SIMULATION MODELING AND OBESITY RESEARCH: DESIGNING MORE SUSTAINABLE PUBLIC HEALTH POLICIES

Saeideh Fallah-Fini, Industrial and Manufacturing Engineering Department, California State Polytechnic University, Pomona, CA 91768, 909-869-4087, sfallahfini@cpp.edu

ABSTRACT

Rates of overweight and obesity have increased dramatically around the world. Over the past decade, the prevalence of obesity among adults in England rose from 14.9% to 24.9%, and close to two third of adults in England are overweight or obese. Obesity is the result of complex interaction among various factors namely biological, behavioral, cultural, psychosocial, economic, and environmental factors. In this paper we use a new system dynamics model that quantifies the energy imbalance gap responsible for the England adult obesity epidemic among gender and racial subpopulations. Such result can be used for designing informed sustainable obesity interventions.

INTRODUCTION

Obesity is a growing global problem. Over the past four decades, the percentage of Americans who are obese has doubled to near 35% [1]. Most disturbingly, obesity rates have more than doubled in children and quadrupled in adolescents over the past 30 years [1]. Among adults in England, the prevalence of obesity rose from 14.9% to 24.9% between 1993 and 2013, and close to two third of adults are overweight or obese [2]. The obesity epidemic has several consequences. It increases the risk for other health problems such as diabetes, heart disease, stroke, and certain types of cancer, some of the leading causes of preventable death. Obesity leads to loss of quality of life and significant cost (in terms of healthcare cost as well as the cost of unhealthy workforce that will burden competitiveness in global economic). Obesity is the result of interplay among various factors namely biological, behavioral, cultural, psychosocial, economic, and environmental factors; these factors operate at multiple levels varying from individual-level health behaviors to family to work, school, community characteristics to local, state, national or international policies [3]. For both public policies and scientific analysis, obesity should be treated as a complex system in which multiple individual and socio-environmental factors affect human behavior. The complexity of the obesity problem, its dynamic nature, and the lack of agreement on the main drivers of obesity have led to an increasing focus on systems approaches to the study of obesity [3-5].

A systems approach looks at problems like obesity as a complex network of factors and their interactions, allowing factors at different levels to be studied together, incorporating linkages and feedbacks that cause changes in one area to affect elsewhere in the system. Systems approach related methods have been recently adopted and adapted by the public health research community due to their strength in assessing and projecting the effectiveness of alternative interventions and policies that can address public health challenges such as obesity. Systems science approaches refers to a family of methodologies (mainly computational modeling and simulation) that enable us to analyze complex systems by looking at the interactions among (heterogeneous) components of a system at multiple levels, assessing the social, environmental, and organizational context in which these complex phenomena occur, and understanding the complex connections between the structure of the system and its behavior over time [5, 6]. Simulation models enable us to examine different scenarios in which assumptions are varied systematically (e.g., examining the effect of different levels of tax on sugar-sweetened beverages; or placing an intervention alone or in combination with other interventions). As a result simulation/computational models can be used as “virtual environments” to examine and understand the trade-offs associated with different obesity policy interventions.

In this paper we illustrate application of simulation and computational techniques in addressing the obesity problem by presenting a system dynamics simulation model developed by the authors of this paper [7] and applied to the data from Health Survey for England (a national health survey for England performed over years 1993 to 2013). This model uses an innovative method developed in system dynamics [7] to connect micro level (individual level) body weight dynamics to the macro level (population level) distribution of body mass index (BMI, defined as weight in kilograms divided by the square of height in meters). Thus this model can capture the shift in distribution of body mass index in a population due to changes in energy intake and/or energy expenditure of individuals in the population. By applying this model to the national health data from England we estimate the energy imbalance gap (EIG) that can explain the shift in distribution of BMI (and as a result prevalence of obesity) in the England adult population. EIG captures the average daily excess energy intake, defined as total energy intake minus total energy expenditure for some unit of time, and governs the speed of change in body mass. EIG is an important factor in the development of obesity and a key target of public health interventions to reduce obesity. In the rest of this paper, the structure of the model as well as the preliminary results from application of the method to national health data from England and corresponding implications will be discussed.

