Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

SENSITIVITY ANALYSIS OF POLICY OPTIONS FOR URBAN MENTAL HEALTH USING SYSTEM DYNAMICS AND FUZZY COGNITIVE MAPS

Elhabib Moustaid
Maksims Kornevs
Sebastiaan Meijer

Department of Biomedical Engineering and Health Systems
KTH Royal Institute of Technology
Halsovagen 11
Huddinge, 14 152, SWEDEN

ABSTRACT

Urban mental health challenges call for new ways of designing policies to address the ongoing mental health issues in cities. Policymaking for mental health in cities is extremely difficult due to the complex nature of mental health, the structure of cities, and their multiple subsystems. This paper presents a general system dynamic model of factors affecting mental health and a method to test the sensitivity of the model to policy options using an approach combining system dynamics and fuzzy cognitive maps. The method is developed and tested to evaluate policies built around feedback loops. The approach succeeded in identifying the factors that substantially improve the mental health of the city population for specific contexts. It also suggests the coordination needed between different subsystems to reach these objectives.

1 INTRODUCTION

Designing policies for mental health in cities is a hard challenge as cities are complex adaptive systems with a significant number of physical, social, economic, and political entities all interacting with each other and responding to an ever-changing environment (Batty 2013). Evidence shows that the epidemic of mental health and other chronic diseases in developed countries today can be affected by the city lifestyle (Gruebner et al. 2017). Urban mental health status is dependent on multiple aspects and systems in cities (Leventhal and Brooks-Gunn 2003). This makes mental health in cities a system that is highly complex to understand and improve.

While being a public health concern, the risks and the challenges regarding mental health cannot be dealt with traditional healthcare provision approaches. As studies show, urban population wellbeing is affected by many aspects of the metropolitan lifestyle. Public transportation, employment, pollution, physical and psychological safety, or even segregation are aspects that can affect the mental health of city populations (Warr et al. 1988; Evans et al. 2003; Evans 2003). The study of mental health in cities has to embrace its multifaceted and multi-aspect nature. We denote by ‘mental health system’ all the elements and components that affect directly or indirectly the mental health of the city populations.

This paper investigates the sensitivity of policies related to a city’s population mental health. To achieve it, a system dynamic (SD) model, which was developed in a participatory method, is used as a general representation of the factors affecting the dynamics of mental health in cities, grouped by the city systems they belong to (Moustaid et al. 2019). The approach showcases a way to identify factors across the city subsystems that can benefit mental health, suggesting ways of effective collaboration beyond system and agency borders. This is achieved by exploring the systems feedback loops through the application of SD and fuzzy cognitive maps (FCMs) modeling techniques.

978-1-7281-3283-9/19/$31.00 ©2019 IEEE

The remainder of this paper contains six more sections. The next section shows the background of this work and summarizes the challenges we face today in policymaking for mental health in cities. The approach section details the methods proposed. Experiments and results are shown in Section 4 and then discussed in Section 5. Finally, we share the conclusions and refer to future work.

2 BACKGROUND

2.1 Complexity of Mental Health

Mental health refers to the emotional, psychological, and social well-being of a person (World Health Organization 2004). It affects how we think, feel, act, and experience life. Mental health problems decrease the quality of life and affect individuals and their environments. These problems can range from mild issues, such as stress, to severe problems that could lead to life-long disabilities or suicide. Effective policies are needed to reduce mental illness and promote better mental health (Thornicroft et al. 2016).

Traditionally mental health is seen as a part of the field of healthcare. However, there is strong evidence that mental health in urban areas, is related to the education, labor market, family support, urban planning, and other fields (Leventhal and Brooks-Gunn 2003). Hence, managing and promoting mental health falls into the responsibility of various organizations and individuals such as politicians, healthcare providers, city planners, law enforcers, teachers, or parents. This makes mental health in cities a complex system with a lot of components and interactions.

The necessity of collaboration across systems makes mental health complex because of the distributed controls, the information asymmetry, and the contradicting goals between the stakeholders with different incentives and responsibilities (Haynes 2015). At the same time, dynamic interactions that take place within the mental health system make this system adaptive and ever-changing. New regulations, a better understanding of mental health, constraints on available resources, internal changes in current stakeholders are among the reasons that can enhance interactions within the mental health system (Sullivan and Skelcher 2002). This requires policymaking in the mental health system to be flexible and adaptable to the changing environment. Often, the need for this adaptivity can be seen in strategic plans and visions of public organizations (Bryson et al. 2015).

The complexity and adaptivity are characteristics of complex adaptive systems (Dekkers 2015); we view urban mental health as such. In a complex adaptive system, the system and the stakeholders cannot be separated, and the system as a whole is more than just a sum of the individual components (Dooley 1997). Complex adaptive systems have many unordered elements where connections between causes and effects are unclear, which makes it hard to analyze complex adaptive systems, and even harder to change those systems toward the desired direction.

