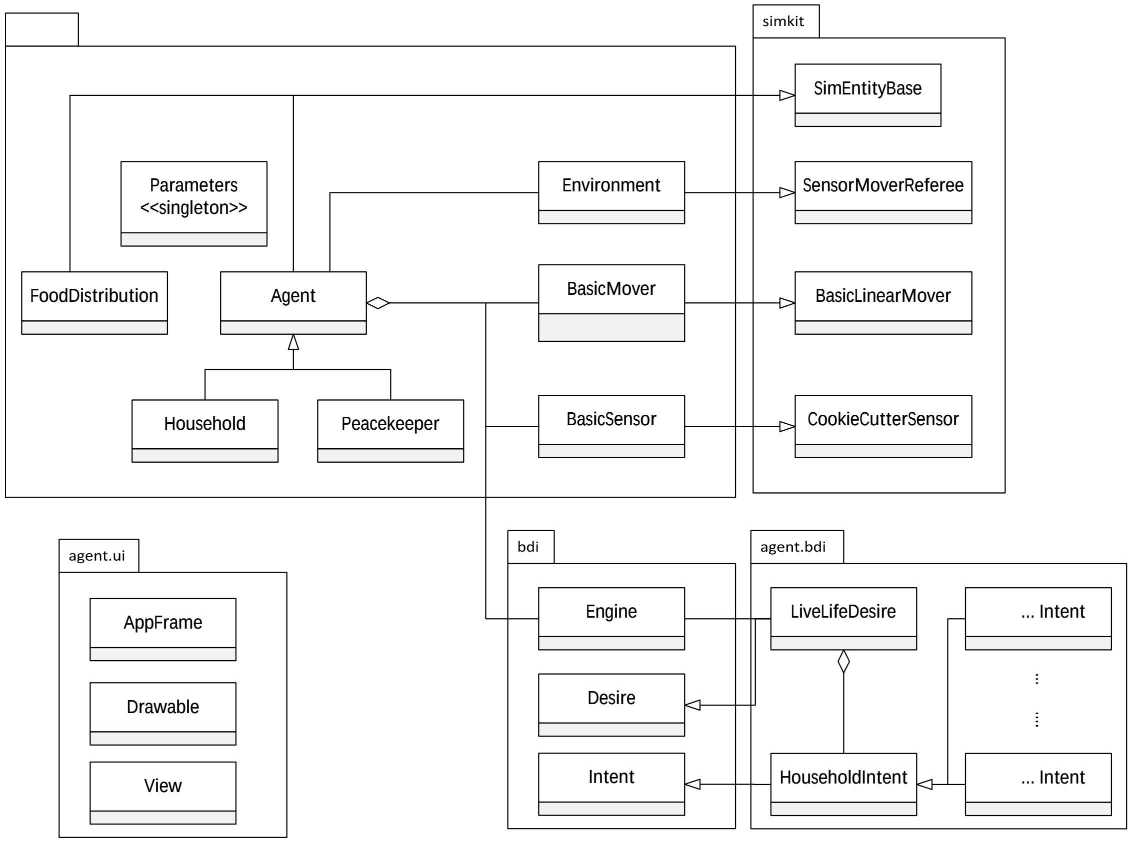

Figure 5.1: Class Diagram for ABM Implemented Using DES

agents for determining if it is the nearest peacekeeper when responding to a crime event. The sensor and mover models are sub-classed from the *BasicMover* and *CookieCutterSensor* classes from *Simkit*. The implementation of these classes may be modified to provide alternative movers or sensors' behavior.

Because of the need to subscribe and unsubscribe to events from other agents, the author chose to implement the agents by sub-classing *SimEntityBase*. The choice of encapsulating the *BasicMover* class inside the *Agent* class rather than subclassing from *simkit.smd.BasicMover* was because events from the *movers* are available only to the immediate object that subscribed to their event, i.e., the *Agent* class, and not to the listeners of the *Agent* class itself. This reduces the number of events that needs to be processed, since listeners of the *Agent* class will only receive events that are generated by the *Agent* class itself.

The *bdi* package provides the classes for the BDI engine, the abstract classes for implementing *Desire* and *Intent*. The BDI package does not currently provide support for rule inference, but rather provides the base structures for a stack-based approach to sequencing intentions based on the agent's desires. That is, desires are ranked in parallel with each other and the current intention in the top-ranked desire is selected for execution. This allows the BDI engine to implement conflicting desires and keep track of the progress of the execution plan within each desire. For the ABM implementation for the PK/HADR operation, the household's only desire is to "live life" because the author deems that the choice to commit crimes is more consistently characterized as a rational decision rather than a "desire."

Parameters for the model are centralized into a *Parameters* class in the main *agents* package. The *Parameters* class uses the SnakeYAML [40] for parsing of the configuration file using the YAML syntax (YAML Ain't Markup Language). The YAML syntax was chosen because it is more readable (human-friendly) compared to XML. The program is initialized with a set of defaults that may be written out to a file for modification by the user via the user interface.

Figure 5.2 shows the graphical user interface (GUI) of the application. Blue circles represent peacekeepers and their effective *response range*. Black circles are FDPs. Green circles represent households and the region that falls within their neighborhood. The green circles turn orange when a household is hungry and red when the household has turned into a criminal.

5.2 Event Graphs

In the DES implementation for the PK/HADR ABM, each agent is a descendant object of *SimEntityBase*. Event graphs are generated to model different entities within the model, such as peacekeepers, households, FDPs and the environment (i.e., markets). The event graphs for these components are described in the following sections:

5.2.1 Households

The implementation of the *Household* agent is based on the BDI architecture (Section 1.5). Hence, the event graph (Figure 5.3) of the *Household* agent is comprised of two key func-

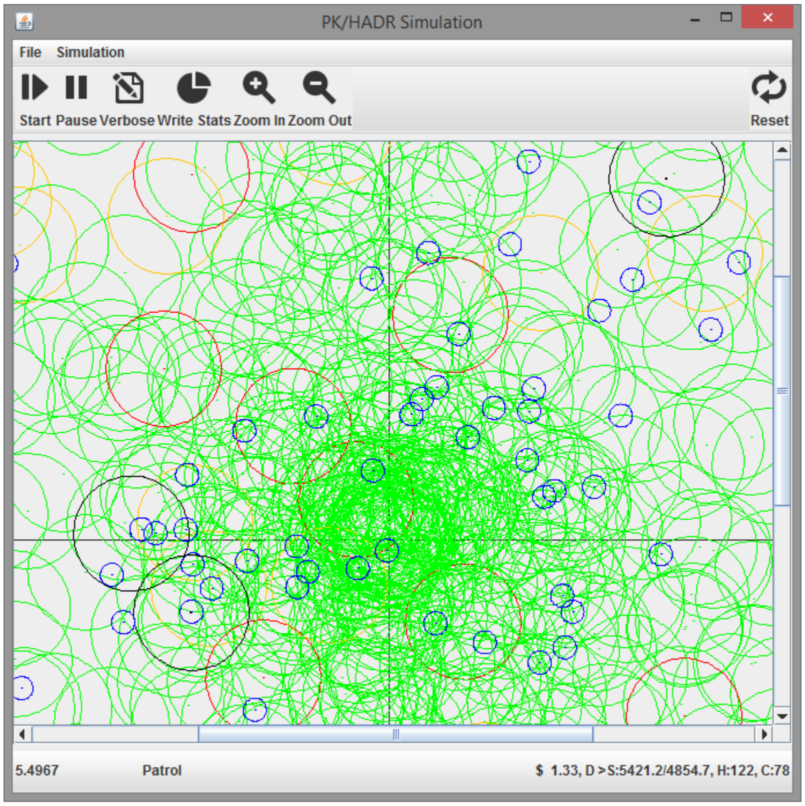

Figure 5.2: Screen Shot of ABM DES Implementation
Blue circles represent peacekeepers and their effective *response range*. Black circles are FDPs. Green circles represent households and the region that falls within their neighborhood. Green circles turn orange when a household is hungry and red when the household has turned into a criminal.

tion groups: events that serve to update the agent's environment state or affect the environment, and a *Think* event that triggers the BDI engine to process the events and its response according to its behavior rules. The behavior rules for the *Household* agent are described in Section 5.3.

The parameters and states of the *Household* agent are as follows (Table 5.1 and Table 5.2):

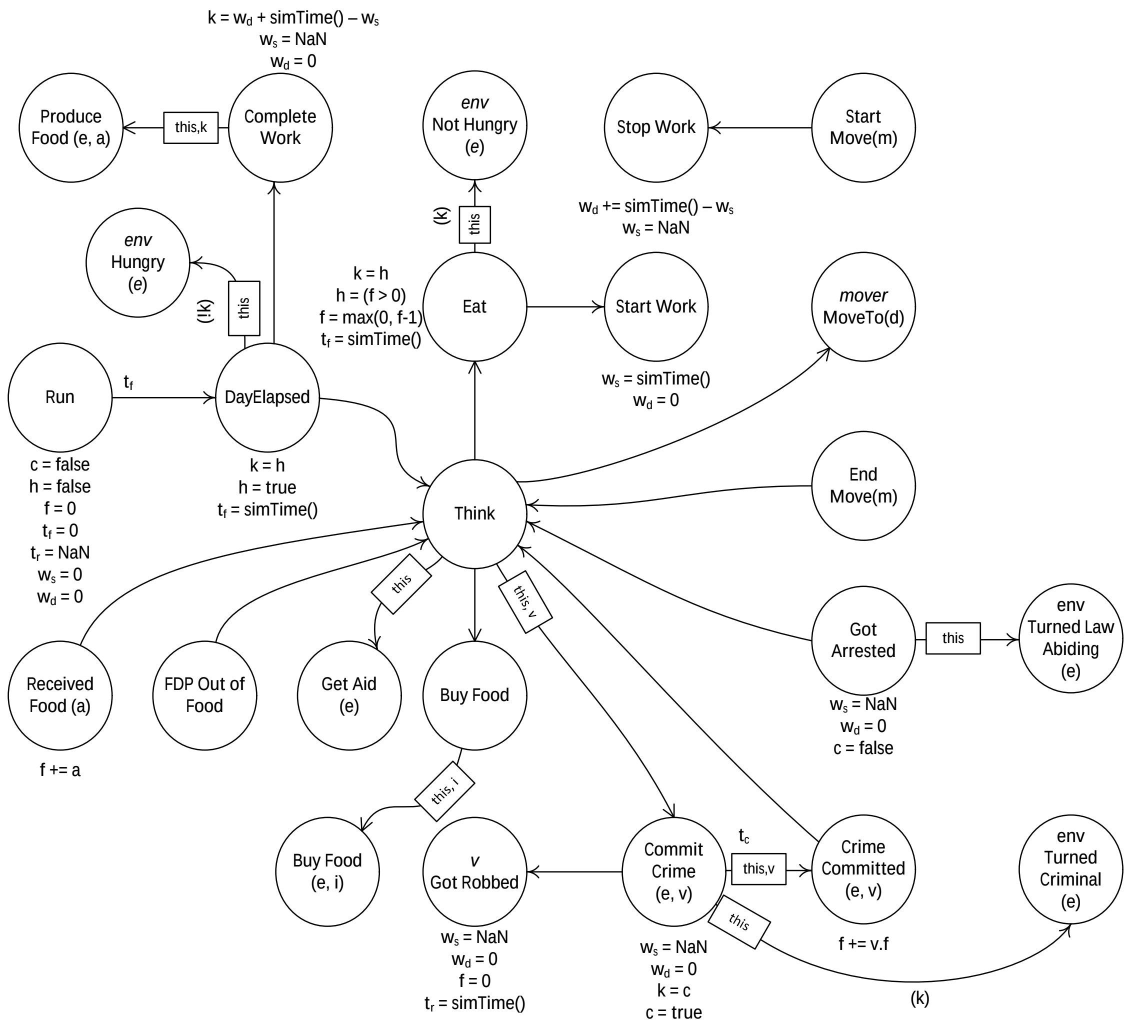

Figure 5.3: Event Graph for Household

5.2.2 Peacekeepers

Unlike the agents for *Household*, the agents for *Peacekeeper* have their behaviors implemented directly using event graph (Figure 5.4), rather than through the BDI engine. The core behavior for peacekeepers is to move constantly between their associated FDP (i.e., their "base") and random points within the operation area. During the process of patrolling, the *Peacekeeper* agents listen for the occurrence of crime events from *Household* agents; any crime committed within the response range of the *Peacekeeper* agent would trigger the *response to crime* event of the *Peacekeeper* agent, which will cause the *Peacekeeper* agent

Table 5.1: Parameters for Household

Parameters	Description
$\{t_f\}$	time between meals
Range	sensor range for neighbors
Speed	movement speed

Table 5.2: States for Household

State	Description	Default Value
c	is a criminal	false
h	is hungry	false
f	amount of food	0.0
w_s	time work started	0
w_d	amount of work done	0

to move towards the crime location. If the *Peacekeeper* agent reaches the crime location before the criminal has escaped, it "arrests" the criminal by scheduling a *GotArrested* event for the criminal agent, r_c , and removes the scheduled *CrimeCommitted* event from event list of the criminal agent. The *Peacekeeper* agent will return to its designated FDP upon completion of the arrest.

If instead, the criminal manages to get away from the crime location before the *Peacekeeper* agent arrives, the *CrimeCommitted* scheduled by the criminal would occur to signify that the crime was successfully committed. Hence, upon the occurrence of the *CrimeCommitted* event from the *Household* agent (i.e., the criminal), the *Peacekeeper* agent would remove the crime event from its task and initiate return to its designated FDP.

The parameters and states of the *Peacekeeper* agent are as follows (Table 5.3 and Table 5.4):

Table 5.3: Parameters for Peacekeeper

Parameters	Description
b	Base (FDP) for Peacekeeper
Range	response range
Speed	movement speed

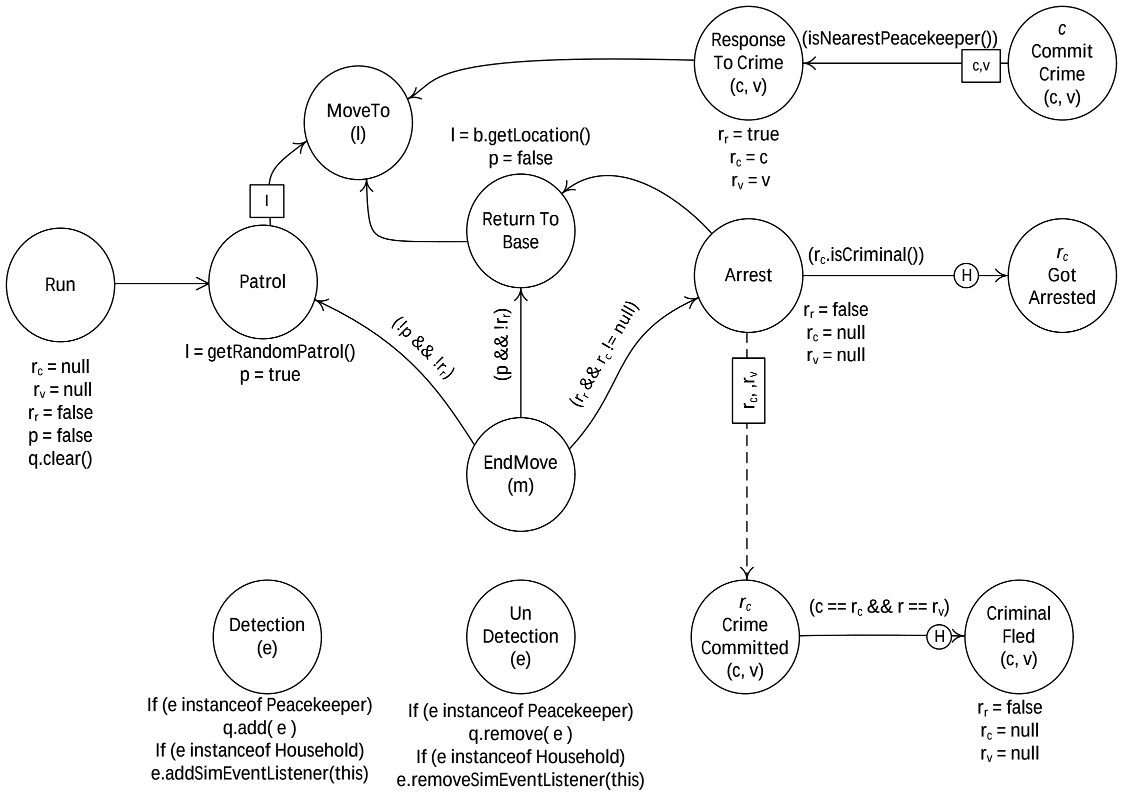

Figure 5.4: Event Graph for Peacekeeper

5.2.3 Food Distribution

The *Food Distribution* model models individual FDPs, each having a fixed location FDP within the operation area. All FDPs share a common initial setup delay specified by t_d , and have the same food distribution capacity given by f_a . Resupplies occur at fixed interval of every t_r days (which defaults to 1.0).

The event graph for the *Food Distribution* is shown in Figure 5.5. As shown in the event graph, the *Food Distribution* agent processes new food aid requests from households (i.e., scheduled by the *Get Aid* event) by placing these requests into a waiting queue, q , if there is sufficient food left to service a request. If there is insufficient food, the request will be rejected and a *FDP Out of Food* event will be scheduled to inform the requester, (e), of the outcome. For successful requests, the FDP will schedule a *Received Food* event to inform the requester (e) of the amount of food that was it was given (i.e., g).