METHODOLOGY

This study was performed in three main steps. In the first step a population level system dynamics model (SDM) which captures BMI distribution and obesity prevalence in adults was developed based on the methodology developed by Fallah-Fini et al [7]. In the second step the energy imbalance gap was modeled. In the third step the SDM was calibrated using the data from Health Survey for England over years 1993 to 2013 to estimate the energy imbalance gap that can explain the prevalence of obesity in adults in the past decade by gender, race, and weight groups.

Step 1: Developing the Population Level System Dynamics Model of BMI Distribution

Since the prevalence of obesity and overweight varies across different genders and races, we first put the England adult population into four subpopulations based on their gender (male and female) and race (white and black). Consequently the energy imbalance gap will be estimated for each subpopulation.

For each gender/race subpopulation, we used the method developed by Fallah-Fini et al. [7] to efficiently simulate the dynamics of BMI distribution over time based on an established individual-level model of adult body weight dynamics from the literature [8]. The following steps summarize the modeling details that we perform for each gender/race subpopulation:

1. The domain of BMI as the attribute of interest was divided into several distinct ranges (not necessarily equal) represented by distinct stocks. Each stock represents the members of the gender/race subpopulation whose BMI values fall within the BMI range associated with that stock. For example, assume the red curve in Figure 1 shows the distribution of BMI in each gender/race group. The population in each group is disaggregated into ***M*** distinct BMI groups. In this study we used 14 BMI groups ([12-15), [15-18), [18-20), [20-23), [23-25), [25-28), [28-30), [30-33), [33-35), [35-38), [38-41), [41-54), [45-50), [50-55)). Let $\boldsymbol{P_k}$ represents frequency of individuals in BMI group *k*, and $\boldsymbol{Xi_k}$ and $\boldsymbol{Xf_k}$ represent the initial and final values of the range of BMI associated with BMI group *k*, respectively. The BMI distribution of each gender/race group was approximated by calculating the height of the vertical bar associated with sub-population group *k* as shown in Equation (1). Those individuals who change their BMI values (e.g., lose or gain weight) will contribute to flows between stocks of population groups (macro population groups).

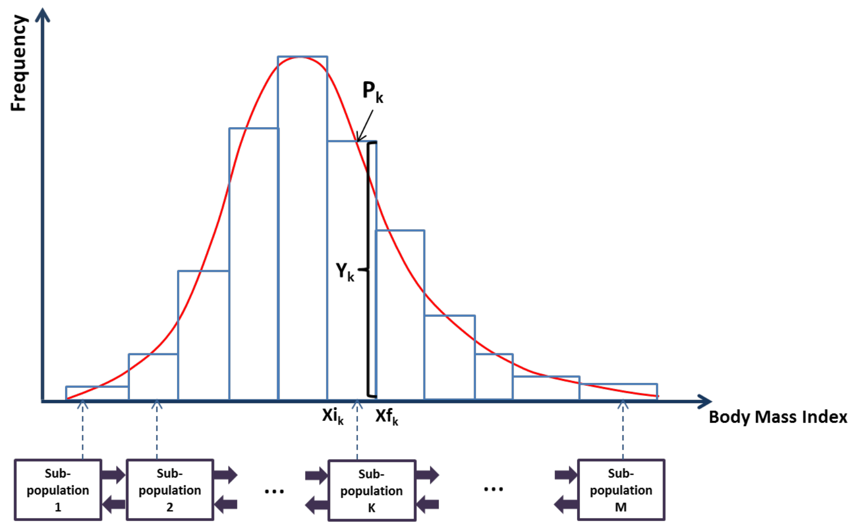

Figure 1: Disaggregation of population in each gender/race group into macro population groups [7]

$$Y_k = \frac{P_k}{Xf_k - Xi_k} \tag{1}$$

2. We assign a representative agent to each BMI group and modeled the weight change dynamics for those representative agents. The representative agent of each BMI group represents average of individuals in that group with respect to their BMI, i.e. an individual with BMI averaging $\boldsymbol{Xi_k}$ and $\boldsymbol{Xf_k}$. Defining representative agents enabled us to connect the individual-level (micro) dynamics of weight gain and loss to the population (macro-level) distribution of BMI. We captured the dynamics of weight gain and loss for representative individuals over time using the Hall's model of adult metabolism and body-weight change [8]. Body weight (BW) in Hall's model is represented by two stocks capturing Fat Mass (FM) and Fat Free Mass (FFM). The change in body weight is then modeled as the result of an imbalance between energy intake (I) and energy expenditure (E) of individuals and is partitioned into/out of FM and FFM.
3. Representative individual's BMI change rate provides the speed by which individuals move from that BMI group to the neighboring BMI groups. Let $\boldsymbol{dBMI_k/dt}$ represent the BMI change rate of representative individual of group ***k*** due to an imbalance between energy