2.2 Mental Health Policies

In order to promote mental health, the relevant stakeholders need to provide their vision of the solution of challenges faced today and the directives to achieve such vision (World Health Organization 2005). The course of actions and directions are officially presented in policies. The primary purpose of policies in mental health is either 1) to increase the positive effect of aspects of the mental health system that leads to the better mental health of populations, and/or 2) to decrease adverse effects of aspects of the mental health system that lead to mental illness (Mehta et al. 2015; Adler et al. 2016; Cairney et al. 2016). While most of the policies in the healthcare system vary in different countries or cities to achieve specific intended effects, the complex adaptive nature of mental health system leads to some unintended consequences. These consequences make it harder to evaluate and to apply policies without deeper investigation (Vedung 2000).

Policies can be assessed based on their sensitivity (Borgonovo and Plischke 2016). Sensitivity analysis allows studying how the uncertainty in the outputs of the system depends on uncertainty in the different input sources. Sensitivity analysis helps to test the robustness of the results, provide more understanding of the relationships and connections in the system, and reduce uncertainties in outcomes of variation in the inputs of the models of the system simulated.

3 APPROACH

3.1 Participatory Model Building

Models and simulations can provide a sensitivity analysis and policy testing for complex systems. However, this requires a model and a simulation that is complex enough to represent the complexity of its target system. Particularly, a model that takes into account the multitude of stakeholders, systems, and agencies over such a system. In order to achieve such a model, a participatory system dynamics model building was applied to model the urban mental health and the factors that affect it.

The model building was done in several steps starting from the choice of participants to developing the model to the validation of the model based on the feedback of participants. Figure 1 is the outcome model of the participatory model building. The details of the model building and preliminary findings are described further in Moustaid et al. (2019).

3.2 System Dynamics and Fuzzy Cognitive Maps

The model Figure 1 represents elements that affect the dynamics of mental health in cities. The model building embraced a bottom-up approach in that it identified primary components and determinants of mental health in cities. It mainly describes its dynamics by focusing on the interactions of the elements that compose the system. The participants who built the model act mostly in the realms of planning and strategy. The model represents an elicitation of their knowledge and their worldviews. Consequently, the nature of the factors identified was very diverse. Some elements are quantitative variables, but some factors are abstract or qualitative entities. Running the model to extract more information on its dynamics requires a quantitative interpretation to be used to generate quantitative results. A way to overcome this difficulty combines elements of SD with FCMs theory (Kosko 1986).

FCMs are an evolution of cognitive map (CM) modeling. This modeling technique is a tool to investigate and analyze causalities in qualitative social systems such as social, political, or economic systems. CMs are characterized by maps of entities affecting each other positively or negatively. CMs were first introduced by Tolman (1948). Their prominence in policy and decision making was mainly attributed to the introduction of graphical ways to elicit the viewpoints of decision makers on social systems they are often interacting with to understand causalities in those systems (Axelrod 1976). FCMs made CMs explorable analytically and hence made them a tool of predicting and analyzing dynamics of systems they represent through the introduction of FCMs by Kosko (1986). This was inspired by SD methodologies developed since the 1970s by Forrester (1971). This enabled modelers and policymakers of extracting more information from CM to understand systems dynamics beyond what can be graphically learned (Carvalho 2013).

FCMs make CMs dynamic by making cognitive maps quantitative by providing all factors a quantitative sense. This is done by representing each of the entities in the model by a value ranging from $[-1,1]$ (or $[0,1]$). This represents a normalization of the values of these entities from their original real-world value. This transformation is valuable even when looking at models that have both quantitative and qualitative entities as it brings all entities to a similar scale. Furthermore, FCM uses weights on the connections to model the sense and the strength of those connections. The weights are also within the interval $[-1,1]$. A higher absolute value of the weights indicates a strong effect. The sign of the weight '+' means an increasing effect, while '-' means a decreasing effect.

3.3 Formalizing the Model

The model Figure 1 shows a general representation of entities that affect mental health in cities. The model contains components classified as follows.

Figure 1: General SD model for urban mental health.