Table 5.4: States for Peacekeeper

State	Description	Default Value
r_c	criminal involved in the crime event	null
r_v	victim involved in the crime event	null
r_r	is responding to a crime event	false
p	is patrolling	false
q	list of nearby peacekeepers	empty

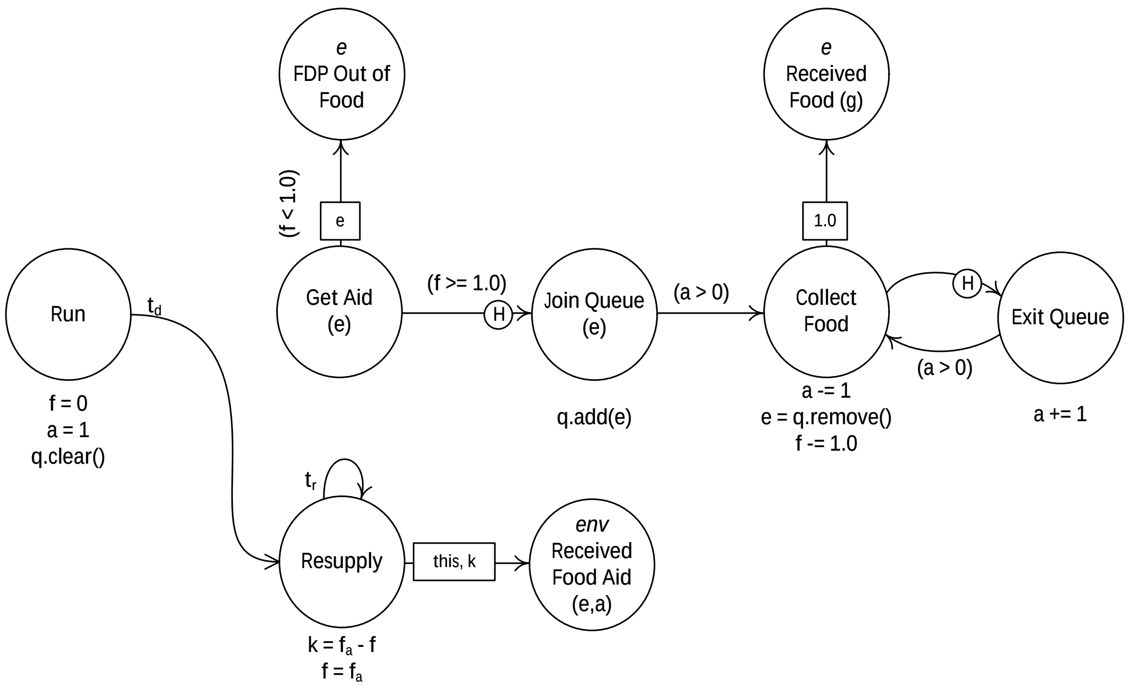

Figure 5.5: Event Graph for Food Distribution

The parameters and states of the *Food Distribution* agent are as follows (Table 5.5 and Table 5.6):

5.2.4 Environment

Unlike the *Household*, *Peacekeeper* and *Food Distribution* agents, there is only one *Environment* agent within the simulation, which serves as the food market. The event graph for the *Environment* agent is shown in Figure 5.6.

The *Environment* agent is responsible for tracking the price of food based on supply and

Table 5.5: Parameters for Food Distribution

Parameters	Description
f_a	amount of food aid at FDP
t_d	initial delay/setup time for FDP
t_r	time between resupplies

Table 5.6: States for Food Distribution

State	Description	Default Value
f	amount of food available	0.0
a	number of available servers at FDP	1
q	queue for households waiting for food	empty

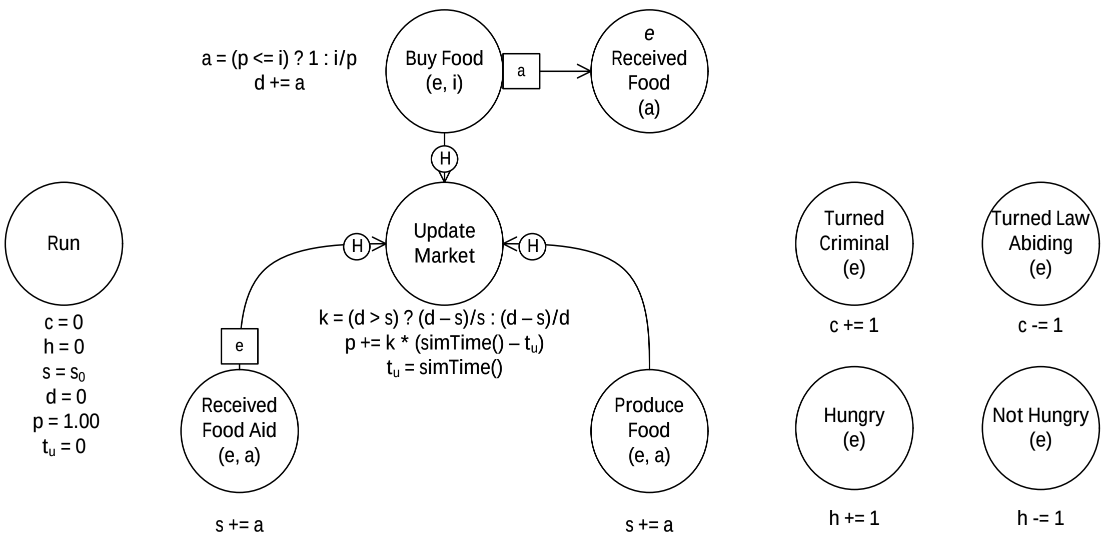

Figure 5.6: Event Graph for Environment

demand it receives from the agents. Whenever a household produces food, the *Household* agent schedules a *Produce Food* event with the *Environment* agent to inform the *Environment* agent of the amount of food that was produced. This amount of food will be considered to have become part of the supply of food available in the market. Likewise, when an FDP receives food (i.e., as part of its resupply), the FDP shall also schedule a *Food Aid Received* event to update the *Environment* agent of the increase in supply of food.

The *Environment* agent is also responsible for the sales of food. A *Household* agent that wishes to buy food places their requests through the *Buy Food* event. To which, the *Environment* agent will respond by scheduling the *Received Food* event of the *Household* agent with the amount of food that it has successfully purchased based on its household income.

The *Environment* agent also serves as the referee for determining interactions (i.e., Simkit's *EnterRange* and *ExitRange* events) between moving agents in the operation area.

The parameters and states of the *Environment* agent are as follows (Table 5.7 and Table 5.8):

Table 5.7: Parameters for Environment

Parameters	Description
f_a	amount of food aid at FDP
t_d	initial delay/setup time for FDP
t_r	time between resupplies

Table 5.8: States for Environment

State	Description	Default Value
s	food supply	s_0
d	food demand	0.0
p	price of food	1.0
t_u	time market was updated	0.0

5.2.5 Interfaces between Event Graphs

The interfaces between the various event graphs are shown in Figure 5.7. As mentioned in Section 5.2.1 and Section 5.2.2, the *Household* and *Peacekeeper* agent uses the Simple Movement and Detection classes of *Simkit* to dynamically change the event sources that it listens to.

Peacekeeper agents listen for the *Commit Crime* and *Crime Committed* events from *Household* agents, which signify their intention to commit crimes and the successful completion of a criminal act, respectively. *Household* agents listen for *Got Arrested* events, which signifies an unsuccessful criminal act.

Request for food is triggered by *Get Aid* event that is scheduled by *Household* agents with the *Food Distribution* agents. The *Food Distribution* agents respond to *Get Aid* by scheduling the *Received Food* or *FDP Out of Food* of the requesting *Household* agent.

Request to buy food is triggered by *Buy Food* event that is scheduled by *Household* agents with the *Environment* agent. The *Evironment* agent responds by scheduling a *Received Food* event with the amount of food for the *Household* agent that made the request.

Statistical data are collected by the *Environment* through the various events that occur to signify that there is a change in supply (i.e., *Produce Food*), there is a change in demand (i.e., *Buy Food*), that a household has turned to crime (i.e., *Turned Criminal*), or the conversion of a criminal back to a law abiding member of the population through arrest by the peacekeeper (i.e., *Turned Law Abiding*).

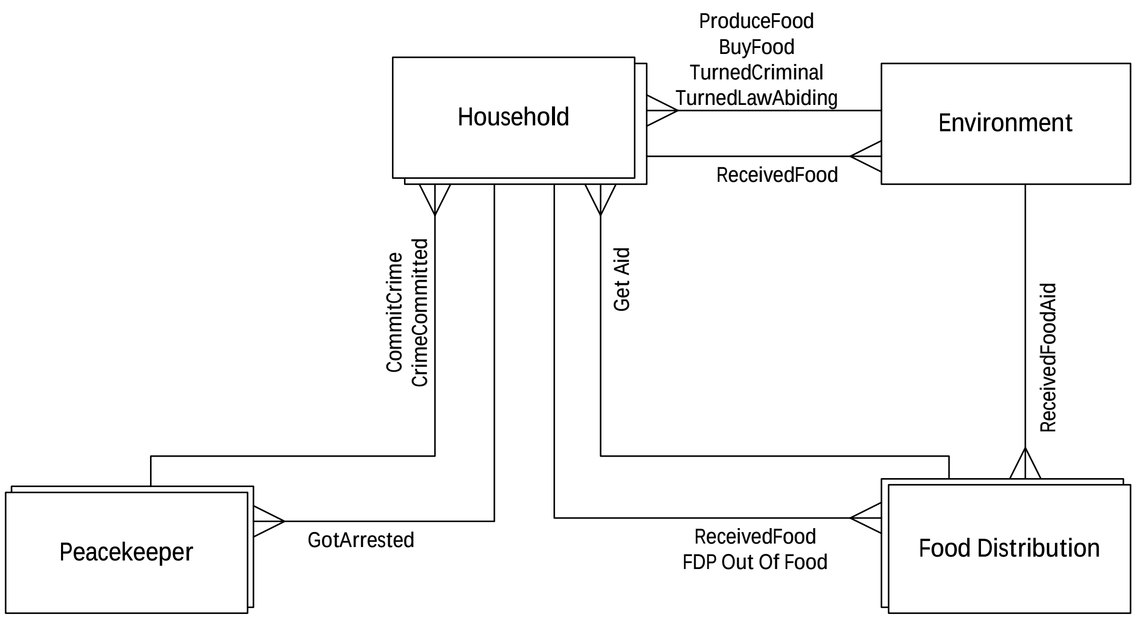

Figure 5.7: Interfaces Between Event Graphs

5.3 Behavior for Household Agents

The BDI intentions for *Household* agents are summarized in Table 5.9. The first column of the table (*Intent*) lists the intention for the *Live Life* desire. The second column (*Condition*) provides the necessary condition for the intent to remain active, i.e., once the necessary condition is not met, the intent is removed from the intention stack of the desire. The third column (*Sub-intents*) lists the sub-intentions that are created (i.e., pushed into the intention stack) when the intent is executed. The fourth column (*Schedules*) lists the DES events that get scheduled during the execution of the intent. Finally, the fifth column lists the triggering event, which will cause the next sub-intention to be executed.

As an example, the *Ask For Aid* intent will push three sub-intentions onto the intention stack (i.e., the *Move to FDP*, *Get Aid* and *Return Home* intents) and schedule a *Move To* event for the *mover* component to initiate a move to the location of the FDP. Upon reaching the FDP, the *mover* component of the *Household* agent will schedule a *End Move* event, which will trigger the next intention (i.e., *Get Aid*) to be executed. The *Get Aid* intent schedules a *Get Aid* event with the FDP, which the FDP will respond to by scheduling either a *FDP Out of Food* or *Received Food* event to the *Household* agent. Upon receiving either of these events, the next intention on the stack, which is the *Return Home* intent, is executed. *Return Home* will in turn push a *Move To* intent onto the intention stack, which schedules the *mover* component to move back to the "home" location of the *Household* agent. The *Move To Home* intent ends when it receives the *End Move* event from the *mover* component. With the completion of the *Move To Home* intent, the *Ask For Aid* intent completes and control returns to the intent that scheduled it, which is *Obtain Food*. Since the *Ask For Aid* intent is the last intent for *Obtain Food*, the top of the intention stack will now contain the next intent from the parent intent of *Obtain Food* (i.e., the *Consider Crime* intent pushed onto the intention stack by the *Find Food* intent).

Table 5.9: Summary of Intents for the *Household* Agent

Intent	Condition	Sub-intents	Schedules	Triggering Event
Live Life	none	Eat	Day Elapsed	Day Elapsed
Eat	is hungry	Find Food Eat Meal		
Find Food	no food	Obtain Food Consider Crime		
Obtain Food	not criminal and no food	Buy Food Ask For Aid		 Received Food
Consider Crime	no food and (hungrier than neighbors or is a criminal)	Rob Somebody		
Buy Food	no food		Buy Food	
Ask For Aid	no food	Move to FDP Get Aid Return Home	Move To	 End Move Receive Food or No Food at FDP
Rob Somebody	no food	Move to victim Commit Crime Return Home	Move To	 End Move Crime Committed or Got Arrested
Move to FDP	not at FDP			
Get Aid	no food		Get Aid	
Return Home	not at home	Move to Home	Move To	End Move
Commit Crime	true		Commit Crime	
Move to Home	not at home			
Eat Meal	is hungry		Eat	

5.4 Differences between ABM and SDM

The implementation for the ABM is fairly similar to the SD model, and shares the same underlying logic. The similarity could be due to the fact that the author had implemented the SD model before the ABM instead of approaching the development of the model from the start. The key difference is that instead of directly using equations to update the various quantities of the system, they are updated based on "action" by the agent, i.e., a change in supply and demand of food is triggered when an individual agent produces food or buys food from the market.

A greater level of detail has also been added to the ABM. For example, in the SD model, a household that is producing food does not take into consideration the time it takes to search for the food. In the ABM, the household does not perform productive work when it is searching for food (i.e., when it is traveling). Hence, the location of the FDP can have an impact on the organic food supply rate.

In terms of crime, the SD modeled the portion of the population that resorted to crime but did not model the process of how crimes are conducted (e.g., there is no specific target). Likewise, there are differences between how the SD and ABM models model the patrols by the peacekeepers. In the SD model, the probability of arrest is based on the coverage of the peacekeepers, whereas in the ABM model, the process of randomly patrolling around the environment is modeled as entities capable of moving and sensing the environment for the occurrence of crime.

The ABM assumes that a household will attempt to rob the household within its neighborhood with the highest income that has not been robbed within the last day. The amount of food that is obtained by a criminal is the amount of remaining food that the victim has, plus the amount of food that is produced by the victim prior to being robbed. The ABM also assumes that criminals will continue robbing until they have enough food to eat, or when there are no other candidates to rob. Victims of robbery will also stop producing food for a day as a result of lost productivity. The SD model assumes that all criminals will successfully obtain one meal of food and does not model the loss of productivity of the victim.

The ABM uses local awareness of its neighbors obtained through its *sensor* component for computing the discord model (i.e., the neighborhood of the agent comprises all the households that are within the sensor range of the agent). The discord model in the ABM is computed using the standard deviation and mean mealtime with the neighbors. If the agent's last meal is older than one standard deviation from the mean mealtime of its neighbors, it considers itself to be an alienated member of the society. The SD model models the alienation by assuming that a fixed lower percentile of the population belongs to the alienated group.

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CHAPTER 6:
Conversion of SD to DES

SD models the system using stocks and flows that are generally continuous. DES, on the other hand, models the system using state variables that change in response to events that occur within processes in the system. While it might be possible to model continuous quantity in DES (e.g., the location of the *Mover* component in *Simkit*) by solving systems of equations for interdependent variables, this approach is difficult and may not be feasible when the number of interdependent variables or the order of the equations is high. The following sections look at a more general approach to implement a SD model using DES and applies it to Lanchester's Equation as a proof-of-concept and subsequently to the SD model described in Chapter 4.

6.1 General Approach

To implement an SD model using DES, the general approach would be to identify events that change the stocks or flows and to use these events to signal either the actual change in quantity of the stocks or the flow rates. The identification of these key events is akin to identifying the key control points of the model, i.e., what are the key factors that would influence the model and what causes these factors to change. Once these events are identified, the rate of change (i.e., the occurrence of the events to trigger changes to the stocks or flow) may be calculated based on the SD equations or approximate usually modelled using the exponential distribution with mean of $\frac{1}{rate}$. The exponential distribution is used due to the time-invariant characteristic of the exponential distribution, i.e.,

$$Pr(T > s+t|T > s) = Pr(T > t), \forall s,t > 0$$

A conceptually similar approach has been described in Borshchev and Filippov's paper (Figure 6.1) as a general scheme for conversion from SD to ABM [15], with the difference being that the an agent in Borshchev and Filippov's approach probably represents one SD model.

