Agent-based Modelling: A Case Study in HIV Epidemic

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Abstract

This research presents an agent-based, bottom-up modelling approach to develop a simulation tool for estimating and predicting the spread of the Human Immunodeficiency Virus (HIV) in a given population. HIV is mainly a sexually transmitted disease (STD) causing a serious problem to human health. The virus is transmitted from an infected person to another who was previously healthy through different biological, social and environmental factors. The research develops the simulation tool by modelling these factors by agents. Although research has and is being conducted to estimate and predict the spread of the HIV epidemic, the proposed research seeks to investigate the spread using a different approach. The previous models used a top-down modelling approach. They are built from the general characteristics and behaviours of the population. They have not explored the potential use of agent technology. This research attempts to investigate the flexibility that the multi-agent system offers. Agent-based models are close to the situations that exist in a given real system that consists of autonomous components interacting with each other. The modelling approach has the advantage of observing the interaction made between agents, which is a difficult task in the top-down modelling approach. The research investigates the performance of the tool and presents the first results obtained.

Keywords: Multi-agent based simulation, human behaviour, modelling HIV.

1. Introduction

The use of multi-agent system approach for modelling complex system consisting of autonomous entities is becoming popular for many researchers. Developing a simulation model using such approach involves modelling the entities by agents. The activities of these agents emerge to give the general behavior of the system.

HIV is causing a severe health and economic problems in many countries around the world. Today millions of people are living with the virus. The rapid spread of the infection also creates challenges to many medical personnel, governments and organisations in terms of controlling and reducing the infecion. The spread of the virus is largely dependent on the characteristics and behaviours of human beings.

Many researchers have developed methods and models to estimate and predict the propagation of the disease in a society. These methods and models are developed from the general characteristics of the population and they follow top-down modelling approach. They do not observe the changes made in the behaviours of individuals due to the interaction among each other and with the environment they live in. These different works on the infection also do not consider the use of the flexibility that the agent technology offers. Therefore, the potential use of such agent technology for the study of HIV spread has not been explored. This research follows a bottom-up approach using a multi-agent system to develop the simulation model. This modelling approach is able to capture the emergence of new behaviours.

The rest of the paper is structured as follows: The next section gives the background of the research. In Section 3, work related to this research is highlighted. Section 4 discusses the approach used to conduct the research. Section 5 presents the results of the research. The paper concludes with conclusions and future work of the research.

2. Background

Simulation in the proposed research involves experimentation with a model. It is the study of the characteristics and behaviours of a model by answering "what-if" types of questions. One can experiment with the behaviours and characteristics of the model by asking questions, such as "What-if the parameters change their values?", "Does it behave similar to the real system it represents?", "What will happen to the model after a certain period of time?". Performing such types of experimentation with a model is one of the advantages of simulation over other types of models, most of which are built using mathematical or statistical equations. The output of the simulation reflects the quality of the model. Therefore, it is crucial to design a model that captures the true and representative properties of a given system [17].

2.1. Top-down vs. bottom-up models

The top-down modelling approach starts by specifying the global characteristics and behaviours at the system level. It then subdivides the system into smaller components. It also specifies the parameters (attributes) and their relationship at the system level [21]. This modelling approach does not generally look at the characteristics and behaviours of the individual components that make up the system. It explores these based on the global characteristics and behaviours of the system [3, 14, 21]. This modelling approach is suitable for modelling relatively stable (or static) and homogenous systems. It promotes the design to address the specific global system level requirements easily [3]. This modelling approach also does not capture new observations which emerge due to the interaction among the individuals [2].

The bottom-up modelling approach specifies characteristics and behaviours at the local (individual) level and constructs the general system level specification. It starts by identifying the characteristics and behaviours of the components. The components that make up the system have their own behaviours and characteristics. The aggregate sum of the characteristics and behaviours of these components and their interaction over a period of time represents system level model [3, 14, 21]. It focuses on specific characteristics and behaviours of the components and the way they contribute to make up system level properties. This approach can work in both static and dynamic systems. System specification is addressed by the requirements and specifications of individual components [2, 14, 21].

A population consisting of human beings is a complex system. Human beings are autonomous and have complex behaviours and interactions among each other. The environment they live in changes very often. Due to the interaction among each other and the environment they live in, individuals tend to change their characteristics and behaviours. It is very difficult to represent such a complex system with specific characteristics and behaviours at the population level. The top-down modelling approach does not explicitly describe the characteristics and behaviours of individuals. It specifies the behaviours and characteristics at the system level. These factors can, however, change over a period of time. Of course, the population is also not stable, and new individuals are constantly being added to the population. Hence the top-down approach has limitations of modelling such population where behaviours and interaction among individual components are important [3, 16, 21].