intake and energy expenditure associated with that representative individual. The rate of population leaving BMI group k is a function of rate of change of the representative individual of group k (i.e., $\boldsymbol{dBMI_k/dt}$) and the height of vertical bar associated with group k (i.e., $\boldsymbol{Y_k}$) and is calculated in Equation (2). Positive values for the rate of change of representative individual of group k imply that some of the population elements in BMI group k will move to BMI group $k+1$. Negative rate of change implies that some of the individuals in BMI group k will move to group $k-1$.

$$\begin{aligned} &Rate\ of\ population\ leaving\ group\ k\ to\ group\ k+1 = Max\ (dAtt_k * Y_k\ , 0) \\ &Rate\ of\ population\ leaving\ group\ k\ to\ group\ k-1 = Max\ (-dAtt_k * Y_k\ , 0) \end{aligned} \tag{2}$$

By calculating the net rate of population change for group k (from/to groups $k+1$ and/or $k-1$ groups) at any simulation time step, we updated the percentage of population in group k in the next time step. New percentages of population in different BMI groups at the start of the next time step provides the new estimate for the distribution of population BMI.

By repeating these steps over time, the dynamics of population BMI over time resulting from the imbalance between energy intake and energy expenditure is captured. To make sure our model is demographically representative of the England adult population, we also modeled both the rate of transition from childhood into adulthood as well as the deaths.

Step 2: Modeling the Energy Imbalance Gap

The energy imbalance gap associated with representative individual of any BMI class k in any gender/race group j at any time t (represented by $\Delta EI_k^j(t)$) was modeled as a function of the equilibrium energy expenditure $E_k^{j*}(t)$ of the representative individual calculated at time t (the energy required for normal activity and maintenance of the body) and an "energy gap multiplier" (represented by $\mu_k^j(t)$) (Equation 3).

$$\Delta EI_k^j(t) = I_k^j(t) - E_k^{j*}(t) = E_k^{j*}(t) * \mu_k^j(t) \tag{3}$$

Energy intake for each representative individual was then calculated by adding the energy gap to the reference energy intake for that individual. A multiplier above zero will lead to BMI growth and one under zero will reduce the BMI for that group as shown in Equation (4).

$$\begin{aligned} &\mu_k^j(\mathrm{t}) = \text{Time effect}^j + \text{BMI effect}_k^j + \text{BMI\&Time Interaction effect}_k^j \\ &\text{where} \quad \text{Time effect}^j = \beta_1 + \beta_2 \text{Time}^j + \beta_3(\text{Time}^j)^2 + \beta_4(\text{Time}^j)^3 \\ &\qquad\quad \text{BMI effect}_k^j = \beta_5 BMI_k^j + \beta_6 (BMI_k^j)^{\beta_7} \\ &\qquad\quad \text{BMI\&Time Interaction effect}_k^j = \beta_8 \text{Time}^j BMI_k^j \end{aligned} \tag{4}$$

Step 3: Model Calibration and Parameter Estimation

A good population-level model should be able to closely replicate those distributions observed in the past after taking into account the sampling errors. This basic intuition was used in our study to estimate the parameters of the model. Specifically, the parameters forming the energy gap multiplier $\mu_k^j(t)$ were estimated such that the BMI distributions over years 1993 to 2013 generated by the model for each subpopulation j got as close as possible to the subpopulation's BMI distribution according to data from Health Survey for England (a national health survey for

England performed over years 1993 to 2013). We used a maximum likelihood method for estimating the unknown model parameters. All simulations and optimizations were conducted in Vensim™ [9] software.

RESULTS AND DISCUSSION

We used data form Health Survey for England over years 1993 to 2013 for white males and females, age 20-74. Figure 2 shows the estimated energy imbalance gaps for white males and females across different BMI groups over time.