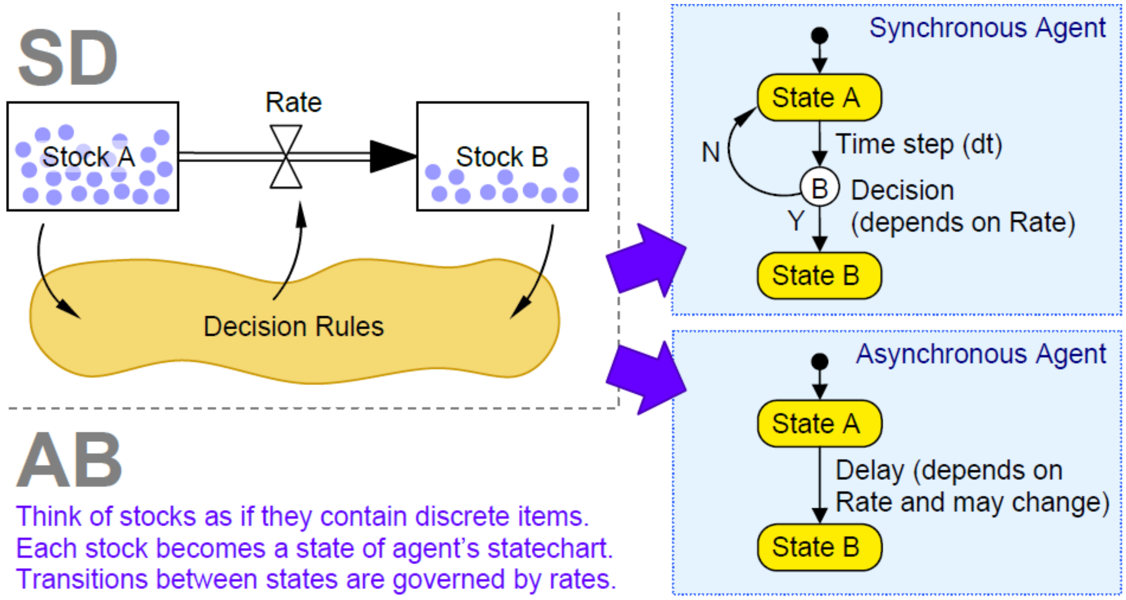

Figure 6.1: Re-Conceptualizing a System Dynamics Model into Agent Based Model. General Scheme (from [15])

6.2 Modeling Lanchester's Square Law Using SD, DES, and ABM

To test out the general approach described in Section 6.1 and to compare the differences between SD, DES and ABM, the author chose to implement Lanchester's Square Law (Aimed Fire), firstly using SD, and then converting the SD model into DES, and finally, as an ABM. Lanchester's Square Law was chosen as it is a fairly simple and well understood differential equation-based model, which allows for easier comparison and analysis.

The parameters for Lanchester's Equations described in the following sections are:

$$x = 1000$$

$$y = 1000$$

$$a = 0.2$$

$$b = 0.1$$

$$\frac{dx}{dt} = -by$$
$$\frac{dy}{dt} = -ax$$

6.2.1 Lanchester's Equation as SD model

Lanchester's Equations implemented as a CLD are shown in Figure 6.2. In implementing Lanchester's Equations as an SD model, the number of entities, i.e., x and y, are modeled as stocks within the SD model and the attrition rate, i.e., a and b, are used as the flow rate for the stocks. The SD model implements Lanchester's Equation exactly as described in the equations in Section 6.2.

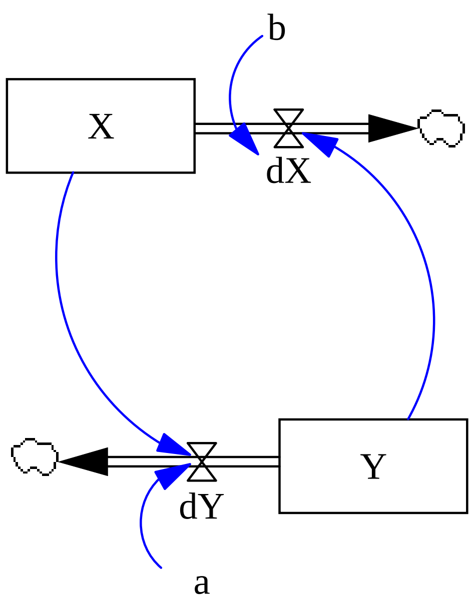

Figure 6.2: Lanchester's Law (Aimed Fire) as Stocks and Flows

6.2.2 Lanchester's Equation Implemented Using DES

The event graph of the DES implementation of the CLD is shown in Figure 6.3. To convert the SD into DES, events which would lead to a change in the flow rate (i.e., the death of either x's or y's entity) are identified. The occurrence of the event is based on the attrition rate, which is $\frac{1}{ax}$ or $\frac{1}{by}$. The death of an entity from either side changes the attrition rate, which changes when the death of the next entity is scheduled to occur.

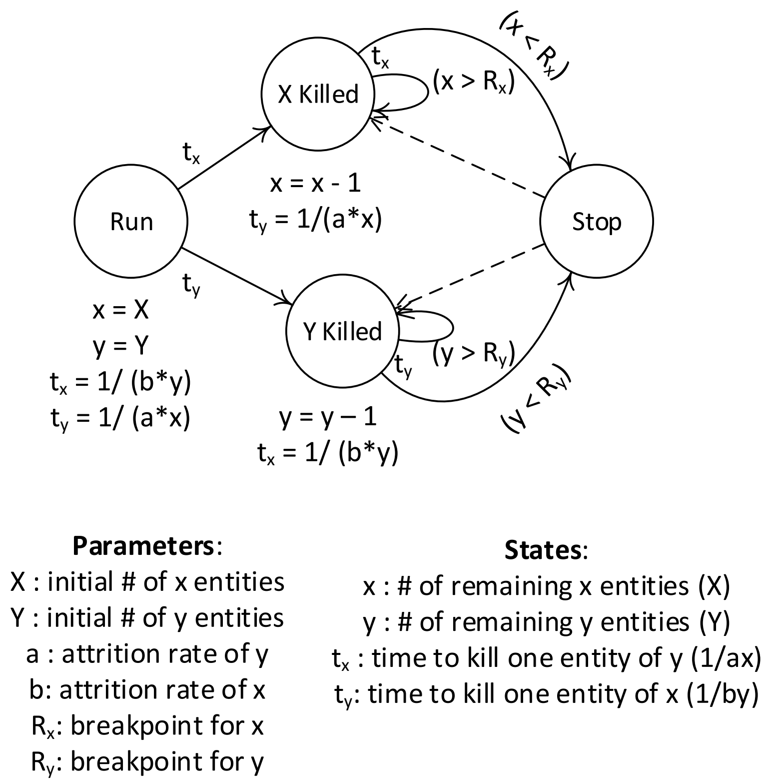

Figure 6.3: Lanchester's Law (Aimed Fire) Implemented as DES Using SD

6.2.3 Lanchester's Equation Implemented Using ABM

The event graph of the ABM implementation is shown in Figure 6.4. The underlying principle in Lanchester's Law for aim-fire is that each entity engages a designated target from the opponent. It is assumed that the agents have perfect coordination, and if both sides are equal in numbers, each entity will be aiming at a unique entity from the other side rather than having entities randomly pick their targets. To implement this principle, a target allocation model was implemented that assigns a target from the opposing side to an agent based on a round robin approach. The time to successfully kill an entity is given by $\{t_s\} \sim Exp(\frac{1}{r})$, where r is the attrition rate (i.e., a or b in Lanchester's Equation). When an agent is killed, it will notify all agents who have it as their target to reselect a new target.

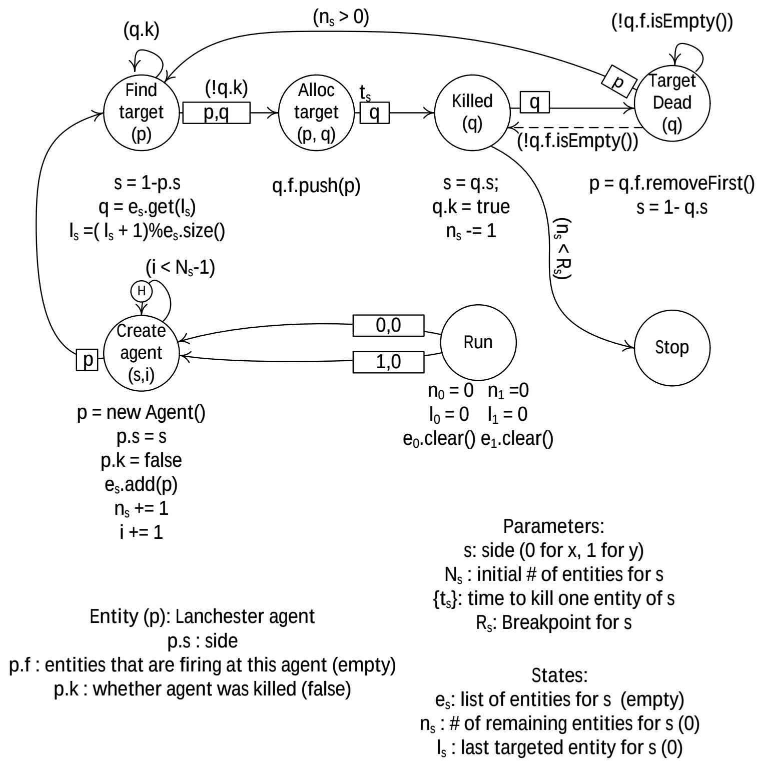

Figure 6.4: Lanchester's Law (Aimed Fire) Implemented as DES Using ABM

6.2.4 Discussion

The outputs of the three different implementation approaches are shown in Figure 6.5, Figure 6.6 and Figure 6.7. From the graph, it can be seen that outputs from the DES implementation are very similar to the SD model. In contrast, even though the output from the ABM model approximates that of the SD model, it is noticeably different from the SD. The difference in the ABM model could be due to the assumptions that were in place, i.e., the target model and the discretization that takes place. The author also observed that the attrition rate is deterministic; the number of entities left after the first salvo exchange would be a large discrete drop rather than a gradual decrease.

6.3 Implement the PK/HADR SD Model Using DES

Following the successful conversion of Lanchester's equation into a DES, the method was applied to implement the SD model described in Chapter 4 using DES. The event graph for the DES implementation is shown in Figure 6.8.

The first step towards the conversion process is to determine what to discretize. The author chose to discretize the *change in the number of households able to afford food* when a change in price occurs. This event was chosen because it impacts the number of hungry households that in turn affects the supply (which also affects food prices) and the crime rate. Consider that, if instead of change in the number of households without food, the food supply was chosen. To discretize the food supply, the events that would lead to a change in one unit of food supply would need to be identified. In the model, the event leading to this change would be when households turn to crime, or become hungry, which leads the household to stop producing food. Hence, this traces back to the basis of when the household becomes unable to obtain food.

Following the SD model, price is modeled as a continuous quantity that changes based on the difference between demand and supply. To implement this, the price at time t is $p = p_t + p_d \times (t - t_u)$, where p_t is the price when the market was last updated, p_d is the rate of change in price based on the last known supply and demand, and t_u is the time that the market was last updated. Likewise, the quantity of supply and demand is computed using a similar method.

Using the price, the DES implementation computes the time it takes for the price to reach the next threshold, i.e., t_h , when the next change in the number of households that will not be able to afford food occurs. The current number of households that are unable to afford to buy one unit of food based on the current price is computed, and the next price that would lead to either increase or decrease in one household is then computed. As illustrated in Figure 6.9, the new food price is the price at which the area under the triangle (i.e., number of households) increases by 1. The derivation of how to compute the number of households without food is given in Section 4.3.3.

The difference between the new price and the current price is divided by the rate of change in price to determine when the next change in the number of households without food will occur, i.e., the *Update Households* event.

To model delay in CLD (i.e., the delay in supply in Figure 6.8), the new supply is not applied directly, but is scheduled to change in an event that occurs after the time elapse (i.e., *Delayed Supply* event).

The implementation of crime is similar to those in the SD model, with the occurrence of the next crime being scheduled using an exponential distribution based on the current computed criminal conversion rate. The criminal conversion rate is computed using the equation of the SD model (Section 3.6.1). The occurrence of the *Commit Crime* event signifies that there is an increase in crime. Since the probability of arrest increases when there is an increase in the number of crimes, a new arrest rate is computed using the same computation from the SD model, and used to schedule the time when a criminal would get arrested based on the exponential distribution.

Any changes that will lead to changes in the Household population would cause the *Update Households* event to be scheduled. The scheduling of a new *Update Households* would also mean that any existing *Update Households* events should be canceled and replaced by the new *Update Households* event (since their impact did not occur before the new changes took effect).