A bottom-up approach is a suitable modelling approach for such complex population with heterogenous individuals. Developing such a model starts by specifying the characteristics and behaviours of individuals within the population. The population can then be modelled by the output of the action and interaction of these individuals with each other and with the environment they live in over a period of time [21]. The population is dynamic, and individuals change their behaviour and properties as they interact among each other and with their environment. These changes can be captured easily at the individual level. Moreover, due to the interaction new individuals can emerge and the behaviours of these new individuals can be captured easily at the individual level [3, 21].

2.2. Agent

There are different definitions of the word "agent" on the notion of different contexts. We can have real world agents and computer system agents. The real world agents live in real environment. They consist of biological agents, like humans, and robots. Based on the environment they live in, the computer system agents can be classified into software agents which live in computer operating system or database and artificial life agents which live in artificial environment like computer screen. The software agents can be further classified based on the task they perform, such as information gathering and information filtering agents [7].

For this research an agent is defined as a computing entity (program) which performs some information processing to achieve specific task [7, 12]. According to [20, page 4], an agent can also be defined as:

> A software-based computer system that enjoys the following properties:
>
> - autonomy: agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state;
> - social ability: agents interact with other agents (and possibly humans) via some kind of agent-communication language;
> - reactivity: agents perceive their environment, (which may be the physical world, a

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user via a graphical user interface, a collection of other agents, the INTERNET, or perhaps all of these combined), and respond in a timely fashion to changes that occur in it;

- pro-activeness: agents do not simply act in response to their environment, they are able to exhibit goal-directed behaviour by taking the initiative.

An agent has believable properties that represents human being characters (personality). These include properties like knowledge, belief, intention, desire, and so on. An agent also has a mobility property, it can move from one machine to another across a network. An agent works to achieve its goals without interfering against other agents goals. In addition, it does not transmit false information to other agents and the environment it lives in. For a program to be an agent there must exist an environment. The agent lives in the environment and has some knowledge and belief of the environment [7, 20].

An agent is part of the environment it lives in and senses the environment. It has a goal and uses its sense knowledge to achieve its goal. It takes action for its input, and uses and interprets the output autonomously by acting upon the environment. It has specific goals and the output of the action it takes can effect the future sensing of the environment. In other words, an agent can change its behaviour due to the action and interaction among other agents and with the environment. The agent then senses the environment with its new behaviours. An agent also acts continuously over a specific time stamp [7, 12, 20].

2.3. Multi-agent system

A multi-agent system consists of components (entities) that represent the features of the system. The entities communicate with each other and with the environment they live in, and are modelled and implemented using agents [4, 10]. The agents have behaviours and characteristics and they represent the various components that make up the model. They have also some communication protocol which helps them understand messages and exchange information among each other. The model is the outcome of the characteristics and behaviours of the agents and their interaction among each other and with the environment they live in [13]. The characteristics and behaviours of agents in a multi-agent system can be viewed from two aspects: the internal and external. The internal aspect corresponds to the agents' internal characteristics and behaviours whereas the external aspect consists of the agents' behaviours and characteristics when interacting with other agents and the environment they live in. Modelling a complex system with multi-agent system considers both these aspects of the agent [11].

In a multi-agent system there exist individual level and system level properties. The individual level properties correspond to the behaviours and characteristics of an agent. System level characteristics and behaviours are the global properties of the environment the agents live in. The individual properties of the agents are part of these global properties. A model to represent a system using multi-agent system is the outcome of the interaction of these different properties of the system [11]. Agents in multi-agent system are created from the environment they live in and only interact through the environment. The environment integrates the action and interaction among the different agents. Thus, when building a model for a system using multi-agent system, the components of the system (agents) should set their properties based on the properties of the environment they live in. System level property emerges as a result of the action and interaction of agents among each other and with their environment [1, 11].

3. Related work

A number of researchers have used multi-agent based simulation to solve some complex problems [5, 9, 12, 16]. These researchers represent a given system components by agents. These agents are capable of capturing the characteristics and behaviours of the components. These researchers show that multi-agent based simulation can be used to simulate the interactions of the various components of the system. The work of these different researchers illustrates that due to close mapping between the way agents are implemented and the behaviours and characteristics of human being, agents are capable of representing real human beings. As the aim of this research is to discover the use of multi-agent application to a specific problem, the concepts introduced by the researchers which are related to the applications of multi-agent system are fundamental to the research.