- *Stocks* represent different states of the city population. The model classifies the population in four possible states. The stocks represent the number of people in the city who are in a particular state. The four stocks (and states) are as follows. First, the stock *Healthy* represents the population without any mental illness. Second, the stock *Troubled and unaware* represents the population with a mental illness of which they are not aware of. Third, the stock *Troubled and aware* represents the population with a mental illness of which they are aware and seek treatment as a consequence. Finally, the stock *Recovery* represents the population who are recovering from a mental illness.
  For future references, we denote by S_i where $i \in \{1,2,3,4\}$ the stocks *healthy*, *troubled and unaware*, *troubled and aware*, and *recovery*, in that same order. We denote by N the total population of the city and by N_{S_i} the population of each stock S_i. Note that N_{S_i} always satisfies the conditions $N_{S_i} \geq 0$ and $\sum_{i=1}^{4} N_{S_i} = N$.
- *Flows* refer to the flow of the population that moves between two stocks at a time iteration. We denote by Q_i the flow from stock S_i to stock S_{i+1} for $i \in \{1,4\}$ (with $S_5 := S_1$, i.e. by definition).
- *Factors* refer to parameters that can affect stocks, flows, or other factors. The factors are linked to each other, the flows, or to the stocks through directed links called connections. The model contains 111 factors ($N_f = 111$). Factors are controllable parameters in SD models.
- *Connections* refer to directed links that connect two entities (factors, flows, or stocks). A connection represents a causal effect. Links are either carrying an increasing or a decreasing causal effect. An increasing effect of a component i on a component j means that increasing the component i will increase component j (i.e., decreasing the component i will result in a decrease of component j). A decreasing effect means that increasing effect of factor i will result in decreasing the factor j (i.e., decreasing the component i will result in an increase of component j). Figure 1 show increasing effects as in green and decreasing effects in red.
- *Systems* refer to the systems of the city to which factors belong. For this model, each factor belongs to one system at the time. We denote by Ω_i a system i where the index $i \in \{1,2,...,8\}$ and represents the following systems: *Labour System, Individual, Family, Education System, Physical Infrastructure, Social System, Education System, Health Care System, Government*. Ω_i is the set of factors that belong to each system, i.e., $f_j \in \Omega_i$ if and only if the factor j is part of the system i.

3.4 Simulating the Model

The model can be simulated by specifying the rules for three sets of dynamic components: flows, stocks, and factors. In line with Carvalho (2013), each of the sub-components of the model is simulated according to specific SD or FCM rules.

3.4.1 Simulating Controls and the Network of Factors

The network of factors is represented as an FCM where the factors interact with each, with control parameters, and with the external effect of stocks or flows on the factors.

The value of each factor f_i is represented by a value $v_i \in [-1,1]$. -1 means absence or the lowest possible level of that factor, while $+1$ means the presence or the highest level of that factor. For example, *Poverty* at the level -1, means low poverty, while a value of 1 means a high level of poverty. Another example is the factor *Lack of Education*; -1 refers to a low level of lack of education within the simulated population meaning a good level of education overall, while 1 refers to a high level of lack of education, meaning the population is predominantly uneducated.

We denote $w_{i,j}$ the strength of the link between the factor f_i and f_j. $w_{i,j} > 0$ (resp. $w_{i,j} < 0$) means the factor f_i has an increasing (resp. decreasing) effect on the factor f_j while $w_{i,j} = 0$ means the absence of any effect. The values $(w_{i,j})_{1 \leq i,j \leq 111}$ are defined in a discrete scale by equation (1). This allows an easy interpretation of the model as it was constructed. The participants in the model building had the chance to show the strength of the effects through the thickness of the connections.

$$|w_{i,j}| = \begin{cases} 0 & \text{factor } i \text{ has no effect on factor } j \\ 0.1 & \text{factor } i \text{ has a weak effect on factor } j \\ 0.5 & \text{factor } i \text{ has a medium effect on factor } j \\ 1 & \text{factor } i \text{ has a strong effect on factor } j \end{cases} \tag{1}$$

The effect of all the factors on a factor i can be expressed through the sum: $\sum_{j=1,j\neq i}^{n_f} w_{j,i} f_j$.

Besides being affected by other factors, f_i can be affected by the stocks in the model (as is the case for *Recovery* affecting *Waiting Times to care*). To simulate these effects, stocks are used as an external influence on the FCM of factors. First, the value of each stock is linearly transformed to the interval $[-1,1]$, let $\hat{N}_{S_i}$ be the transformed value. It is defined as $\hat{N}_{S_i} = \frac{2N_{S_i}}{N} - 1$. Note that $\hat{N}_{S_i}$ satisfies the conditions 1) $-1 \leq \hat{N}_{S_i} \leq 1$, and 2) a low $\hat{N}_{S_i}$ means a low population N_{S_i} and a high value means a high population. Then, let $(w^s_{i,j})_{1\leq i\leq 4, 1\leq j\leq 111}$ be the strength of the effects of the stocks on the factors. $w^s_{i,j}$ admit the same value as $w_{i,j}$ defined in equation (1). This means that a value 0 (resp. $0.1, 0.5, 1$) means that there is no (resp. a weak, a medium, a strong) effect of the stock S_i on the factor f_j.

The total effect of stocks on a factor f_j is the sum: $\sum_{i=1}^{4} w^s_{i,j} \hat{N}_{S_i}$.