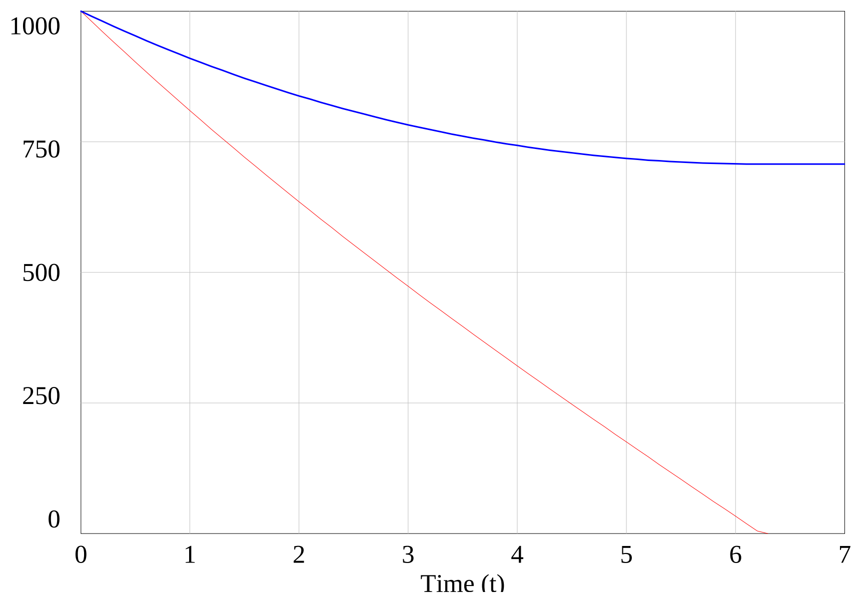

Figure 6.5: Lanchester's Law (Aimed Fire) Output from SD

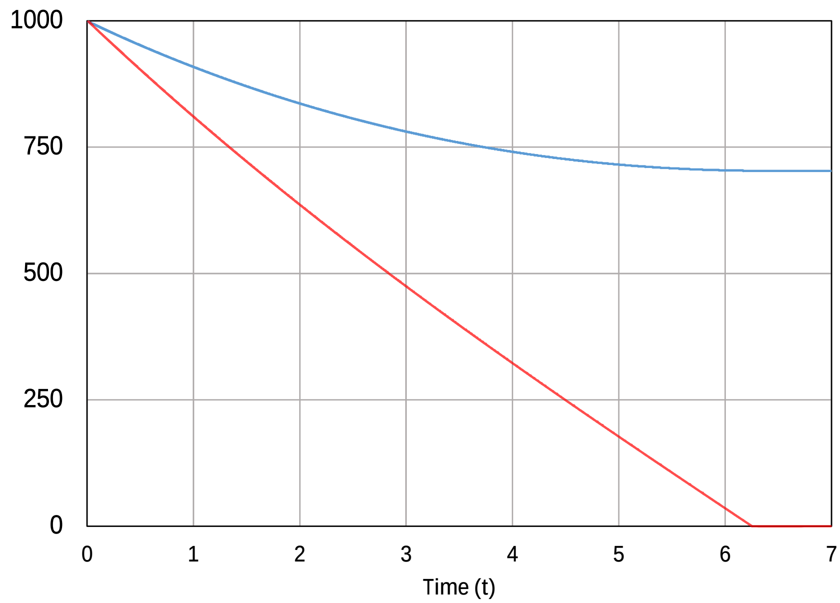

Figure 6.6: Lanchester's Law (Aimed Fire) Output from SD Implemented using DES

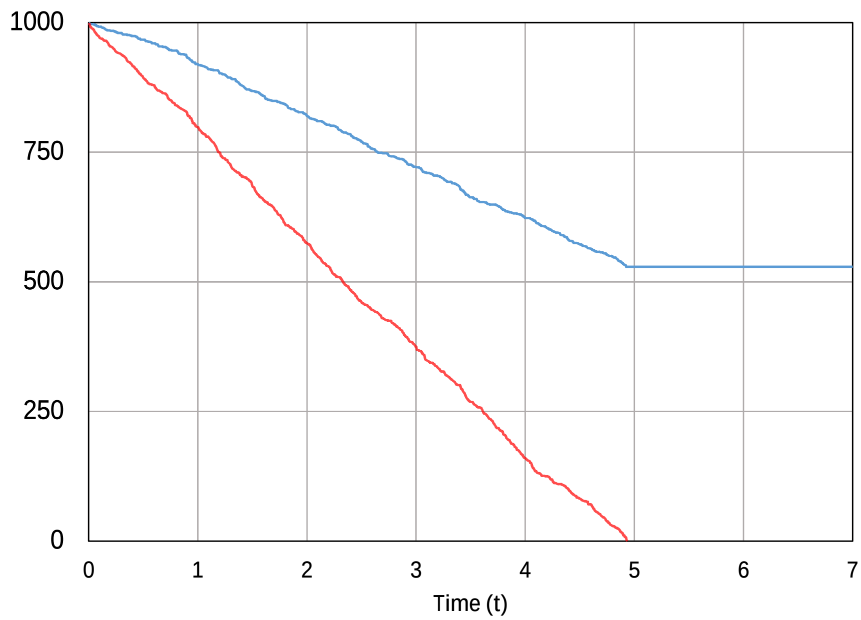

Figure 6.7: Lanchester's Law (Aimed Fire) Output from ABM

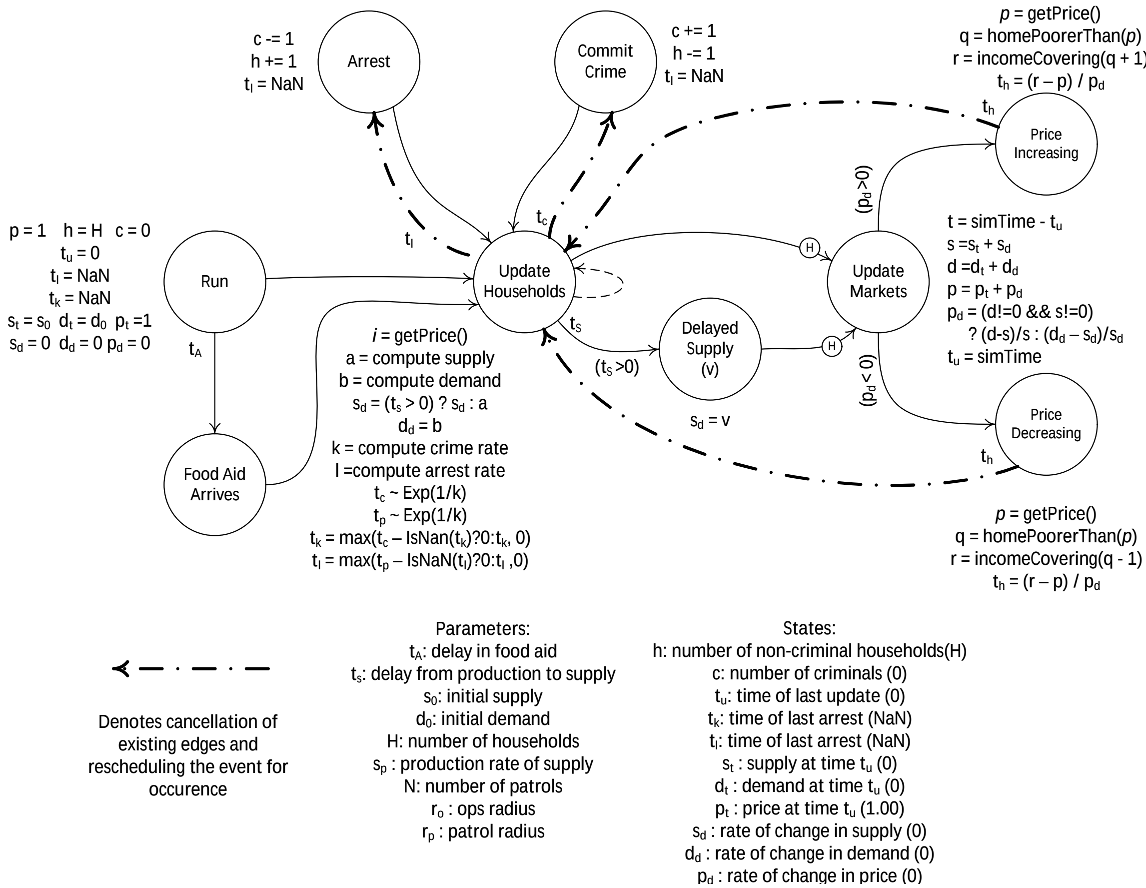

Figure 6.8: PK/HADR SD Model Implemented Using DES

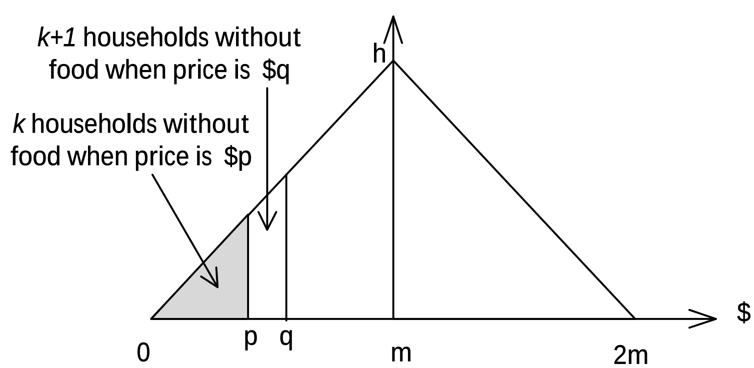

Figure 6.9: Price of Food at Which Next Household is Affected

CHAPTER 7:
Results

In Section 1.9, the author defined the following research questions:

- Can we model the desired behavior directly using system dynamics instead of agent-based modeling?
- Can we take a simple causal loop diagram and build a discrete event simulation out of it?
- How does this compare to the agent-based model for the same problem?

Chapter 6 attempts to answer the second research question by providing a general approach towards conversion of the SD model into a DES model. The approach has been applied successfully to model Lanchester's Equation. In the following sections, the output of the DES implementation of the SD model for the PK/HADR shall be compared to the Vensim SD model using a few test cases to check for differences.

To investigate the first and third questions, the model for a fictitious PK/HADR scenario was built using the SD and ABM approach (Chapter 4 and Chapter 5). The second part of this chapter shall attempt to compare the output of the model of the SD and ABM.

7.1 Analysis of Effect of Time Step on SD Model

Before the analysis of the differences between models can be carried out, the effect of using different time step durations on the SD was analyzed. This step was carried out as it provides an intuition to the stability of the system to internal variability. The reason for intuition is because approximation errors increase with the increase in time step duration. Hence, if the system is sensitive to small changes in parameters, the error introduced by the approximation error would lead to changes in system behavior.

Figure 7.1 shows the output of the system for different time step durations. From the graphs, it can be observed that as the time step duration is increased, the food price increases.

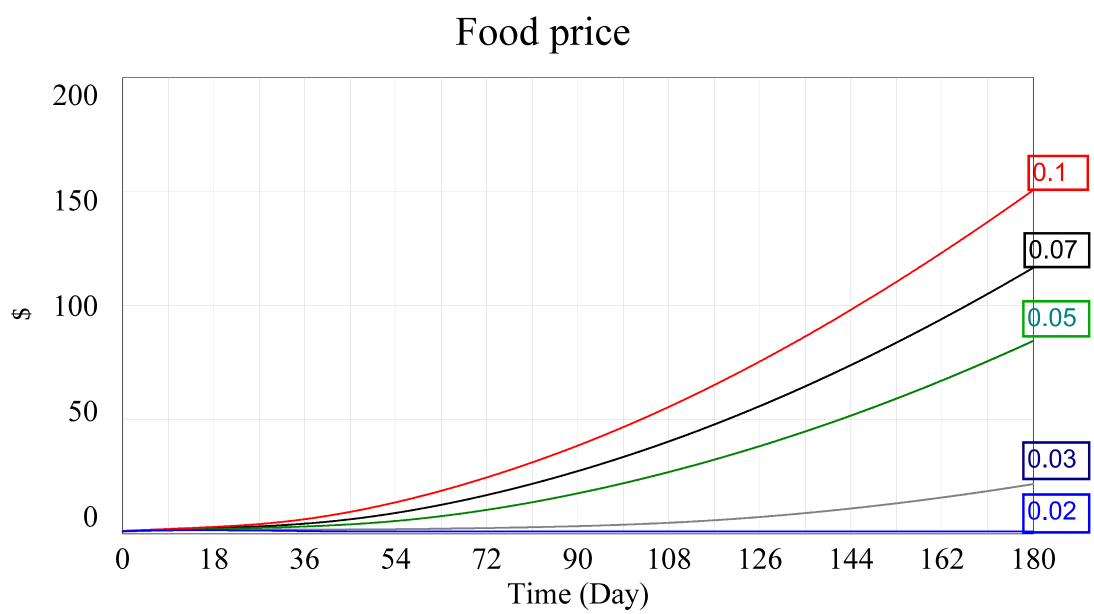

Figure 7.1: Output from SD with Different Time Steps Using Euler Integration

A further test was conducted that shows that the "success" of the PK/HADR can be affected by the different time step duration and integration methods. Figure 7.2, Figure 7.3 and Figure 7.4 show the output from the SD model when the same set of parameters is run using different integration type and time steps. From the outputs, it can be seen that the PK/HADR was successful, i.e., the price of food stabilized when time step duration of 0.02 days with Euler integration technique was used, but not for cases with time step duration of 0.1 days. A plausible reason for this observation is because small changes in food prices would lead to a non-linear increase/decrease in the number of households that can afford food, which has a cascading effect on the outcome of the system. This test showed that the differences in integration methods can have an impact on the result of the simulation.

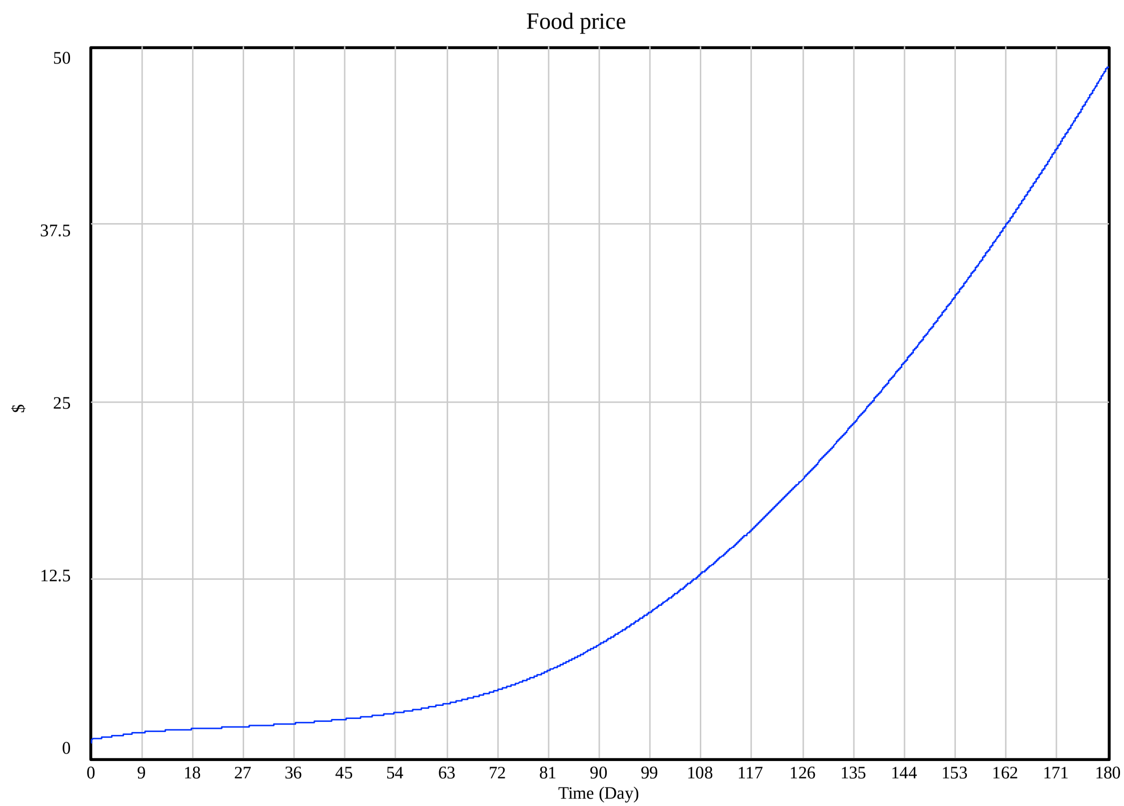

Figure 7.2: Output from SD with Runge-Kutta Integration, Time Step of 0.1 Days

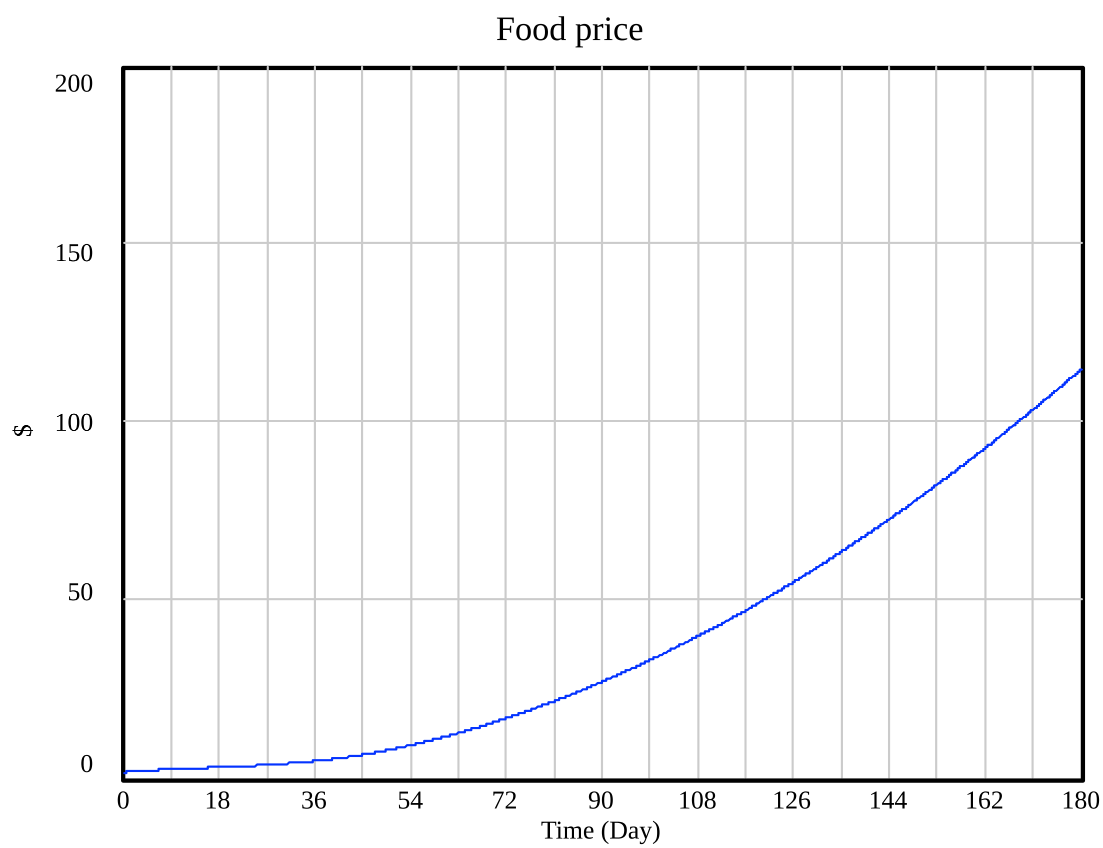

Figure 7.3: Output from SD with Euler Integration, Time Step of 0.1 Days

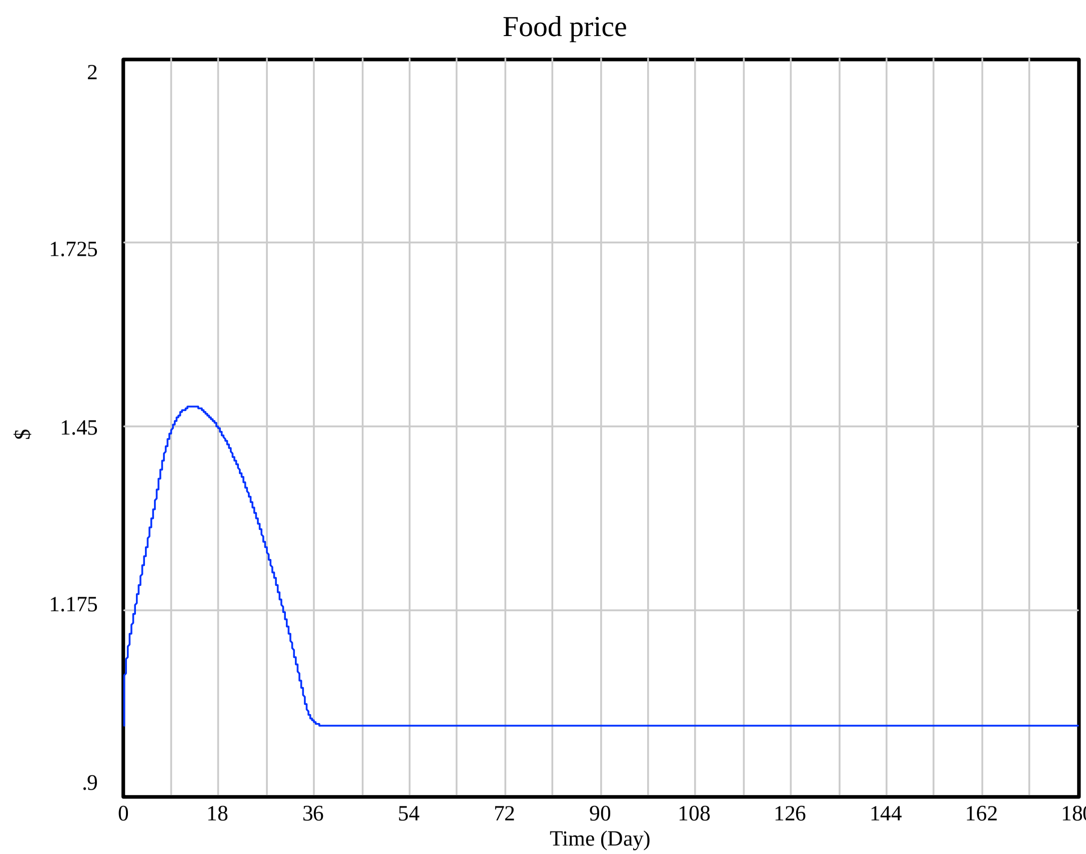

Figure 7.4: Output from SD with Euler Integration, Time Step of 0.02 Days

To analyze the cause of the error, the author looked at the raw values of the *Food Supply* and *Food Demand* in the Vensim model. The output of the SD model in Vensim is shown in Table 7.1 and Table 7.2. From the tables, it can be seen that while the differences between the value of *Food Demand* are small at the same time value, there is a significant difference in the value of *Food Supply* due to the time step. It seems that the computation of *Food Supply* was delayed by one time step as compared to the *Food Demand*. In the ideal case, where the time step is zero, the lead or lag between *Food Supply* and *Food Demand* should be close to zero. Hence, this lag is the probable cause of the approximation error.