4. Methodology

The research starts by identifying the characteristics, behaviours and assumptions of the real population that will be represented by a model. These factors play an important role in developing the model. The resulting model is a reflection of these factors and the assumptions made about the population. In order to create a population which approximates the real human beings and their environment, different types of agents are developed. By considering different steps of the simulation process, the following agents are identified: Controller agent, Person agents, Environment agent and Statistical agent. Their role in the simulation environment is described below.

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A. **Controller agent:**
This agent starts the simulation process and controls the creation of all other agents. It provides input to agents. The input are population size, characteristics, behaviours, assumptions about the population, time for completing the simulation and number of executions.

B. **Person agents:**
These agents represent the individuals in the population. Thus, the number of Person agents will be the same as the size of the population to be taken during the simulation process. Each Person agent has characteristics and behaviours that represent it. These include the person's gender, HIV-status, type of personality, experience with safe sex, alcohol or drug addiction satus, outgoing and having stable relationship.

C. **Environment agent:**
This agent represents the environment in which the Person agents live. The agent has characteristics and behaviours. The properties of the Environment agent can change based on the emergence of new changes which is caused by the interaction of the different Person agents.

D. **Statistical agent:**
The Statistical agent receives the average result of the expected output. The agent contains the results of all the information obtained from the simulation process. It has number of persons living with HIV-positive and number of new HIV infections.

Java Agent DEvelopment Framework (JADE), which is an agent construction tool, is used to implement the simulation tool. It is a collection of Java libraries that helps in the development of multi-agent systems [8].

4.1. Multi-agent system architecture

Figure 1 shows the architecture of the multi-agent based simulation tool. It outlines the four types of agents that are involved in developing the simulation model. The interaction that is made among the agents is shown in this figure.

As shown in Figure 1, the Controller agent creates the agents based on the information supplied from the data collected. These include different characteristics and behaviours of the population, simulation time, number of executions, etc. This information is given to the Controller agent by the user. Thus, the whole simulation process is centrally controlled by the Controller agent. In the simulation environment Person agents can interact among each other and with the environment they live in. They can interact with one another choosing their partners randomly. Many requests can be sent to a particular Person agent and a particular Person agent can send many requests to the other Person agents. The Controller agent is responsible for synchronising the message passing among the different agents. Due to the interactions they make, the Person agents can change their behaviours. The behaviours of the Environment agent, where the Person agents live, will also be changed based on the result of the interactions made among the different Person agents. The Statistical agent receives the initial information about the characteristics and behaviours of the Environment agent. It then updates the information based on the change made to the Environment agent.

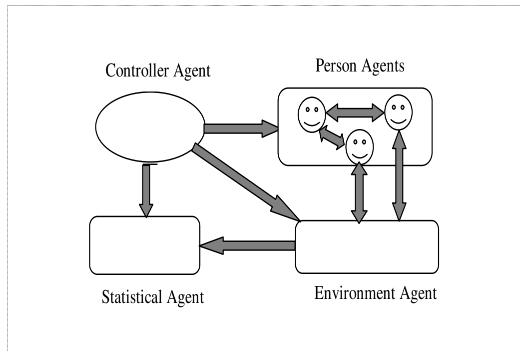

Figure 1. Multi-agent system architecture of the simulation process

Four decision-making functions are used to calibrate the output of the model. They are: deciding the number of agents a Person agent has to approach, deciding to propose for sex, deciding to send reply for the proposal for sex and decision to be infected during interaction. These different decision making functions take a number of fine tuning parameters. The parameters are values of properties of the Person agents. For example, based on its properties, a Person agent can decide a number of other Person agents it will approach. During sexual interaction Person agents can be infected by HIV based on their property of safe sex or unsafe sex experience. This can be the use of condom or not. If one of the interacting Person agents become infected then the agent changes its HIV status. Based on the result of the interaction of two Person agents, the Environment agent updates its properties.

One simulation is executed 4 times. For a single execution a Person agent decides a number of agents, chooses them randomly and start to interact. When it finishes it reports to the Controller agent. When one execution finishes, the second execution starts with the updated properties of the Environment and Person agents.