Figure 2: Estimated Energy Imbalance Gap (Kcal/day) Across BMI Groups (White Male and Female, age 20-74)

	BMI Class	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
White Male	15-18	12.8	15.6	17.7	19.1	19.9	20.3	20.2	19.9	19.3	18.5	17.7	16.8	16.1	15.5	15.1	15.1	15.5	16.4	17.8	19.9	22.7
	18-20	9.1	12.1	14.3	15.9	16.8	17.2	17.1	16.7	16.0	15.1	14.2	13.2	12.4	11.7	11.3	11.3	11.7	12.6	14.2	16.5	19.5
	20-23	6.4	9.7	12.1	13.7	14.7	15.1	15.0	14.5	13.8	12.8	11.8	10.7	9.8	9.0	8.5	8.5	8.9	9.9	11.6	14.0	17.3
	23-35	4.7	8.2	10.8	12.6	13.6	14.0	13.8	13.3	12.5	11.4	10.2	9.1	8.0	7.2	6.7	6.6	7.0	8.1	9.8	12.5	16.0
	25-28	4.0	7.7	10.4	12.2	13.3	13.7	13.5	12.9	12.0	10.8	9.6	8.3	7.2	6.3	5.7	5.5	6.0	7.1	8.9	11.7	15.5
	28-30	4.0	7.9	10.8	12.7	13.8	14.2	14.0	13.3	12.3	11.1	9.7	8.3	7.1	6.1	5.4	5.3	5.7	6.8	8.8	11.7	15.7
	30-33	4.8	8.9	11.9	13.9	15.1	15.4	15.2	14.5	13.4	12.0	10.5	9.1	7.7	6.6	5.9	5.7	6.1	7.3	9.3	12.4	16.6
	33-35	6.3	10.6	13.8	15.8	17.0	17.4	17.1	16.3	15.1	13.6	12.1	10.5	9.0	7.9	7.1	6.8	7.2	8.4	10.6	13.7	18.1
	35-38	8.6	13.0	16.3	18.4	19.6	19.9	19.6	18.7	17.5	15.9	14.2	12.5	11.0	9.7	8.9	8.6	9.0	10.2	12.4	15.7	20.2
	38-40	11.4	16.0	19.4	21.6	22.8	23.1	22.7	21.8	20.4	18.8	17.0	15.2	13.5	12.2	11.3	10.9	11.3	12.5	14.8	18.2	22.9
	>=40	17.2	22.0	25.5	27.8	29.0	29.3	28.9	27.8	26.3	24.5	22.5	20.6	18.8	17.3	16.2	15.8	16.2	17.4	19.8	23.3	28.3
White Female	15-18	2.7	3.8	4.5	5.0	5.3	5.4	5.4	5.2	4.8	4.4	3.9	3.3	2.8	2.2	1.7	1.2	0.7	0.4	0.2	0.1	0.2
	18-20	4.4	5.5	6.3	6.9	7.2	7.3	7.2	7.0	6.6	6.2	5.6	5.0	4.4	3.7	3.1	2.6	2.1	1.7	1.5	1.4	1.5
	20-23	5.9	7.1	8.0	8.6	8.9	9.0	8.9	8.7	8.3	7.7	7.1	6.5	5.8	5.1	4.4	3.8	3.3	2.9	2.6	2.5	2.6
	23-35	7.2	8.5	9.5	10.1	10.4	10.5	10.4	10.1	9.7	9.1	8.5	7.7	7.0	6.2	5.5	4.9	4.3	3.8	3.5	3.4	3.5
	25-28	8.4	9.7	10.7	11.4	11.8	11.9	11.7	11.4	10.9	10.3	9.6	8.8	8.0	7.2	6.4	5.7	5.1	4.6	4.3	4.1	4.2
	28-30	9.3	10.7	11.8	12.5	12.9	13.0	12.8	12.5	11.9	11.3	10.5	9.7	8.8	7.9	7.1	6.3	5.6	5.1	4.8	4.6	4.7
	30-33	10.0	11.5	12.6	13.3	13.7	13.8	13.7	13.3	12.7	12.0	11.2	10.3	9.4	8.4	7.5	6.7	6.0	5.4	5.0	4.9	5.0
	33-35	10.5	12.1	13.2	14.0	14.4	14.5	14.3	13.9	13.3	12.5	11.6	10.7	9.7	8.7	7.7	6.8	6.1	5.5	5.1	4.9	5.0
	35-38	10.8	12.4	13.6	14.4	14.8	14.9	14.7	14.2	13.6	12.8	11.8	10.8	9.8	8.7	7.7	6.8	5.9	5.3	4.8	4.6	4.7
	38-40	10.8	12.5	13.7	14.5	15.0	15.0	14.8	14.3	13.6	12.8	11.8	10.7	9.6	8.5	7.4	6.4	5.5	4.8	4.4	4.1	4.2
	>=40	10.3	12.1	13.4	14.3	14.7	14.8	14.5	14.0	13.2	12.3	11.2	10.0	8.8	7.6	6.4	5.3	4.4	3.6	3.1	2.8	2.9