Table 7.1: Food Supply and Demand for Time Step of 0.1 Days, Euler Integration

Time (Day)	Food Supply	Food Demand
0.0	0	0
0.1	0	97.4972
0.2	94.9944	194.994

Table 7.2: Food Supply and Demand for Time Step of 0.02 Days, Euler Integration

Time (Day)	Food Supply	Food Demand
0.0	0	0
0.02	0	19.4994
0.04	18.9989	38.9989
0.06	37.9978	58.4983
0.08	56.9967	77.9765
0.1	75.953	97.4435
0.12	94.8871	116.903
0.14	113.806	136.356
0.16	132.713	155.805
0.18	151.61	175.25
0.2	170.499	194.69

To see how much of an effect the time step duration has on the system, the author tried to adjust the parameters of the model to obtain a similar result as shown in Figure 7.4 using a time step of 0.1 days with *Euler* integration technique. In order to do so, a *food aid amount* of 65 and a *production rate* of 1.4 was required. Interestingly, changing the *production rate* slightly to 1.359 with the *food aid amount* remaining at 65 would lead to a destabilized system, i.e., the food prices keep increasing instead of falling back to $1.00. There are two significances to this result; first, the model is capable of returning to a stable state with different sets of values, i.e., the approximation error causes the operation characterizing the system to shift, and second, that the model is indeed sensitive to changes in parameters.

7.2 Test Cases

As explained in Section 7.1, a direct comparison of the models based on the output for different sets of input values may not be meaningful due to the approximation error that may be introduced by the integration technique used for computing the SD model. The other reason against direct comparison is that these models were built using different approaches with slightly different assumptions and implementations. For example, the SD model does not use the patrol speed or duration of the crime in its model for crime, but uses a single *response range* parameter that encompasses these two factors. What is a more interesting comparison between the two models to answer the basic research question of 'Can we model the desired behavior directly using system dynamics instead of agent-based modeling?' is whether the models exhibit any emergent behaviors in one implementation as opposed to another implementation.

Hence, the author proposes that the comparison be done through testing for the general behavior of the models under the following test cases.

7.2.1 Test Case 1

This test case tests that the model is stable and is capable of maintaining a stable state under the right condition, i.e. the stable state. In this test case, the scenario starts off without sufficient food supply (i.e., initial supply that is equal to the number of households, since each household consumes one food unit per day). The population is expected to be able to self-sustain its own demand through food generated by the population.The following sections discuss the results obtained from the various models for this test cases.

System Dynamics Model

To enable the town to be self-sufficient in the SD model, i.e., the organic food supply of the town can meet its own food demand, a *food production rate* greater than 1.2 is required.

A *production rate* of 1.2 means that each household has to produce 1.2 food unit for every one food unit that it consumes. The higher *production rate* is required because a small percentage of the households are unable to afford food. Since the mean income of the lower income group is \$3 and food price of \$1, using the triangle distribution, the portion of households that is unable to afford food is $\frac{1}{2} \times \frac{1}{3} \times \frac{1}{3}$, or approximately 5.5%. Therefore, the system should have required a *production rate* of $\frac{1}{1-0.055}$, i.e., 1.058, instead of 1.2. The higher *production rate* could be due to approximation errors shown in Section 7.1.

DES Implementation of SD Model

In the DES implementation of the SD model, the system was found to be able to remain stable with a *food production rate* of 1.05 as compared to 1.2 for the time step model. A value of 1.05 is close to the value required to compensate for the 5.5% of the population that is unable to afford food. This observation suggests that the SD model implemented using DES simulation might be a better approximation compared to the time-stepped model.

Agent-based Model

The ABM uses a normal distribution with mean of \$3 and a standard deviation of \$1 for generation of the income of lower-income households. Hence, 9% of households have income below \$1 and are unable to afford food. Since households that are hungry do not contribute to the production of food, the demand for food for these 9% would have to be made up for by the remaining population. Hence, the ABM is expected to need a *production rate* of greater than $\frac{1}{1-0.09}$ (i.e., 1.1). A *production rate* of 1.18 was found to be needed for the system to be self-sustaining, however. This makes sense if we consider that the 9% may resort to crime in order to obtain food. Since households that are victims of crime in the ABM lose the food they produced when they got robbed, under such circumstances the *production rate* would need to be increased to $\frac{1}{1-0.09\times 2}$ (i.e., 1.22) to be self-sustaining.

7.2.2 Test Case 2

For this test case, the scenario starts off with no initial food supply and absence of food aid and intervention by the peacekeepers. The conditions are set such that they would invoke a situation where the food supply should become destabilized, i.e., the unstable state. This test case is also used to check for the “emergent behavior” that is exhibited by the observation that households do not resort to crime when everyone is equally affected by the situation. This “emergent behavior” was coded into the ABM in their decision process for deciding if they would commit a crime, and in the SD as the “discord” percentile. The following sections discuss the results obtained from the various models for this test cases.

System Dynamics Model

Figure 7.5, Figure 7.8 and Figure 7.11 show the graphs for which the system is left without food aid for the entire 180 days duration.

From the graphs, it can be observed that the price of food rises quickly. The number of criminals was observed to initially increase as the number of households without food increases, but as the general population becomes hungry (i.e., majority of the households can no longer afford to buy food when the price of food increases beyond $6), the number of criminals falls back to a relatively low number. Unlike the stable state, the number of criminals does not return to zero. The probable reason for this behavior is that most households are without food. In accordance with the behavior in Section 3.6.1, if the situation affects everyone equally, people are less likely to resort to criminal activities. The drive to commit crimes is still there (i.e., the households are still hungry given that there are no food aids in place), however; therefore, some crimes are still being committed.

DES Implementation of SD Model

Figure 7.6, Figure 7.9 and Figure 7.12 show the graphs for which the system is left without food aid for the entire 180 days duration. From the graph, it can be seen that the DES output of the SD model is similar for the price of food, number of households that are hungry and number of criminals.

Like in the time-stepped SD model, the DES implementation showed a spike in the initial number of criminals (Section 7.2.2), which subsequently dropped back to a level of approximately 20 households. This is expected as the DES implementation of the SD model is essentially still implementing the same model. Hence, other than for approximate errors that may have been introduced as a result of discretization, their behaviors are expected to be the same.

Agent-based Model

Figure 7.7, Figure 7.10 and Figure 7.13 show the graphs for which the system is left without food aid for the entire 180 days duration.

The key difference between the ABM output and the System Dynamics Model (SDM) output is in the graph for the criminals. In the SDM, a sharper peak of approximately 145 households was observed, and the number of criminals dropped to around 20 households after the peak. In the ABM, a lower peak of approximately 110 households, which drops to approximately 60 households after the peak, was observed. This difference is likely to be due to the differences in the way ABM implements the behavior of peacekeepers and criminals. That is, instead of using the entire population, households utilize only information about their neighbors obtained through sensors when determining if they should commit crimes. Likewise, peacekeepers respond to crime during their random patrols based on their proximity to the crime, rather than through deterministic equations used in SDM.

7.2.3 Test Case 3

In this test case, the scenario starts off with no initial food supply, with food aid and intervention by the peacekeeper starting after the first week. This test case serves to check that under appropriate intervention by the peacekeepers, the system is able to return to a stable state. The following sections discuss the results obtained from the various models for this test case.

System Dynamics Model

Figure 7.14, Figure 7.17 and Figure 7.20 show the graphs for which the system starts off without food, with 100 units of food aid being available starting from the seventh day. With the availability of the food aid, the system can return to a stable state, with the price of food returning to $1; no criminals and approximately 50 hungry households, which matches the calculation that 5.5% of the population are unable to afford food priced at $1. Another interesting observation is that unlike in Test Case 2, the number of criminals eventually dropped to zero. The probable reason for this observation is that the presence of food aid means that households need not resort to crime to obtain food.

DES Implementation of SD Model

Figure 7.6, Figure 7.9 and Figure 7.12 show the graphs for which the system starts off without food, with 100 units of food aid being available starting from the seventh day.

As with Test Case 2, the DES output of the SD model showed a similar trend in its output as compared to the time-stepped SD model. The approximately 50 hungry households after the food prices have stabilized is also consistent with the 5.5% of households that are unable to afford food priced at $1. The differences in the peak number of criminals and the non-zero criminals (i.e., two criminals) after the availability of food aid in the DES implementation could be due to the fact that the DES utilizes stochastic random variable for generation of when households turn to crime and when criminals get arrested.

Agent-based Model

Figure 7.16, Figure 7.19 and Figure 7.22 show the graphs for which the system starts off without food. Ten units of food aid are available for each of the 10 FDP starting from the seventh day.

Like the SD model, the number of criminals falls sharply and reaches zero after the availability of the food aid. Unlike the SD model, however, the number of households without food starts to fall rapidly upon the availability of the food aid. The probable reason for this is that in the SD model, the computation of the number of hungry households is based on whether the agent has food rather than through estimating the number of households that are unable to afford.

7.3 Discussion

Both the time-stepped SD model and the DES implementation of the SD model may introduce approximation errors due to quantization, either in time or other quantities in the system. While these errors change the values of the system output, however, they do not change the model characteristics. The SD, DES implementation of the SD model, and the ABM all exhibited characteristics of their planned behaviors (i.e., the behaviors outlined in Chapter 3).

Another interesting observation is that despite the differences in the modeling approach between SD and ABM, the author was able to get both of them to produce similar model characteristics. This suggests that it is possible to model a system's behavior directly using SD instead of through ABM, if we know what the emergent behaviors of the model.

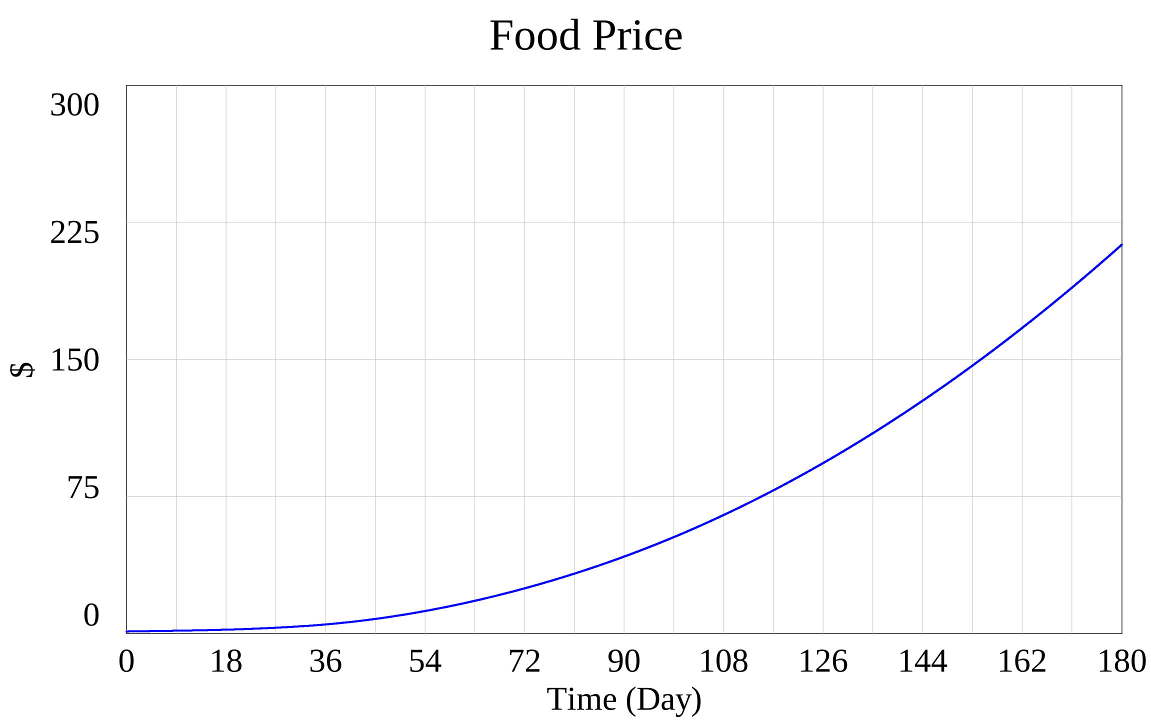

Figure 7.5: Food Prices for Test Case 2 (SD Model)

Figure 7.6: Food Prices for Test Case 2 (DES Implementation of SD Model)

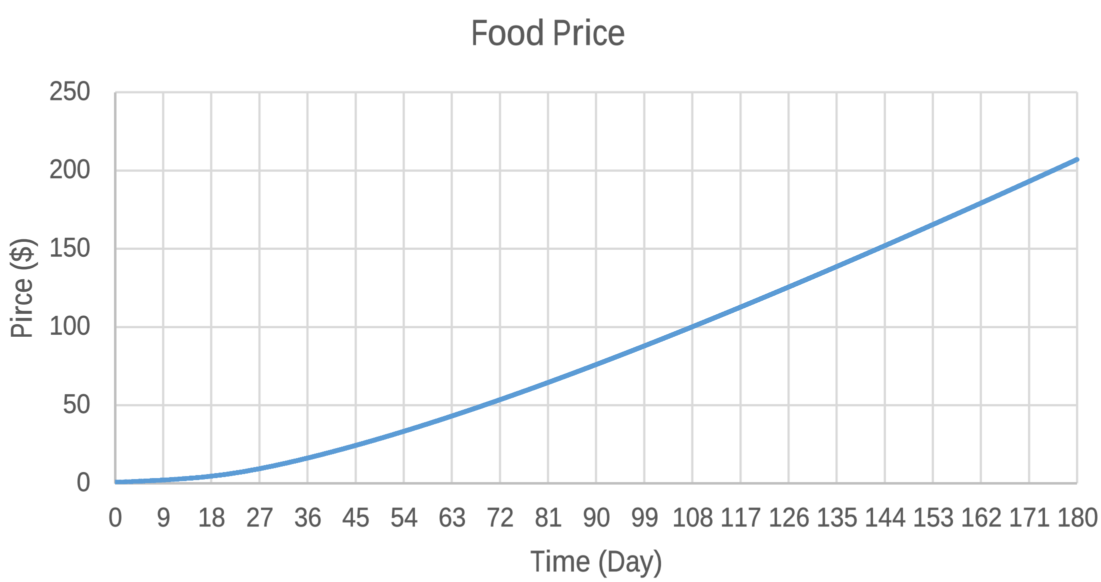

Figure 7.7: Food Prices for Test Case 2 (ABM)

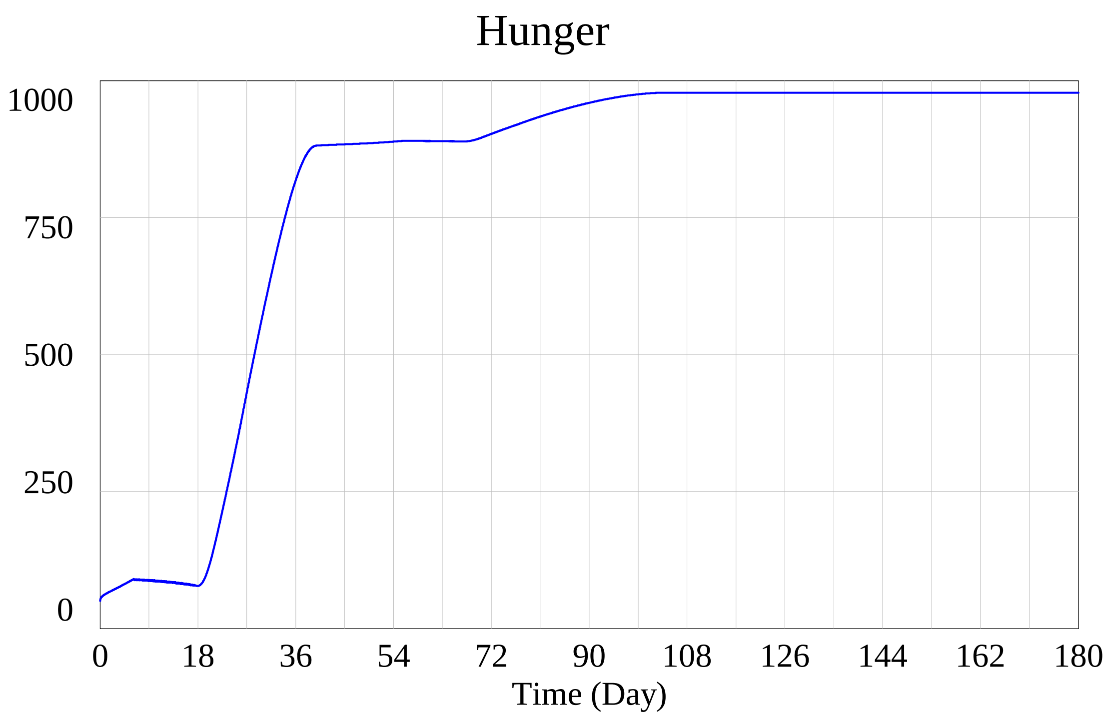

Figure 7.8: Number of Households Without Food for Test Case 2 (SD Model)