4.2. Model input assumptions

The research used data from the Republic of South Africa to calibrate the input sets for the simulation tool. Sources from [6], [15] and [18] are used as input for the different values and assumptions of the simulation model and for the comparison of the predicted result. The adult HIV prevalence rate of a given year is used as an input to predict the HIV prevalence for the subsequent year. During sexual interaction the probability of a male being infected is assumed to be 85% of female being infected. One execution is assumed to represent 3 months. Therefore, 4 executions were performed to determine the prevalece for one year.

5. Experimental results

The simulation tool is run in a single platform. The Controller Agent creates the Environment agent, Person agents and Statistical agent. The different weighting functions discussed in Section 4.1 are used to fine tune the output of the simulation model. The performance of the tool is assessed based on its behaviour and the reasonablity of the outputs obtained. The properties of the tool include: its ability to give unique results for the different runs of the simulation, how it behaves as more sample size and more properties are used and its properties when extreme and unlikely values and assumtions on the input data sources are used. The output obtained from the simulation tool are also compared with the outputs of other models that estimated and predicted the HIV prevalence of a given population. The results discussed in the paragraphs below are the predictions obtained by the simulation tool for the 2003 year. The tool is calibrated data from the 2002 findings.

Table 1 shows the number of adult HIV infections when 100, 500, 1000, 1500 and 2000 Person agents are used. Six simulations are performed. The average number of interactions a Person agent made for one simulation ranges between 39 and 48. This indicates that on average a Person agent has sexual frequency four or less times a month.

Figure 2 illustrates a graph describing the results obtained for different simulation processes. It indicates the prevalence predicted for the different groups of agents. From the graphs one can notice a stable oscilation for different simulation steps. This phenomenon is explained by the fact that there is a strong relationship among the outcomes of the simulation steps for a particuler group of agents.

Table 2 shows the average adult HIV prevalence rates predicted by the simulation tool for the different groups of agents. Based on the study conducted by the Department of Health, South Africa, the 2003 adult HIV prevalence was estimated to be 22.8% [6]. Furthermore, for the same year Shisana and Simbayi have estimated the prevalence to be 17% [18]. US Census Bureau also estimated it to be 28.6% [19]. The comparison of the results of the prediction made by the simulation tool indicated in Table 2 and the predictions made by these various other organizations shows a difference in prediction. These differences are due to different input values used, different sample population taken and also different assumptions about the given population made. When compared to the findings of the Department of Health, South Africa, the prevalences predicted by the simulation tool have more than 90% accuracy.

The graph illustrated in Figure 3 indicates the average consistecy among the different simulation steps for different group of agents. This consistency is calculated by performing a number of simulations and taking the average of the pairwise consistencies. It shows that taking a large sam-

Table 1. Total number of HIV infections

Sim.	infec. 100	infec. 500	infec. 1000	infec. 1500	infec. 2000
1	20	115	194	304	422
2	23	107	212	333	412
3	16	111	223	296	427
4	27	112	205	353	411
5	18	94	213	290	418
6	20	120	209	294	443

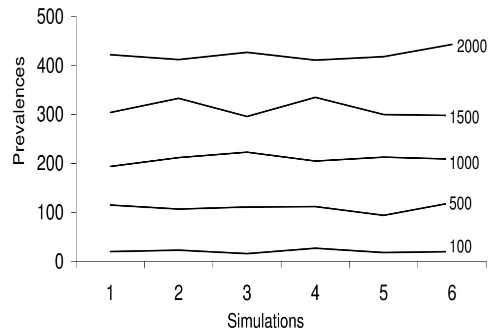

Figure 2. Prevalence for the different agent numbers

Table 2. The adult HIV prevalence rate(%)

100 agents	500 agents	1000 agents	1500 agents	2000 agents
20.7	21.97	20.9	20.78	21.1

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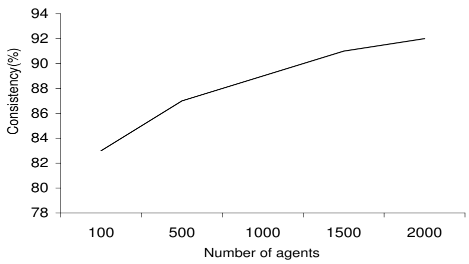

Figure 3. Consistency vs number of agents

ple size can give a result which can have strong consistency for a result of several simulations. Extreme condition tests are also performed on the tool. The findings of these tests supports the correctness of the output of the model.

6. Conclusions and future work

Th objective of this paper was to develop a bottom-up simulation tool by modelling the behaviours of human beings. Multi-agent system is used to implement the tool. Agents in multi-agent system have the capability to build models of individuals. The tool is used to predict the spread of the HIV infection in a given population. This research revealed possibility of such approach by representing the entities of a population by agents. The tool is developed through the action and interacion of these agents among each other.