Finally, a factor can be affected by a control parameter c_i which represents external controls on the factors f_i. This additional variable represents input value from the simulation user to test the effects of moving the value of a factor towards a direction. Without loss of generality, we assume that c_i effect is weighted with a value 1. This means that the control parameters take the value of the strength of the effect one wants to exhibit on the factor affected.

To simulate the network over time, the values v_i are updated at each simulated time step. The effects on factor are carried over the iterations, where the values of stocks, factors, control parameters at a time iteration t determine the value of factors at the time iteration $t+1$. We introduce α as an updating rate term that controls the rate of convergence of the model, and F a sigmoid function taking values in the interval [-1,1]. $v_i(t)$, the value of a factor f_i, at the time step t, can be updated using the formula equation (2).

$$v_i(t+1) = F(\alpha(\sum_{j=1}^{n_f} w_{j,i} v_j(t) + \sum_{j=1}^{4} w^s_{j,i} \hat{N}_{S_j}(t) + c_i(t)) + (1-\alpha) v_i(t)) \tag{2}$$

For the experiments, the sigmoid fuction used is $F(x) = tanh(x)$ as it satisfies $tan(x) \in [-1,1]$, $\forall x$.

3.4.2 Simulating the Stocks and Flows over Time

Let $Q_i(t)$ be the value of the flow Q_i at the time iteration t. As Moustaid et al. (2019) shows that these can be regulated by 4 factors; *prevention, awareness, intervention, and remission* (denoted respectively, f_1, f_2, f_3, f_4). Good *prevention* in fact limits the amount of people who can be affected by mental troubles. Hence a high prevention would reduce the flow Q_1. Similarly, a high level of *awareness* (respectively *intervention* and *remission*) would increase the flow Q_2 (respectively Q_3 and Q_4). Since flows are non-negative ($Q_i \geq 0\ \forall i$), we use the linear transformation $g(x) = \frac{x+1}{2}$ to transform the value of the factors f_1, f_2, f_3, and f_4 from the interval $[-1,1]$ to $[0,1]$. This transformation allows to express flows $(Q_i)_{i\in\{1,2,..,4\}}$ as shown in equation (3).

$$Q_1(t) = (1 - g(v_1(t)))N_{S_1}(t) \text{ and } Q_i(t) = g(v_i(t))N_{S_i}(t) \text{ for } i \in \{2,3,4\} \tag{3}$$

Let $N_{S_i}(t)$ be the amount of stock S_i at time iteration t, the population can be updated using equation (4).

$$N_{S_i}(t+1) = N_{S_i}(t) + Q_{i-1}(t) - Q_i(t) \text{ and } Q_0(t) := Q_4(t) \tag{4}$$

3.4.3 Simulation Formulation

Now that the model has been defined in dynamic terms, it is possible to simulate over time. The update rules differ between the stocks and the factors. The simulation is run as follows.

- Initialize all factors value ($v_i(0)$) and populations ($N_{S_i}(0)$) from a scenario of interest.
- Define values of control options of interest given the scenarios.
- For $t = 1,2,...,n$
  - Update the values of factors using equation (2).
  - Update the values of flows using equation (3).
  - Update the values of stocks (populations) using equation (4).

3.5 The Simulation as a Tool to Test Sensitivity of Policy

Feedback loops are crucial to the study of complex systems in general and SD models in particular. Feedback loops are often responsible for reinforcing or stabilizing the dynamics of the systems they are part of. SD and FCM are examples of causal models that explore feedback loops effects in systems. The model Figure 1 contains a total of 535 feedback loops. Most of these feedback loops span over multiple systems. This suggests that exploring the effects that these feedback loops can provide policymakers who have agency these systems the tools to collectively affect the system overall through coordination of policies. In such a way, it can enable policymakers to build valuable bridges between different systems and agencies to manage collectively mental health.

To explore the effect of each feedback loop, we simulate the effects of simultaneous control of all the factors belonging to the feedback loop. We do that by setting the control value c_i of each factor f_i in the feedback loop to a value that aims to improve that factor. This simulates effects of policy on that specific factor. This does not mean that the factor will be at a better value, as a combination of controls and feedback from other system components determine the final value of the factor (equation (2)). This makes it hard to predict the effect of policy over time over the whole system. Section 4.2 shows through experiments feedback loops that can affect the system in specific cases.

4 EXPERIMENTS AND RESULTS

Running the model described in section 3.4.3 requires having scenarios of interest. We design two experiments to explore the dynamics of the model and to showcase the possibility of the use of the model to test policymaking for mental health in cities. In these experiments, we assume that each factor admits an optimal value either at -1 or 1. Trying to improve a factor then means providing controls that have the objective to move that factor towards its optimal value, denoted $\hat{v}_i$.