Our results for both white male and female show no negative energy imbalance gap across different weight groups meaning that white population in the past decade has always eaten more than what they needed. For white female, the magnitude of the gap shows a spike around late 1990s. However, the values start to decrease toward late 2000s and early 2010s, meaning that prevalence of obesity is still growing although at a slower rate. Moreover, magnitude of energy imbalance gap was higher in overweight and obese white females. Among white males, the magnitude of the gap was much higher among obese and severely obese weight groups. White male also show a spike in the magnitude of the gap in late 1990s followed by a gradual drop in early 2000s. However, our results show an increasing behavior in the magnitude of energy imbalance gap toward early 2010s which shows prevalence of obesity among white male is increasing at a faster rate in comparison with white females. Our results show that obesity continues at different rates across different BMI groups.

Figure 3 shows the average energy gap across different BMI classes weighted by the population in that class for different subpopulations. On average, the magnitude of the energy gap for white male is larger than white female. Moreover, on average, the magnitude of the drop in energy gap over the past decade is larger for white female than white male.

Figure 3: Estimated Energy Imbalance Gap (Kcal/day) (White Male and Female, age 20-74)

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
White Male	5.0	8.6	11.4	13.2	14.3	14.7	14.6	14.0	13.1	12.0	10.7	9.4	8.3	7.3	6.7	6.6	7.0	8.1	10.1	12.9	16.9
White Female	7.7	9.1	10.1	10.8	11.2	11.3	11.2	11.0	10.5	9.9	9.2	8.5	7.7	6.8	6.0	5.3	4.7	4.2	3.8	3.7	3.8

Our results show the strengths of a multidisciplinary, systems science approach to the study of energy imbalance and suggest several areas for future public health research. As the next step, we can model the magnitude of the estimated trend in energy imbalance gap as a function of the socio-environmental factors over time. Such study enables us to find those socio-environmental factors that have a significant role in prevalence of obesity in England over the past decades. Another important direction is to assess the impact of public health interventions on subgroups and BMI classes by evaluating the effect of such interventions on the magnitude of the energy imbalance gap of individuals and consequently the shifts in distribution of body mass index (which is translated into change in prevalence of obesity). As a result we can identify those interventions that may have the greatest potential impact on prevalence of obesity.

References:

1. Ogden, C., et al., *Prevalence of childhood and adult obesity in the United States, 2011-2012.* Journal of the American Medical Association, 2014. **311**(8): p. 806-814.
2. Niblett, P., *Statistics on Obesity, Physical Activity and Diet, England 2015*, in *Lifestyles Statistics Team, Health and Social Care Information Centre*2015.
3. Huang, T.T., et al., *A systems-oriented multilevel framework for addressing obesity in the 21st century.* Preventing Chronic Disease, 2009. **6**(3): p. 1-10.
4. Bures, R.M., et al., *Systems Science: A Tool for Understanding Obesity.* American Journal of Public Health, 2014. **104**(7): p. e1.
5. Mabry, P.L. and R.M. Bures, *Systems Science for Obesity-Related Research Questions: An Introduction to the Theme Issue.* American Journal of Public Health, 2014. **104**(7).
6. Midgley, G., *Systems Thinking*. 2003, Thousand Oaks, CA: Sage Publications.
7. Fallah-Fini, S., et al., *Connecting micro dynamics and population distributions in system dynamics models.* System Dynamics Review, 2013. **Accepted with Minor Revision**
8. Hall, K.D., et al., *The progressive increase of food waste in America and its environmental impact.* PLoS ONE, 2009. **4** (11): p. e7940. doi:10.1371/journal.pone.0007940.
9. *Vensim, Ventana Systems, Inc.*, in http://www.vensim.com2012: Harward, MA.