Future work on this research include modelling demographic projection of a population and incorprating the findings of the research to give demographic projection of the population with and without HIV/AIDS cases.

References

[1] S. Brueckner, D. Parunak, and J. Sauter. ERIM's Approach to Fine-Grained Agents. In *Proceedings of the NASA/JPL Workshop on Radial Agent Concepts(WRAC'2001)*. Greenbelt, MD, 2001.

[2] B. Chadha and J. Welsh. Architecture Concepts for Simulation-Based Acquisition of Complex System, 2000. Lockheed Martin Advanced Technology Laboratories.

[3] P. Charteris. Assessing industry-wide impact of beef cattle genetic technology. Presented at Beef Improvement Federation, 33rd Annual Convention. San Antonio, July 2001.

[4] P. Davidsson. Multi Agent Based Simulation: Beyond Social Simulation. *In Multi-Agent Based Simulation, Springer Verlag LNCS Series*, 1979, 2000. (http://www.ide.hk-r.se/ pdv/Papers/MABS2000.pdf).

[5] P. Davidsson and M. Boman. Saving energy and providing value added services in intelligent buildings: A MAS approach. In *ASA/MA*, pages 166–177, 2000.

[6] Department of Health. *Summary Report National HIV and Syphilis Antental Sero-prevalence Survey in South Africa*, 2002. Pretoria, South Africa.

[7] S. Franklin and A. Graesser. Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents. In *Intelligent Agents III. Agent Theories, Architectures and Languages (ATAL'96)*, volume 1193, Berlin, Germany, 1996. Springer-Verlag.

[8] JADE. Java Agent Development Application Environment, Dec. 2003. http://sharon.cselt.it/projects/jade/.

[9] A. Moreno, A. Valls, and M. Marin. Multi-agent simulation of work teams, Mar. 2003. Computer Science & Mathematics Department Universitat Rovira i Virgili. Tarragona, Spain.

[10] C. Oechslein, A. Hornlein, and F. Klugl. Evolutionary Optimization of Societies In Simulated Multi-Agent Systems. In *Modelling Artificial Societies and Hybrid Organizations; workshop on the ECAI*, 2001. (http://citeseer.nj.nec.com/oechslein00evolutionary.html).

[11] A. Omicini. SODA: Societies and infrastructures in the analysis and design of agent-based systems. In *AOSE*, pages 185–193, 2000.

[12] P. Paruchuri, A. Pullalarevu, and K. Karlapalem. Multi Agent Simulation of Unorganized Traffic. In *Proceedings of the first international joint conference on Autonomous agents and multiagent systems: part*, pages 176–183. ACM press, 2002.

[13] H. Parunak, R. Savit, and R. Riolo. Agent-Based Modeling vs. Equation-Based Modeling: A Case Study and Users' Guide. In *Proceedings of Multi-agent systems and Agent-based Simulation (MABS 98)*, pages 10–25, 1998.

[14] B. Paul. Bottom-up simulation for evaluation of recreational boat traffic monitoring, 1998. University of Florida, Department of Geography.

[15] T. M. Rehle and O. Shisana. Epidemiological and demographic HIV/AIDS projections: South Africa. *African Journal of AIDS Research: AJAR. NISC Pty Ltd*, 2(1):1–8, 2003.

[16] L. B. Said, T. Bouron, and A. Drogoul. Agent-based interaction analysis of consumer behavior. In *Proceedings of the first international joint conference on Autonomous agents and multiagent systems*, pages 184–190. ACM Press, 2002.

[17] R. E. Shannon. Introduction to the art and science of simulation. In *Proceedings of the 30th conference on Winter simulation*, pages 7–14. IEEE Computer Society Press, 1998.

[18] O. Shisana and L. Simbayi. *Nelson Mandela/HRSC study of HIV/AIDS*. the Human Science Research Council Publishers, 2002. South African National HIV Prevalence, Behavioural Risks and MASS media : Executive Summary.

[19] US Census Bureau. *Demographic Estimation and Projections.*, 2002. Washington DC, USA.

[20] M. J. Wooldridge and N. R. Jennings. Intelligent Agents: Theory and Practice. *Knowledge Engineering Review*, 10(2):115–152, June 1995.

[21] P. Zvirinsky. A Bottom-up Approach to Immune System Modelling. In *Intelligent and Adaptive Systems in Medicine*, Mar. 2003.

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