4.1 Exploration of the Model Behaviour

4.1.1 Experiment

FCMs are characterized by having unpredictable behavior. The study of convergence and dynamics of FCM have been extensively studied (Napoles et al. 2016). In order to see the behavior of the model, it is important to run several scenarios with different initial states. It helps to investigate the unpredictable behavior of FCMs. It also provides a better understanding of effects that the context of each city matters and the initial states have on the outcomes of the model. We test the convergence of the model under four different initial states that cover the spectrum of the values of factors as follows:

- *Scenario 1,* starts from a state where all factors are at their optimal values. Each factor has a value that represents its local optimum. Hence for this scenario, the initial conditions is such that $v_i(0) = \hat{v}_i$.

- *Scenario 2,* starts is the exact opposite state of the scenario 1. Each factor value is initiated with its worst value. This means $v_i(0) = -\hat{v}_i$.
- *Scenario 3 and 4,* start from two distinct random initial states that yield different dynamics.

These scenarios are interesting as they represent different states in which cities can be today. The scenarios 1 and 2 are the two extremes of the spectrum as scenario 1 is a perfect city (all factors are at their optimal values), while 2 is a city that is suffering in all aspects. Scenario 2 and 3 are representing cities between these two extremes and provide a case to show how the model can be used to improve mental health given a specific context. The four scenario start from a population without any additional controls throughout the simulation time iterations (i.e. $c_i(t) = 0\ \forall i,t$). We simulate a total population of $N = 1{,}000{,}000$ inhabitants, with the initial condition $N_{S_i} = 250{,}000$ inhabitants, i.e., the population are equally distributed between the four possible states.

4.1.2 Results

Figure 2 shows the total population under each stock over 500 time iterations. The four scenarios converge to 4 different population distributions. The first scenario converges to a distribution where most of the population is healthy. Scenario 2 converges to a state where a healthy population is almost a negligible number. Scenario 3 after a short warm-up period converges to a state with a mostly healthy population. Scenario 4 also has a short warm-up period before converging to a perfect split between the four possible states of the population.

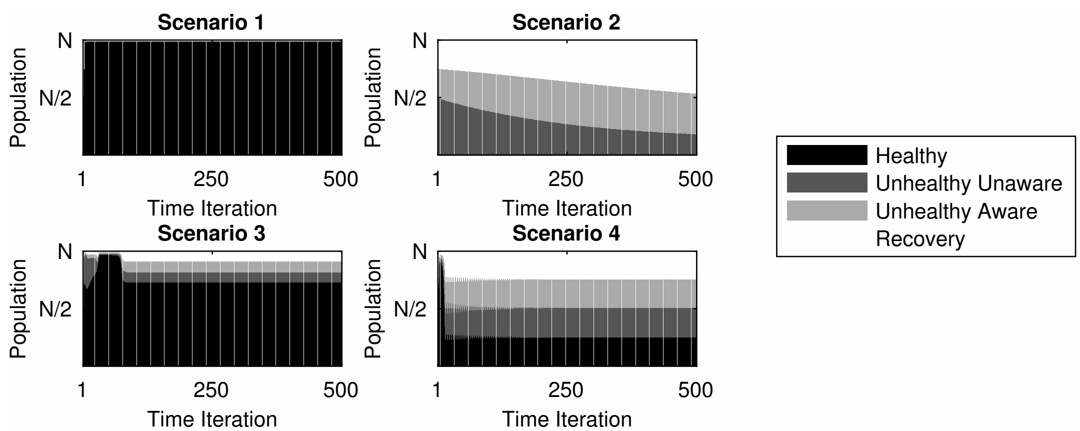

Figure 2: Distribution of the population over different states over simulation iterations.

To understand better how the simulation is producing these results, we analyze the performance of all individual factors in the model. The performance indexes of factors allow to see the performance of all factors in the same scale ($[-1,1]$). Let p_i be the factor f_i performance index, it is defined by equation (5).

$$p_i = \begin{cases} v_i & \text{if } \hat{v}_i = 1 \\ -v_i & \text{if } \hat{v}_i = -1 \end{cases} \tag{5}$$

The performance index of factor takes a value between -1 and 1, where 1 means the factor is at its optimal value, while -1 means it is at its worst value. Figure 3 shows the performance of all the model factors over time for each of the scenarios. The y-axis represents different factors, while the x-axis represents the time iterations. Each row in the plot represents the values of a factor throughout the simulation. The darker is the value of a factor, the closer it is to its optimal value. The four scenarios show the model to converge to a stable point from the initial conditions. Overall, the results show that indeed, the performance of the factors overall is reflected by the population status.