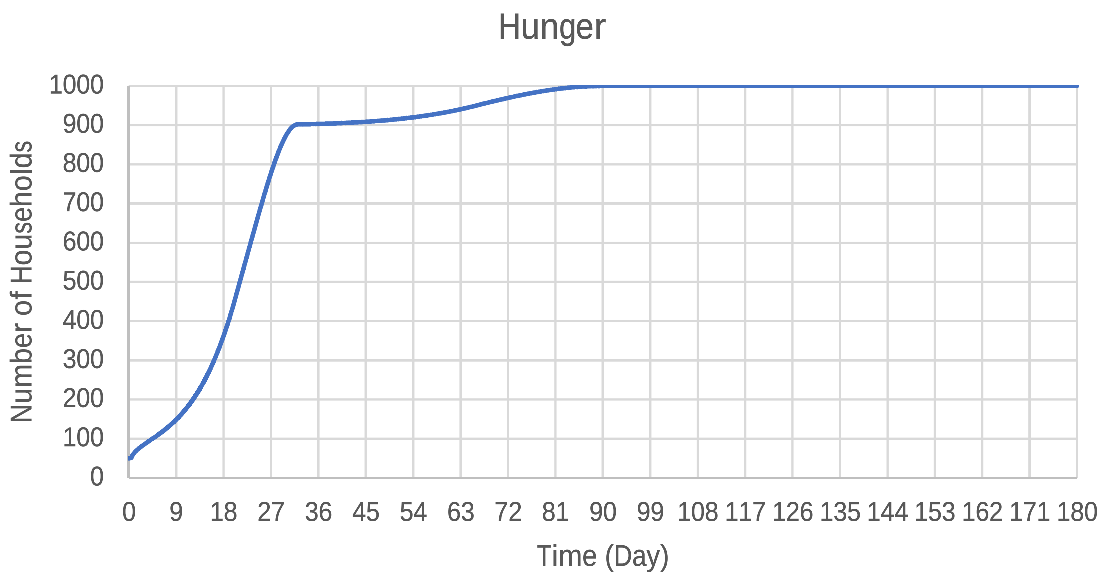

Figure 7.9: Number of Households Without Food for Test Case 2 (DES Implementation of SD Model)

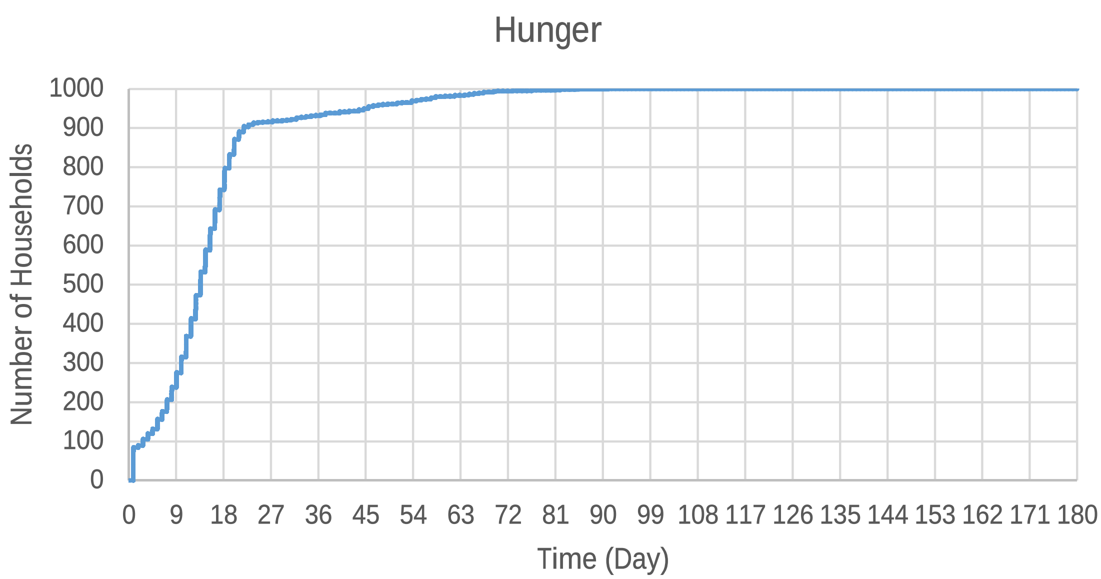

Figure 7.10: Number of Households Without Food for Test Case 2 (ABM)

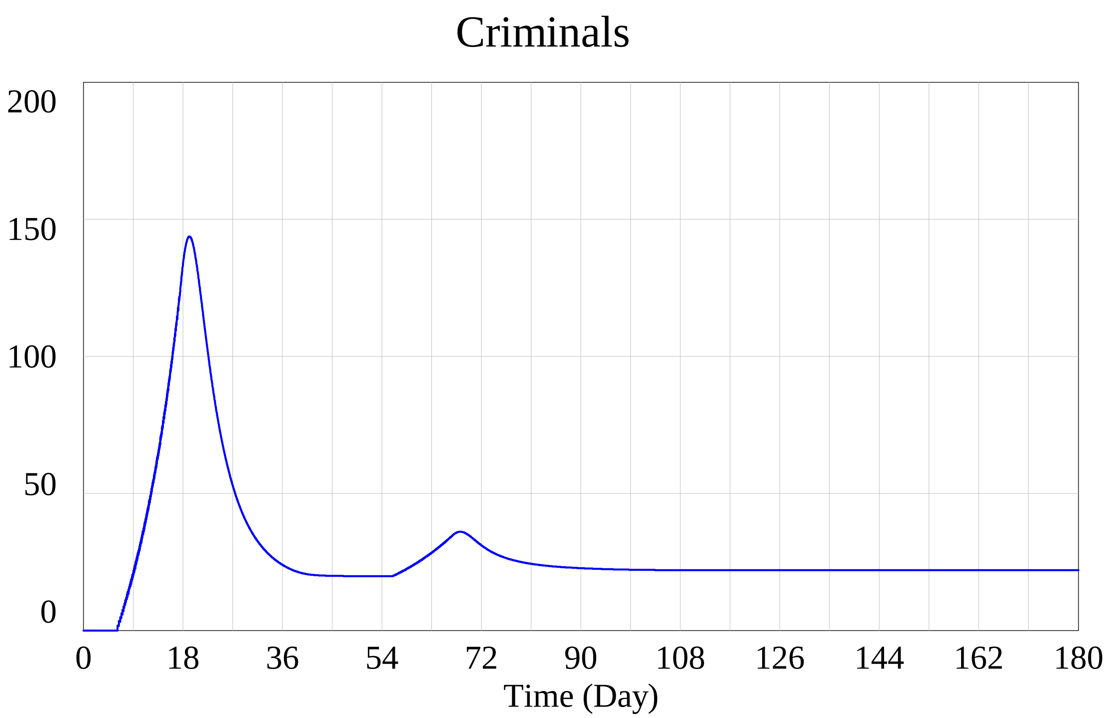

Figure 7.11: Number of Criminals for Test Case 2 (SD Model)

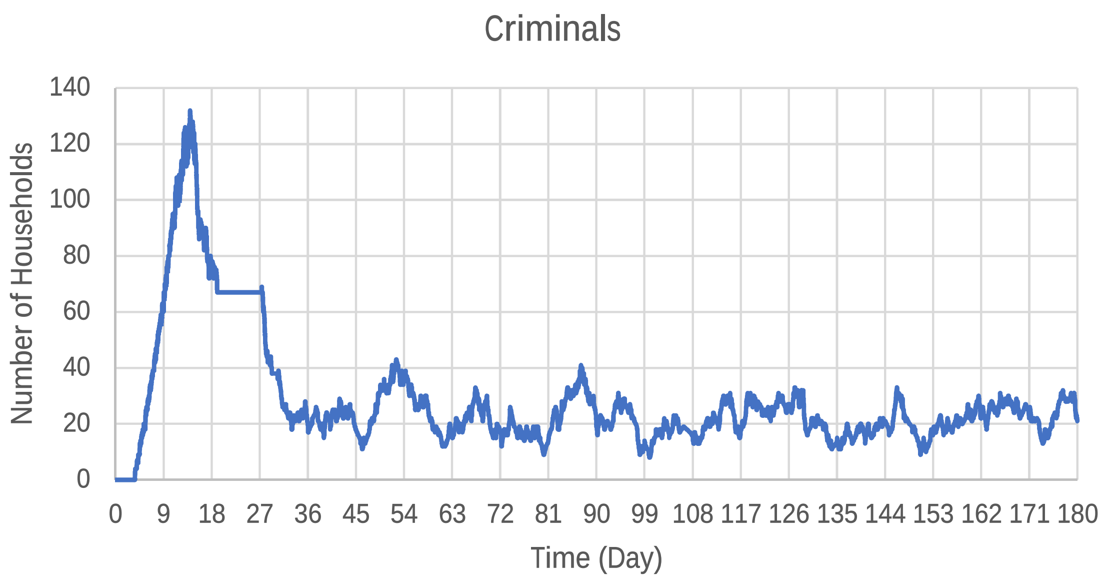

Figure 7.12: Number of Criminals for Test Case 2 (DES Implementation of SD Model)

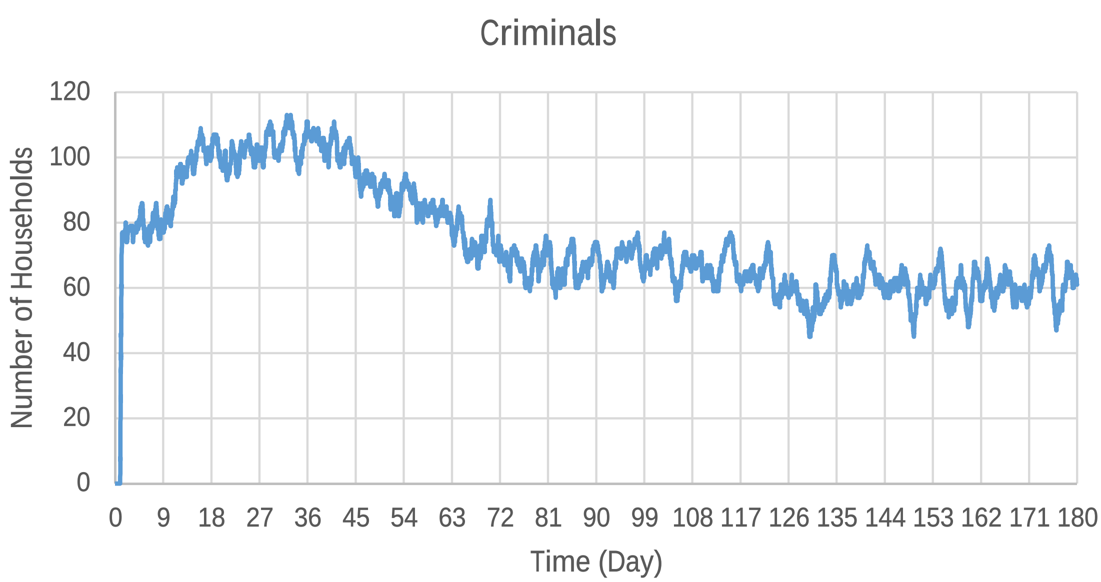

Figure 7.13: Number of Criminals for Test Case 2 (ABM)

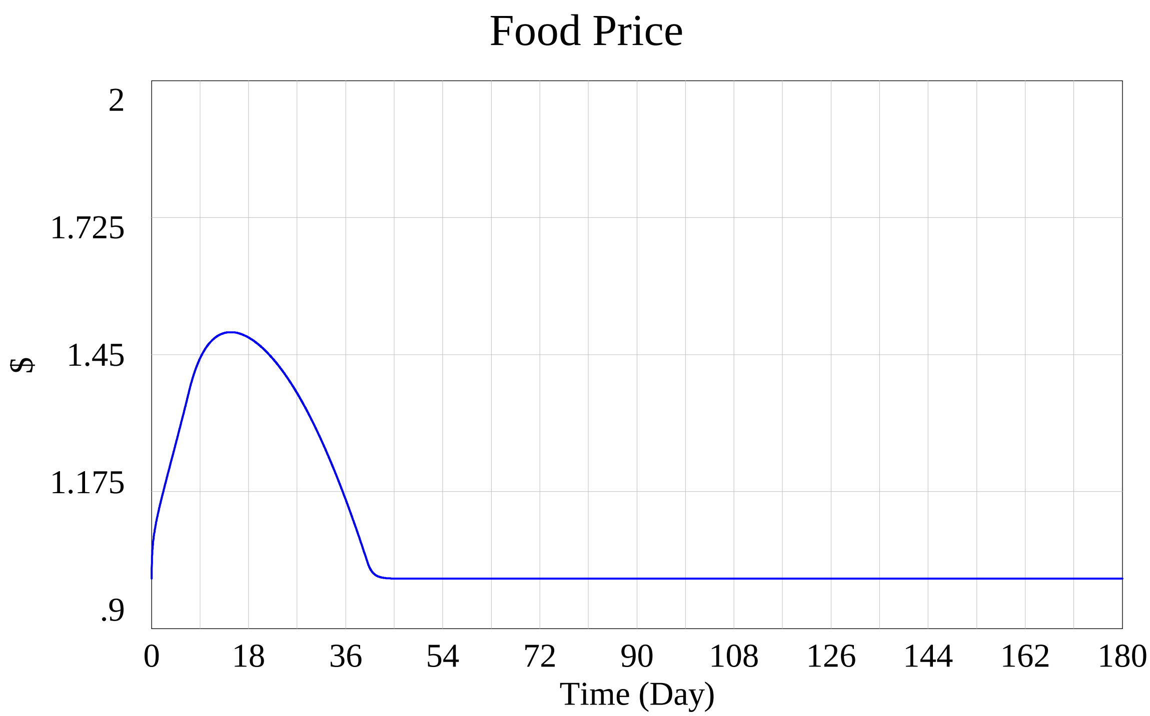

Figure 7.14: Food Prices for Test Case 3 (SD Model)

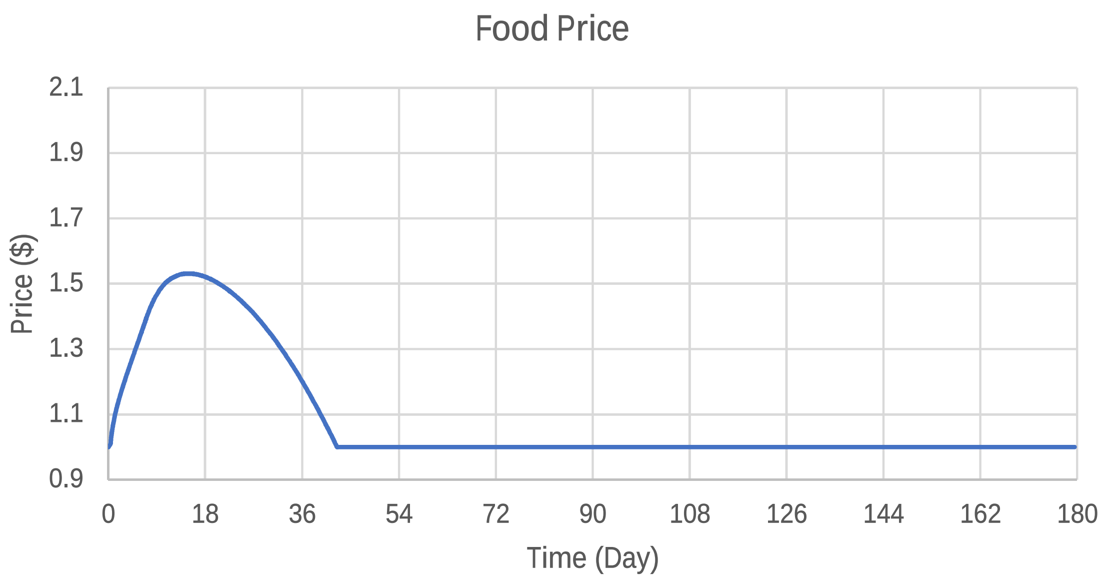

Figure 7.15: Food Prices for Test Case 3 (DES Implementation of SD Model)

Figure 7.16: Food Prices for Test Case 3 (ABM)