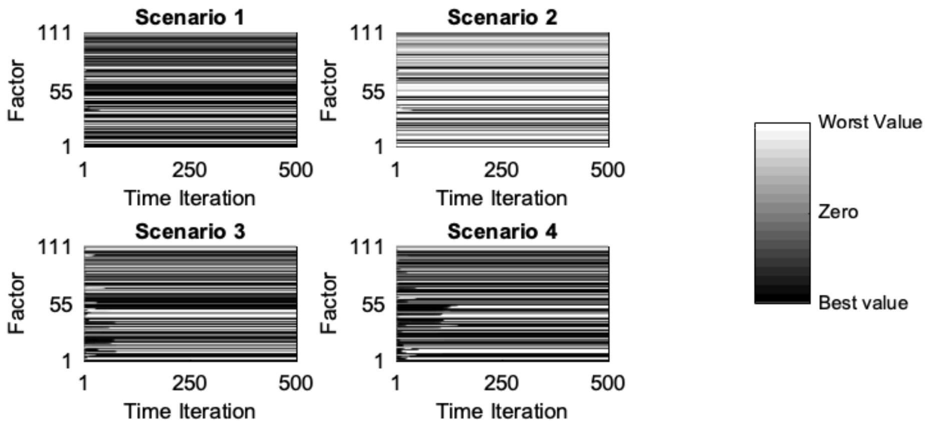

Figure 3: Visualization of the performance of factors over simulation iterations for different scenarios.

The results in Figure 2 and Figure 3 show that the model exhibits a chaotic nature as different initial conditions yield different behaviors. The system hence admits more than one attractor. The results Figure 3 explain the outcomes seen on Figure 2. In scenario 3, there is a steady but slow decrease in healthy population between time step 37 and 73, before it becomes a sharp decrease and ultimately converges around the time step 90. Analyzing the values of the factors that change during this time allows understanding which effects led to such a change. *Prevention* is one of the factors that changed values. *Prevention*, which determines the number of healthy people that are prevented from getting a mental illness, experiences a sharp decrease causing a reduction in the number of the healthy population. The decrease of *Prevention* can be explained by the slow decrease of multiple factors affecting it. Such factors include *Job Stability*. *Income Stability*, *Physical Activities*, and *Affordable Housing*. This change shows further the chaotic nature of these systems, as minor changes in some factors, can affect other factors after several time steps ultimately having effects on populations.

The scenarios simulated also show that the model can converge to desired attractor as well as non-desired ones. For policymaking, this model can be useful to identify factors that can make the system behave better; we do that through the investigation of all the feedback loops in the system over the scenarios shown in this experiment.

4.2 Analysis of the Sensitivity of Coordinated Policy through the Use of Feedback Loops

4.2.1 Experiment

To find the feedback loops that have the highest potential of taking the system from an attractor state to a different attractor state with improved population mental health, we perform the following experiment. Starting from a known stable initial state, for all the feedback loops in the systems, the model is run for a controlled phase followed by an uncontrolled phase. During the controlled phase, the values of the control parameters for each factor in the feedback loop (denoted FBL) are set to their optimal values based on the corresponding policies, i.e. $c_i = \hat{v}_i, \forall f_i \in FBL$. The uncontrolled phase starts right after the control phase. The control values are again set $c_i = 0$ during this phase. The goal of the experiment is to test the sensitivity of the system to controls that represents a coordinated improvement of factors belonging to the same feedback loop.

The sensitivity of the system to coordinated policy is evaluated during the control phase and the uncontrolled phase by looking at the effects of the control values on the health of the population, i.e., if the amount of healthy individuals increases or decreases (N_{S_1}). We define the performance of the controls on a feedback loop and the sensitivity of the systems to it as follows.

- *Continuous Improvement:* the system improves population health during the control phase and keeps improving the health status even after control has ended.
- *Stable Improvement:* refers to an overall improvement of the population health. The system improves under the control phase but does not keep improving after the end of controls. It stabilizes in a health status better than the initial phase.
- *Unstable Improvement:* the system falls back to an attractor very close to the original state after having improved during the control phase (no improvement higher than 1%).
- *No effect:* refers to absence of improvement or degradation during neither the controlled or the uncontrolled phase.
- *Adverse Effect:* the system falls into an attractor state worse than the initial state, or behave in a cyclic or chaotic way including going through states worse that the initial health status.

4.2.2 Results

Table 1 shows the results of running the experiment starting from the final iterations of scenarios 2, 3, and 4 as an initial state. Since scenario 1 presents a case of perfect mental health, there is no direction in which the system could improve the population health.

Table 1: The number of feedback loops triggering different types of change in the system.

Initial State	Continuous Improvement	Stable Improvement	Unstable Improvement	No effect	Adverse effect
Scenario 2	128	407	0	0	0
Scenario 3	15	463	20	37	0
Scenario 4	0	281	163	91	0

While no feedback loop control resulted in adverse effects in any of the scenarios simulated, the results are generally scenario dependent. Scenario 2, which is the worst case possible for urban mental health, all feedback loop showed to have a positive effect on mental health and increasing patients health. However, not all feedback loops result in continuous improvement.

Scenario 3 and 4 results show the difficulty of improving mental health with so many unknowns. As Figure 2 shows, scenario 3 represents a system that is behaving better than scenario 4. The results show that improving city mental health in scenario 3 can be easier than doing so in scenario 4. This suggests that the system can evolve towards better attractor states in scenario 3 than in scenario 4, and that in scenario 4 the system would need more that one feedback loop being reinforced to change course continuously.

The study of scenarios 3 and 4 provide two distinct outcomes. Further analysis of scenario 3 shows that the 15 feedback loops that improve the system continuously intersect in some elements. Those elements are *Job Purpose, Job Stability, Wellbeing, Free Urban Space, Urban Planning, Financial Resources*. This result means that improving the system in those conditions can be best achieved through developing policies around these factors. These policies require coordination between the systems to which these factors belong. In this case, enabling a coordinated policy between labor (employers), urban planning, individuals, and local governments.

The further analysis of scenario 4 has not provided a similar conclusion as there are no factors that are part of all feedback loops improving the system. It, however, singled out policies that can improve the system in a stable way and policies that produce unstable changes. This is all the same an essential input to policymaking. This scenario also shows that the system moving into a state of continuous improvement would require policy coordination around more than one feedback loop at the time.

5 DISCUSSION

The approach in this paper presents a way to fully explore the potential of using a model to provide a sensitivity analysis of policies for mental health. Specifically, we looked at the sensitivity of policies articulated around feedback loops, given their ability to transform and make systems evolve. Apart from formalizing the model, this approach embraced completely the inherent complexity of the model it studies and its target without reducing its size, or investigating only a few feedback loops. In order to analyze the sensitivity of the system to policies, the simulation allowed for a phase of controls and a phase of autonomy to see the stability of the state to which the model was dragged to under the control phase.

The results showed that the dynamics of the model has different sensitivities to different policies and that investigating feedback loops can provide answers on which factors to focus on and the type of collaboration needed to achieve a goal given specific conditions and scenarios. The results Table 1 show the potential of the method to detect, given a scenario, the feedback loops that can change the course of the dynamics of the system and the type of the change they produce.

It is crucial to note that the results were scenario dependent. This makes sense as no unique solution or policy can improve the mental health system no matter the context and the conditions it starts from. In reality, this means that an improvement over a system is context dependent. This requires the model to describe more real-world context and cities in order to be useful for the context of these cities. As the model used in this paper is a general one, it can only give general conclusions on general contexts it simulates. For example, the feedback loops that show to improve continuously scenario 3 are the result of the system at first being not perfect in its prevention for mental illness. Hence the feedback loops that sustainably increased prevention were the ones that showed high positive sensitivity overall in population health.

6 CONCLUSION

This work presented a method to study the sensitivity of complex adaptive systems to policy options. In particular, we focused on investigating policies that capitalize on the existence of feedback loops in complex adaptive systems to build policies that can put the system in a course for improvement. The method is used to investigate the feedback loops in an SD city mental health model using SD and FCMs methods. It successfully showcased how the method can determine policies, factors, and loops that can improve the system through analysis of the sensitivity of the model to input control parameters. The approach presented in this work can be used for problems that share the same structure as complex systems often deal with wicked problems with a significant number of components and a distributed agency.

The analysis performed through this approach is bound to the model limitations and assumptions. The model, as a general representation of city mental health, lacks the specificity of one target city and hence cannot itself provide detailed policy analysis. Specifying the model further through adding relevant factors, and substantiating it with data to simulate realistic scenarios can provide the approach with a use-case to test the sensitivity of policies.

ACKNOWLEDGMENTS

The authors thank Fredrik Lindencrona and the International Initiative for Mental Health Leadership IIMHL for participating in the model building process.

REFERENCES

Adler, N. E., M. M. Glymour, and J. Fielding. 2016. "Addressing Social Determinants of Health and Health Inequalities". *JAMA* 316(16):1641–1642.

Axelrod, R. 1976. *Structure of Decision: The Cognitive Maps of Political Elites*. Princeton, New Jersey, USA: Princeton University Press.

Batty, M. 2013. *The New Science of Cities*. Cambridge, Massachusetts: MIT Press.

Borgonovo, E., and E. Plischke. 2016. “Sensitivity Analysis: A Review of Recent Advances”. *European Journal of Operational Research* 248(3):869–887.

Bryson, J. M., B. C. Crosby, and M. M. Stone. 2015. “Designing and Implementing Cross-Sector Collaborations: Needed and Challenging”. *Public Administration Review* 75(5):647–663.

Cairney, P., K. Oliver, and A. Wellstead. 2016. “To Bridge the Divide between Evidence and Policy: Reduce Ambiguity as Much as Uncertainty”. *Public Administration Review* 76(3):399–402.