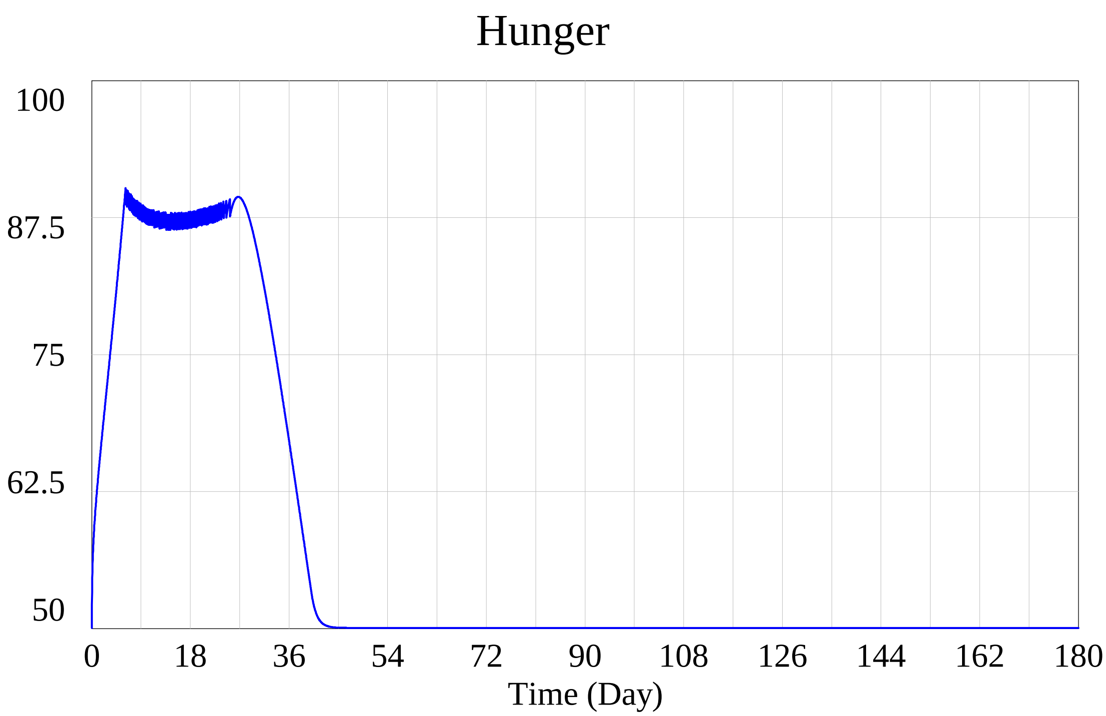

Figure 7.17: Number of Households Without Food for Test Case 3 (SD Model)

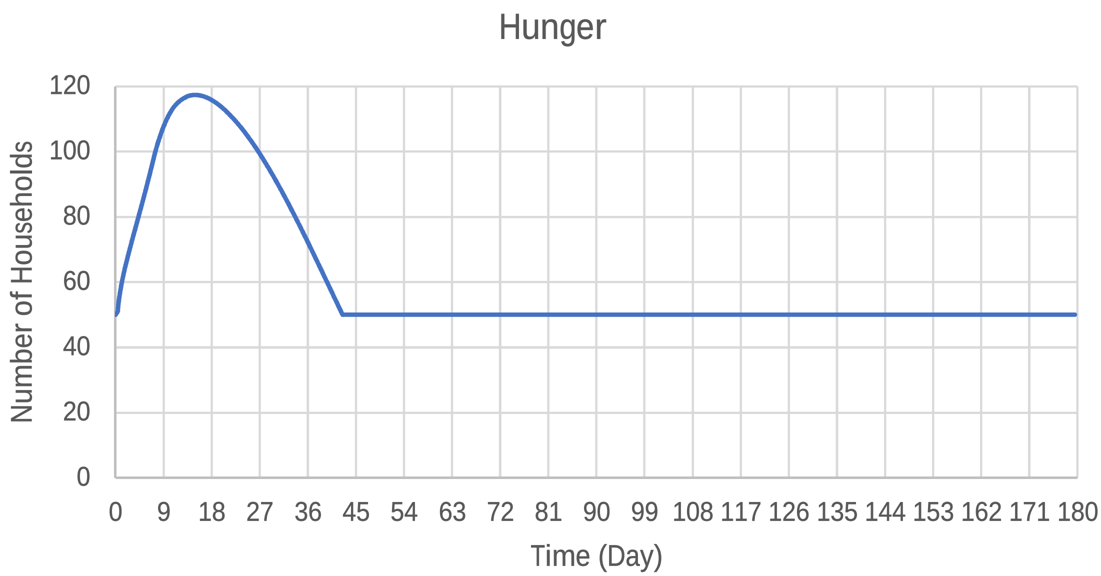

Figure 7.18: Number of Households Without Food for Test Case 3 (DES Implementation of SD Model)

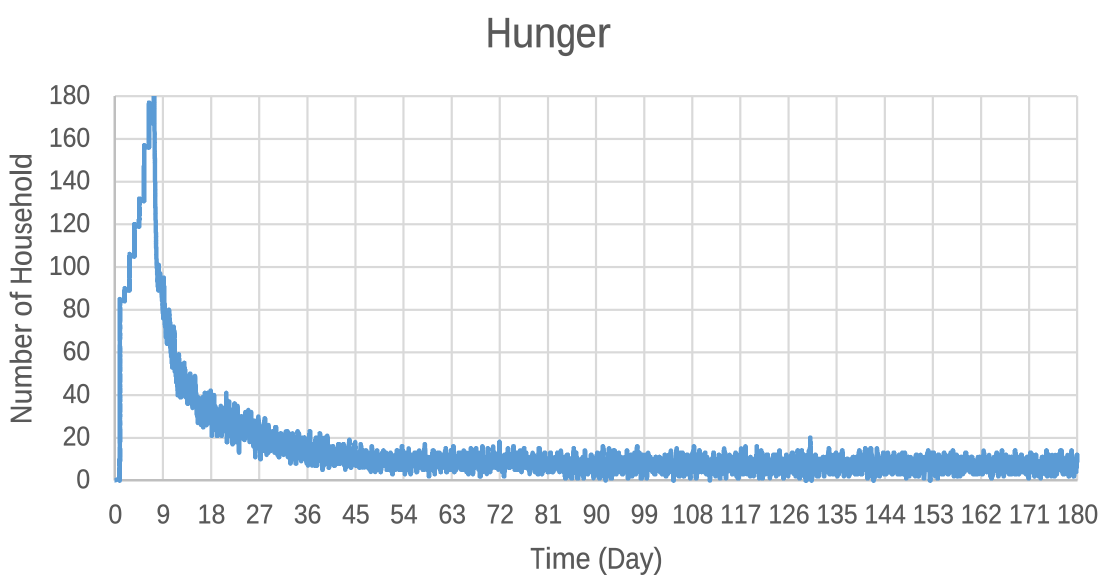

Figure 7.19: Number of Households Without Food for Test Case 3 (ABM)

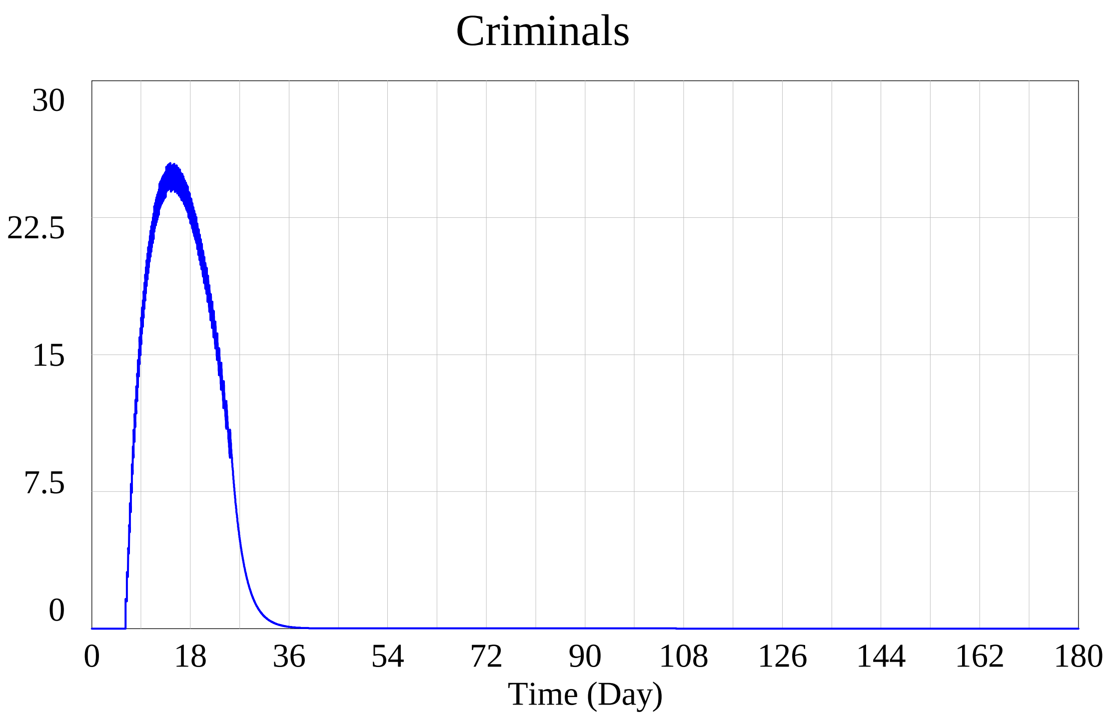

Figure 7.20: Number of Criminals for Test Case 3 (SD Model)

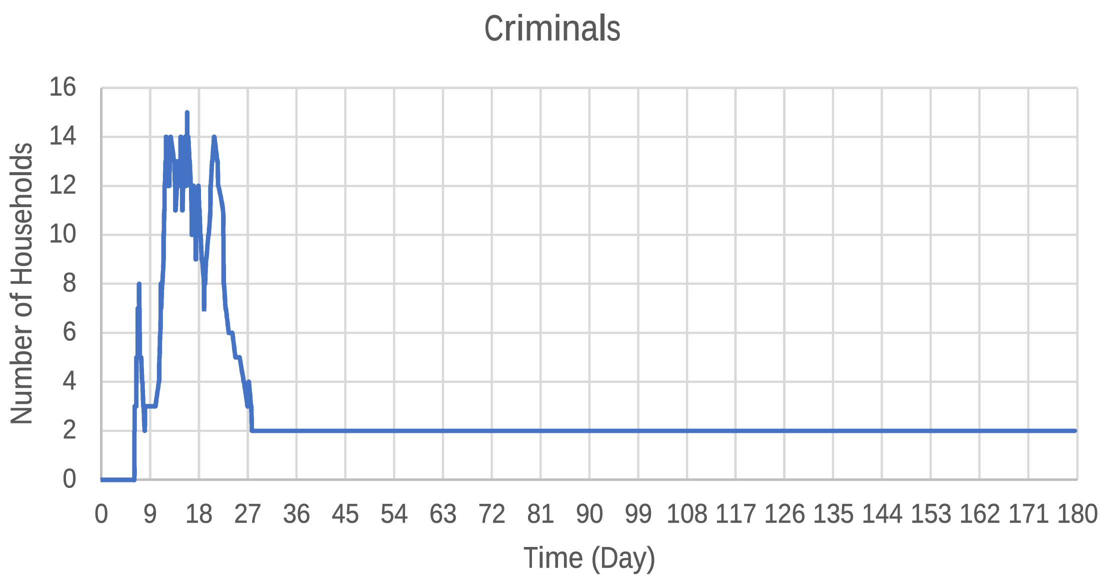

Figure 7.21: Number of Criminals for Test Case 3 (DES Implementation of SD Model)

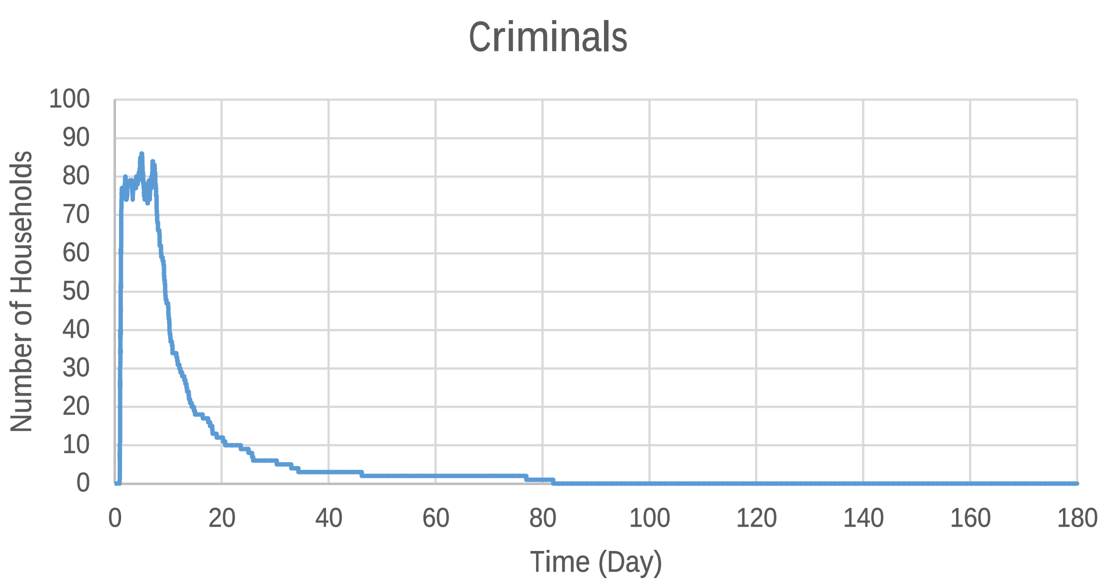

Figure 7.22: Number of Criminals for Test Case 3 (ABM)

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CHAPTER 8: Conclusion and Recommendations

The author started of working on a thesis motivated by a belief that applying System Dynamics modeling techniques to the PK/HADR domain provided a more direct and pragmatic approach to modeling the target domain than attempting to create an agent based model that would generate the understood behaviors through 'emergence.' The author was able to implement a fairly simple model of the effect of food distribution during the initial HADR operation using simple equations with an SD model, as well as obtaining similar results relative to those generated from using a more complex ABM.

The results in Chapter 7 demonstrated that using SD to model a system as opposed to using ABM is a viable option, if the modeler already has some idea of how the system should behave.

The following sections attempt to answer the problem statements of the thesis. A list of some possible extensions of the thesis is also given at the end of the chapter.

8.1 Conclusion

The author defined three research questions in Section 1.9 to be addressed in the thesis:

8.1.1 Can We Model the Desired Behavior Directly Using SD Instead of ABM?

The results in Chapter 7 demonstrated that the PK/HADR SD model was able to capture what the author deems to be key characteristics of the ABM. Both the SD and ABM captured the effect of delays in food distribution on the food market and displayed the effect that relative deprivation has on affecting the number of criminals in the system. As shown in Section 7.1, however, when implementing a model using SD, the implementer should be aware that the different integration technique and duration of the time step could have a impact on the outcome of the simulation.

8.1.2 Can We Take a Simple CLD and Build a DES out of it?

The thesis has demonstrated that it is possible to model the SD model using DES. The most trivial method to do so would simply be to implement a 'tick' to advance the DES model. Alternatively, the general approach of quantizing stocks and flow rates within the system could be used. Both approaches are approximation of the equations (i.e., an approximation of a continuous quantity) and can introduce error as a consequence of the quantization.

8.1.3 How Does a SD Approach Compare to ABM for the Same Problem?

From a modeling perspective, ABM would be more useful as it allows for its user to explore the model for emergent behaviors. Here, the modeling of simple, well-understood behaviors of the model are a double-edged sword; it could offer insights if the characteristics to be analyzed could be synthesized from the simple behaviors, or it could just be that the characteristics would never appear in the model. For example, if the PK/HADR ABM did not have a condition that states that a household will consider crimes only when it believes that it is hungrier than its neighbors, the relative deprivation characteristics of the model would not have appeared.

From the modeling perspective, the author has shown that it is possible to model behavior of an ABM using SD. Since one of the desired uses of ABM is for observing emergent behavior, it would seem that implementing ABM using SD would defeat the purpose of using ABM in the first place. If we think of the addition of the conditions to the ABM as similar in principle to adding equations to represent part of the model in SD, however, but instead of modeling using individual agents, we are trying to describe different parts of the system using differential equations and synthesizing the system from these smaller, simpler equations, then the SD and ABM approaches are not too different. Instead of emergent behaviors from interactions between agents, emergent behaviors could be formed through the interactions of different equations within the SD model.

The key difference between ABM and SD is the level of abstraction that the modeler would need to think about. In SD, the modeler would need to think how a desired characteristic would affect the entire system; he or she also usually needs to work with mathematical equations to model the characteristics. In ABM, the modeler would think how a simple rule or condition would change the interactions between agents and how the effect might cascade to the system level. In ABM, the modeler usually works with logical expressions rather than mathematical equations. Hence, in the author's opinion, changes in the behavior of the model can usually be made more directly in ABM compared to SDM.

In summary, it is possible to implement a SD model of a system if the desired characteristics of the system are known. The advantage of the SD model is that it is typically faster since the simulation is really just calculating one set of equations versus simulating the behavior of all the agents. The disadvantage of the SD model is that it is harder to model intuitively and harder to modify to incorporate new behaviors compared to ABM.

8.2 Future Work

The author mainly focused on the effect of food distribution for the early phases in an HADR operation. Future work could expand the model to include some of the factors that were left out in Chapter 3. This could include:

- Support later phases of the SSTR operation; this could include modeling the building up of the host nation capabilities.
- Modeling the effect that businesses, other organizations such as criminal groups and the local authority have on the HADR operation
- Modeling the influence of the external towns /nation on the HADR operation
- Modeling how certain portions of the population may revolt against the PK/HADR in response to situations where there is discrimination that occurs within the population. For example, instead of turning to crime when the household has no food, is hungrier than its neighbor and has no alternative ways to get food, a household can decide to commit crime to obtain food for sharing with its neighbors, i.e., to "right the wrong" in the society.

Besides enhancing the model, other possible research could involve:

- Using SD to model ABM behaviors, e.g., using an SD model to drive an agent's behavior; since SD provides a more top-down whereas ABM provides more of a bottom-up approach towards modeling a system, the synergy of both techniques could potentially leverage on the advantages of both approaches.

- Comparison of non-temporal discretization (e.g., the effect of discretization of households) versus temporal discretization of used by Euler/Runge-Kutta integration. The intuition is that discretization of households should be a more realistic approximation to the real world because time is a continuous quantity, but households is a discrete quantity.

APPENDIX A. Vensim Model

```
(01)    area of ops=
        3.1412 * ops radius * ops radius

(02)    civilian range=
        4

(03)    confidence in food aid=
      if then else (high income without food + low income without food > 0,
        min( food aids amount / (high income without food + low income without
    food ), 1),
          1
        )

(04)    coverage per fdp=
        3.1412 * civilian range * civilian range

(05)    coverage per patrol=
        3.1412 * patrol range * patrol range

(06)    discord percentile=
        0.1

(07)    fdp coverage=
        min ( coverage per fdp * number of fdps / area of ops, 1 )

(08)    FINAL TIME  = 180
    The final time for the simulation.

(09)    food aid delay= 7
```

```
(10)    food aids=
        DELAY FIXED( food aids amount, food aid delay, 0)

(11)    food aids amount=
        100

(12)    Food demand= INTEG (
        high income purchases+low income purchases,
            0)
(13)    Food price= INTEG (
        if then else ( Food price + supply demand rate >= 1,
          supply demand rate,
          1 - Food price
        ),
            1)

(14)    food production delay=
        0

(15)    Food supply= INTEG (
        food supply rate,
            initial supply)

(16)    food supply rate=
        local food supply + food aids

(17)    high income amount=
        30

(18)    high income arrest rate=
        high income criminals * patrol coverage
```

```
(19)    high income crime rate=
      if then else (high income without food > discord percentile * high
    , income households
        (discord percentile * high income households)^2 / high income without
        food
     * ( 1 - confidence in food aid ),
         0 )

(20)    high income criminals= INTEG (
        high income crime rate-high income arrest rate,
            0)

(21)    high income households= INTEG (
        high income arrest rate-high income crime rate,
            number of high income)

(22)    high income purchases=
      high income with food + + high income criminals + 0.5 * high income
      without food
(23)    high income with food=
        high income households - high income without food

(24)    high income without food=
        max( 0, if then else (Food price > 2*high income amount,
          1,
          if then else (Food price < high income amount,
            0.5 * ( Food price/high income amount )^2,
          1 - 0.5 * ( (2*high income amount - Food price)/high income amount )^
    2
          )
        ) * number of high income - high income criminals)
```

(25) initial supply=
0

(26) INITIAL TIME = 0
Units: Day
The initial time for the simulation.

(27) local food supply=
DELAY FIXED(production rate*high income with food+low income with food,
food production delay , 0)

(28) low income amount=
3

(29) low income arrest rate=
patrol coverage * low income criminals

(30) low income crime rate=
if then else (low income without food > discord percentile * low income households,
(discord percentile * low income households)^2 / low income without food
* (1 - confidence in food aid),
0)

(31) low income criminals= INTEG (
low income crime rate-low income arrest rate,
0)

(32) low income households= INTEG (
low income arrest rate-low income crime rate,
number of low income)

(33) low income purchases=
low income with food + low income criminals + 0.5 * low income without food

(34) low income with food=
low income households - low income without food

(35) low income without food=

```
max( if then else (Food price > 2*low income amount,
  1,
  if then else (Food price < low income amount,
    0.5 * ( Food price/low income amount )^2,
  1 - 0.5 * ( (2*low income amount - Food price)/low income amount )^2
  )
) * number of low income - low income criminals, 0 )
```

(36) number of fdps=
5

(37) number of high income=
100

(38) number of low income=
900

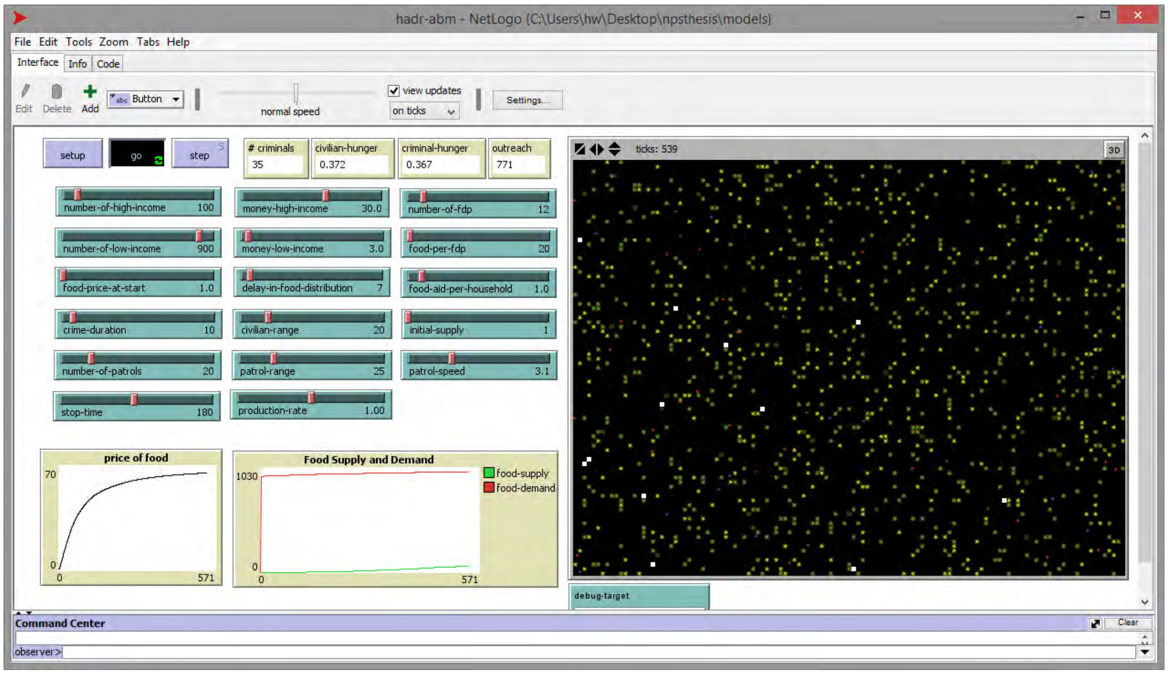
(39) number of patrols=
100

(40) ops radius=
30

(41) patrol coverage=

```
        min ( coverage per patrol*number of patrols / area of ops, 1 )

(42)    patrol range=
        2

(43)    production rate=
        1
    Units: Dmnl [0,2,0.05]

(44)    SAVEPER  =
            TIME STEP

(45)    supply demand rate=
        if then else ( Food demand > 0 :AND: Food supply > 0,
          if then else ( Food demand > Food supply,
            (Food demand - Food supply) / Food supply,
            (Food demand - Food supply) / Food demand
          ),
          0
        )
    Units: $/Day

(46)    TIME STEP  = 0.02
```

APPENDIX B. Netlogo Model




```
; Time-scale: 1 tick = 1 min

globals [
  close-enough
  one-day
  food-price food-demand food-supply
  fdps
  high-income-households
  low-income-households
]

breed [households household]
breed [pks pk]
```

```
pks-own [
  pk-state
  base-patch
  patrol-patch
  crime-patch
]

households-own [
  state
  home-patch
  money
  last-meal-time
  next-meal-time
  last-crime-time
  amount-of-food
  is-criminal?
  aids-received
  aids-requested
  victim
  idle-until
  food-generated
  nearest-fdp
]

patches-own [
  food-left
  last-repenish
]

to setup
  clear-all
```

```
set one-day 24 * 60
set close-enough 0.1

set food-price 1
set food-supply initial-supply
set high-income-households turtle-set (nobody)
set low-income-households turtle-set (nobody)


let household-left number-of-low-income + number-of-high-income

ask n-of household-left patches  [
  set pcolor yellow - 4
  sprout-households 1 [
    if-else household-left > number-of-low-income
    [ ; high income
     set money random-normal money-high-income ( money-high-income / 2 )
     set high-income-households (turtle-set high-income-households self)
    ]
    [ ; low income
      set money random-normal money-low-income ( money-low-income / 2 )
      set low-income-households (turtle-set low-income-households self)
    ]

    setxy pxcor pycor
    set color green
    set home-patch myself
    set amount-of-food 0
    set is-criminal? false

    set next-meal-time 0
    set household-left household-left - 1
```

```
    set aids-received 0
    set aids-requested 0
    set food-generated 0
    set idle-until 0
  ]
]

let pk-left number-of-patrols
let pk-per-fdp floor(number-of-patrols / number-of-fdp)

ask n-of number-of-fdp patches with [pcolor = black ] [
  set pcolor white
  set food-left 0
  sprout-pks pk-per-fdp [
    set color blue
    set pk-state 0
    set crime-patch nobody
    set base-patch myself
  ]
  set pk-left pk-left - pk-per-fdp
]
set fdps patches with [pcolor = white]

while [pk-left > 0]
[
  let base one-of fdps
  ask base [
    sprout-pks 1 [
      set color blue
      set pk-state 0
      set crime-patch nobody
      set base-patch base
```

```
      ]
    ]
    set pk-left pk-left - 1
  ]

  reset-ticks
end

to go
  update-market
  ask fdps [ resupply ]
  ask households [ live-life ]
  ask pks [ patrol ]
  tick
end

to update-market
  ; if there's no supply or demand,
  ; price wouldn't move because there's buying or selling!
  if food-supply > 0 and food-demand > 0
  [
    if-else food-demand > food-supply
    [set food-price
     food-price + ( ( food-demand - food-supply ) / food-supply ) / one-day ]
    [set food-price
     food-price + ( ( food-demand - food-supply ) / food-demand ) / one-day ]
  ]

  if food-price < 1.00 [ set food-price 1.00 ] ; assume minimum cost price
end

to resupply
```

```
  if  ( ticks - last-repenish > one-day )
  and ( ticks > delay-in-food-distribution * one-day )
  [
    set food-supply food-supply + ( food-per-fdp - food-left )
    set food-left food-per-fdp
    set last-repenish ticks
  ]
end

to live-life
  if state = 0
  [
    if-else ticks > next-meal-time
    [ ; one-day has passed
      set food-supply food-supply + food-generated
      set food-generated 0
      set state  1 ; find-food
    ]
    [ ; work and produce food - if we are productive, we should be capable
      ; of sustaining ourselves but if we are hungry and looking for food,
      ; we do not work and therefore economically, we suffer
      if  ticks < last-meal-time + one-day
      and ticks > idle-until and not is-criminal?
      [
        ; criminal don't earn money, the rest earn their pay each day
       set food-generated ( food-generated + ( production-rate / one-day ) )
      ]
    ]
  ]
  if state = 1 [ find-food ]
  if state = 2 [ ask-for-aid ]
  if state = 3 [ consider-crime ]
```

```
  if state = 4 [ return-home ]
  if state = 5 [ rob-somebody ]
  if state = 6 [ rob-in-progress ]
end

to find-food
  if-else not is-criminal?
  [
    if amount-of-food < 1 and ticks > idle-until
    [ ; buy from market if we can afford it,
      ; the amount to buy = food price / income per day,
      ; capped at 1, could be < 1 for partial meal
      ; cannot buy from market if we just got robbed
      let amount-to-buy (money / food-price)
      if amount-to-buy > 1 [ set amount-to-buy 1 ]
      set food-demand ( food-demand + amount-to-buy )
      set amount-of-food ( amount-of-food + amount-to-buy )
    ]

    if-else amount-of-food < 1
    [ ; seek aid if we cannot even afford to eat 1 meal per day
      ; and if we think that there's a good chance that we get food
      let confidence 0
      if-else aids-requested < 1
        [ set confidence 1 ]
        [ set confidence aids-received / aids-requested ]

      set nearest-fdp min-one-of fdps
       with [ food-left > 1 and distancexy pxcor pycor < civilian-range ]
            [ distancexy pxcor pycor ]
     if-else nearest-fdp != nobody and confidence > 0.5 and not is-criminal?
      [
```

```
        set aids-requested aids-requested + 1
        set state 2
      ]
      [
        ; otherwise, we have to take more drastic measures!
        set state 3
      ]
    ]
    [ ; eat whatever we can each day (no concept of saving)
      ;    set amount-of-food ( amount-of-food - amount-to-buy )
      set amount-of-food ( amount-of-food - 1 )
      set next-meal-time ticks + random-exponential one-day
      set last-meal-time ticks
      set state 0
      set color green
    ]
  ]
  [
    if-else amount-of-food < 1
    [
      set state 3
    ]
    [
      set amount-of-food ( amount-of-food - 1 )
      set next-meal-time ticks + random-exponential one-day
      set last-meal-time ticks
      set state 0
    ]
  ]
end

to ask-for-aid
```

```
  ; seems like there's a possibility of getting food from the FDP ...
  if-else distance nearest-fdp < close-enough
  [ ; reached fdp - let's hope there's food
    if [food-left] of nearest-fdp  > food-aid-per-household
    [
      ; got helped
      set aids-received aids-received + 1
      set amount-of-food ( amount-of-food + food-aid-per-household )
     ask nearest-fdp [ set food-left ( food-left - food-aid-per-household ) ]
    ]
   ; move back home if we have food, otherwise find another way? consider
   crime?
    if-else amount-of-food >= 1 [ set state 4 ] [ set state 3 ]
  ]
  [
    face nearest-fdp
    forward patrol-speed / 60
  ]
end

to consider-crime
  let neighbor-households households
    with [ distance self < civilian-range and idle-until < ticks ]
  let lower-limit 0
  let upper-limit one-day

  ; decision to commit crime is based on
  ; whether self is lower the normal food-level of the neighorhood
  ; whether past experience suggest that food can be obtained from fdp
  ; whether past experience suggest that crime can be caught

  if count neighbor-households > 2
  [ ; use actual stats from the neighborhood
```

```
  let neighbors-mean mean [ last-meal-time ] of neighbor-households
  let neighbors-stdev standard-deviation [ last-meal-time ] of neighbor-
  households
  set lower-limit ( neighbors-mean - neighbors-stdev )
  set upper-limit ( neighbors-mean + neighbors-stdev )
]
if-else ( last-meal-time < lower-limit ) or is-criminal?
[ ; poorer than average or already made the decision to rob
  set color red
  set is-criminal? true
  set victim max-one-of neighbor-households [ last-meal-time ]
  if-else victim != nobody
  [ ; let's rob somebody!
    if debug-target = [who] of self
    [
      write [who] of self
      write " intending to rob "
      print [who] of victim
    ]
    set state 5
  ]
  [ ; no one to rob! go home and try again
    if debug-target = [who] of self
    [
      write [who] of self
      write " could not find any victim "
    ]
    set state 4
  ]
]
[
  ; everyone is suffering from lack of food
```

```
    set color yellow
    set state 0
    set next-meal-time ( ticks + random-exponential one-day )
;    set next-meal-time ticks + one-day
  ]
end

to rob-somebody
  if-else distance [home-patch] of victim < close-enough
  [
    ; inform min-one-of pk to come and arrest me, if any :)
   let pk min-one-of pks with [ crime-patch = nobody ] [ distance myself ]
    if pk != nobody
    [
      let victim-patch [home-patch] of victim
      ask pk [ set crime-patch victim-patch ]
    ]

    ; wait for crime-duration to allow for arrest
    set last-crime-time ticks
    set state 6
  ]
  [
    face [home-patch] of victim
    forward patrol-speed / 60.0
  ]
end

to rob-in-progress
  if ticks - last-crime-time > crime-duration
  [
    set amount-of-food amount-of-food + [ amount-of-food ] of victim
```

```
    set amount-of-food amount-of-food + [ money ] of victim / food-price

    ask victim
    [
      set idle-until ticks + one-day
      set food-generated  0
      set amount-of-food 0
    ]

    if-else amount-of-food > 1
    [ ; enough food for now, return home to eat
      set state 4
    ]
    [ ; continue to rob until we have enough for food
      set state 3
    ]
  ]
end

to return-home
  if-else distance home-patch < close-enough
  [
    set state 0
    set xcor [pxcor] of home-patch
    set ycor [pycor] of home-patch
;     set next-meal-time ( ticks + random-exponential one-day )
  ]
  [
    face home-patch
    forward patrol-speed / 60
  ]
end
```

```
to patrol
  if-else crime-patch != nobody
  [
    if-else distance crime-patch < close-enough
    [
      ; is the criminal still there?
      let the-crime-patch crime-patch
     let criminals households with [ distance the-crime-patch < close-enough
     and ticks - last-crime-time < crime-duration ]
      ask criminals
      [
        set is-criminal? false
        set color orange
      ]
      set crime-patch nobody
    ]
    [
     face crime-patch
     forward patrol-speed / 60
   ]
  ]
  [
     if pk-state = 0
     [
       if-else distance base-patch < close-enough
       [ ; select a new patrol location
        set pk-state 1
       set patrol-patch patch-at-heading-and-distance random 360 patrol-
       range ]
       [ ; move toward base
         face base-patch
         forward patrol-speed / 60.0
```

```
      ]
    ]

    if pk-state = 1
    [
      if-else distance patrol-patch < close-enough
      [ ; return to base
        set pk-state 0
      ]
      [ ; move towards patrol location
        face patrol-patch
        forward patrol-speed / 60
      ]
    ]
  ]
end
```

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