Carvalho, J. P. 2013. “On the Semantics and the Use of Fuzzy Cognitive Maps and Dynamic Cognitive Maps in Social Sciences”. *Fuzzy Sets and Systems* 214:6–19.

Dekkers, R. 2015. *Applied Systems Theory*. New York, New York, USA: Springer International Publishing.

Dooley, K. J. 1997. “A Complex Adaptive Systems Model of Organization Change”. *Nonlinear Dynamics, Psychology, and Life Sciences* 1(1):69–97.

Evans, G. W. 2003. “The Built Environment and Mental Health”. *Journal of Urban Health* 80(4):536–555.

Evans, G. W., N. M. Wells, and A. Moch. 2003. “Housing and Mental Health: A Review of the Evidence and a Methodological and Conceptual Critique”. *Journal of Social Issues* 59(3):475–500.

Forrester, J. W. 1971. “Counterintuitive Behavior of Social Systems”. *Technological Forecasting and Social Change* 3:1–22.

Gruebner, O., M. A. Rapp, M. Adli, U. Kluge, S. Galea, and A. Heinz. 2017. “Cities and Mental Health”. *Deutsches rzteblatt International* 114(8):121–127.

Haynes, P. 2015. *Managing Complexity in the Public Services*. 2nd ed ed. New York, NY, USA: Routledge.

Kosko, B. 1986. “Fuzzy Cognitive Maps”. *International Journal of Man-Machine Studies* 24(1):65–75.

Leventhal, T., and J. Brooks-Gunn. 2003. “Moving to Opportunity: an Experimental Study of Neighborhood Effects on Mental Health”. *American Journal of Public Health* 93(9):1576–1582.

Mehta, N., S. Clement, E. Marcus, A.-C. Stona, N. Bezborodovs, S. Evans-Lacko, J. Palacios, M. Docherty, E. Barley, D. Rose, M. Koschorke, R. Shidhaye, C. Henderson, and G. Thornicroft. 2015. “Evidence for Effective Interventions to Reduce Mental Health-related Stigma and Discrimination in the Medium and Long Term: Systematic Review”. *The British Journal of Psychiatry: The Journal of Mental Science* 207(5):377–384.

Moustaid, E., M. Kornevs, F. Lindencrona, and S. Meijer. 2019. “A System of Systems of Mental Health in Cities : Digging Deep into the Origins of Complexity”. Working Paper, available at http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-243017, accessed 9th August 2019.

Napoles, G., E. Papageorgiou, R. Bello, and K. Vanhoof. 2016. “On the Convergence of Sigmoid Fuzzy Cognitive Maps”. *Information Sciences* 349-350:154–171.

Sullivan, H., and C. Skelcher. 2002. *Working Across Boundaries: Collaboration in Public Services*. Basingstoke, Hampshire, USA: Palgrave.

Thornicroft, G., T. Deb, and C. Henderson. 2016. “Community Mental Health Care Worldwide: Current Status and Further Developments”. *World Psychiatry* 15(3):276–286.

Tolman, E. C. 1948. “Cognitive Maps in Rats and Men”. *Psychological Review* 55(4):189–208.

Vedung, E. 2000. *Public Policy and Program Evaluation*. 1st ed ed. New York, NY, USA: Routledge.

Warr, P., P. Jackson, and M. Banks. 1988. “Unemployment and Mental Health: Some British Studies”. *Journal of Social Issues* 44(4):47–68.

World Health Organization 2004. “Promoting Mental Health”. https://www.who.int/mental_health/evidence/en/promoting_mhh.pdf, accessed 9th August 2019.

World Health Organization 2005. “Mental Health Policy, Plans and Programmes”. https://www.who.int/mental_health/policy/en/policy_plans_revision.pdf, accessed 9th August 2019.

AUTHOR BIOGRAPHIES

ELHABIB MOUSTAID is a doctoral student at the KTH Royal Institute of Technology in Sweden. Moustaid holds a Masters of Science in Engineering in Computer Science and Communication from KTH. His research interests are in modeling of social complex adaptive systems using simulation, optimization and statistics. His email address is elhabib@kth.se.

MAKSIMS KORNEVS is a Postdoc at the KTH Royal Institute of Technology in Sweden. His research interests include participatory methods and mixed-methods approaches for simulations in complex adaptive systems. He works in home care and mental health fields. His email address is kornevs@kth.se.

SEBASTIAAN MEIJER is a Professor of health care logistics at KTH Royal Institute of Technology in Sweden. He leads a simulation and gaming laboratory working on the design of large-scale systems, with a particular focus on health care. With a background in simulation in a wide range of sectors, he is particularly interested in the role of validity in systems that are difficult to model formally. His email address is smeijer@kth.se.