AGENT BASED SIMULATION MODEL FOR OBESITY EPIDEMIC ANALYSIS

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ABSTRACT

This research proposes a simulation model based on Intelligent Agents to reproduce human behavior and its influence on the evolution and impact of obesity epidemics.
Based on our previous experiences on Human Behavior Models, we have developed a Library including Intelligent Agents for Computer Generated Forces (IA-CGF Libraries), designated to reproduce complex scenarios, with particular attention to non-conventional frameworks mediated by human behaviors on progression of obesity epidemics in the world. In this paper, we compared two scenarios (in Italy (obesity prevalence ~10%) and in the U.S. (obesity prevalence ~35%) based on different social and cultural condition in order to test, validate and calibrate the simulation model.
The authors are interested in analyzing how simulation model results change by considering different social and cultural conditions in different countries.
Actually Obesity is a real big problem for both USA and European countries, so it is necessary to take under control this phenomenon and above all to provide people and government with simulation models in order to promote specific actions and to guarantee population healthy and even less social costs.

Keywords: Simulation, Intelligent Agents, Human Behavior Modeling, Health Care, Obesity

1. INTRODUCTION

Obesity is becoming an increasingly common and growing public health problem in America and in European Countries. Currently, two of three Americans are considered overweight, while one out of three people in America is obese.. According to the Centre for Disease Control report, U.S. Obesity Trends 1985-2007, in 1985, there were only 8 states in the U.S. with prevalence of obesity ~ 10%, while in 2010, prevalence of obesity increased dramatically, and at least 35.7% of the adult population was obese, affecting all 50 states and men and women (Figure 1a,b). Even more importantly, obesity affects 16.9% of U.S. children and adolescents (Ogden et al. 2010). There was no change in prevalence of obesity from 2009-to 2010, and adults over age 60 were more likely to be obese than younger adults. The question how the growing prevalence of obesity in younger population will affect the overall trend in epidemic.

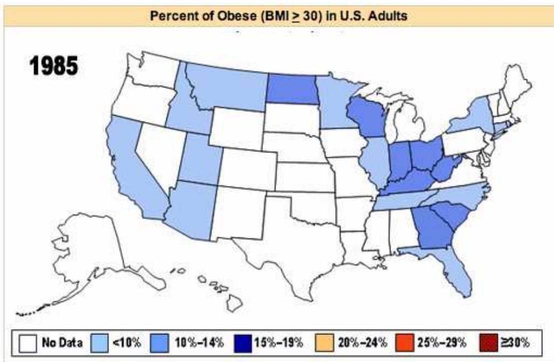

Figure 1a. Obesity Rates in United States in 1985

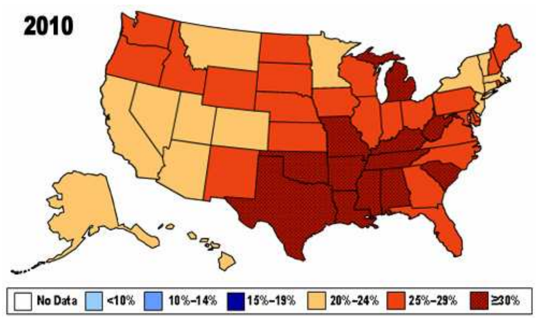

Figure 1b. Obesity Rates in United States in 2010

Obesity is a global problem. Obesity epidemic (Wolf et al. 2007) has been increasingly spreading around the world in the past three decades, involving countries that never in the past reported obesity in their population. Recently, special scientific series published in leading medical journals such as Lancet examine the global obesity pandemic (Swinburn et al. 2011; Gortmaker et al. 2011) and emphasize that obesity is a global issue and and these reports call upon for government interference to turn around the epidemic with cost-effective programs and policies, supported with continuous evaluation and monitoring (Wang et al. 2010; Bruzzone 2004).
In European Region, since 1980s, obesity prevalence has tripled in many countries and the numbers of those affected continue to rise at an alarming rate, particularly among children (Figure 2 and Figure 3).

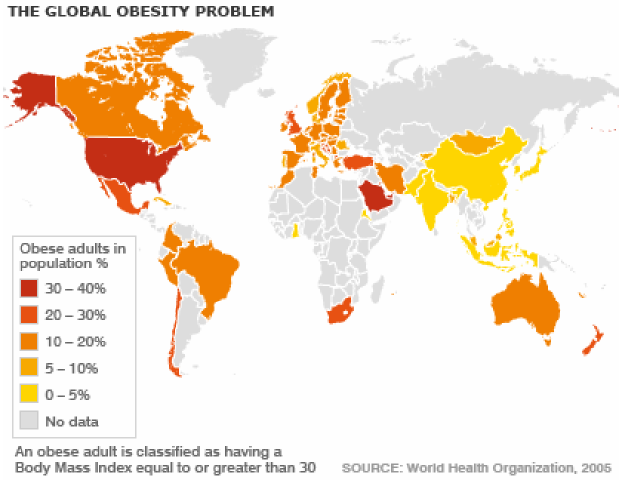

Figure 2. Obesity as a Global Problem

The European Commission and the Organisation for Economic Co-operation and Development (OECD) published the Health at a Glance Europe 2010 report to encourage better eating habits in children.
This report emphasized that the rate of obesity has more than doubled over the past 20 years in most European countries and that just over 50 percent of Europeans are now either overweight or obese (OECD 2010).

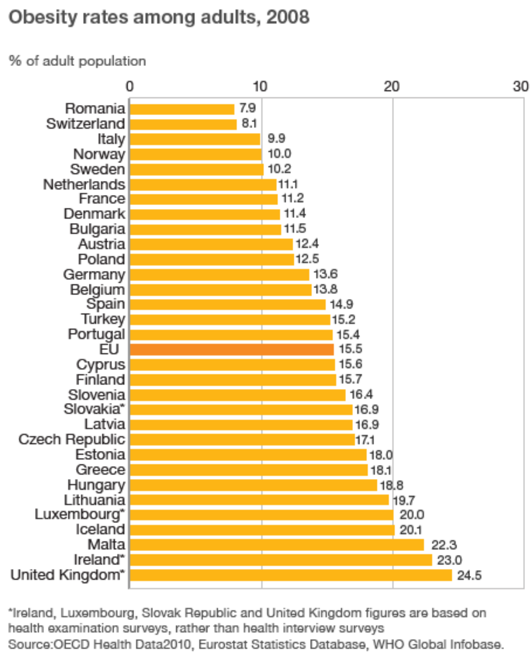

Figure 3. Obesity rates in Europe

The current lifestyle based on a diet with excessive calories intake (fast food and carbonated beverages) and lack of an adequate physical exercise has widely contributed to the obesity increase.
The consequences affect the whole society from a social and economic point of view i.e. health care burden, increased consumption demands and special needs to adapt to normal life in many different sectors i.e. furniture, transportation, and consumer spending, increased waste and lifestyle cost. Furthermore, obesity problem is related to many other factors such as urban environments, transport systems, socio-economic conditions, and cultural factors, population aging, etc.
Obese people are susceptible to various health problems i.e. cardiovascular diseases, certain types of cancer, and type 2 diabetes, musculoskeletal, neurological and psychiatric disorders, increased overall morbidity, disability and mortality.
The impact of obesity is evident in health care more than in other sectors, because of the strong influence of stochastic factors and very complex correlations that make analysis of large scale data difficult without using modeling and simulation. Therefore obesity poses an important and very complex problem, that is suitable for modeling and simulation that may take into account into account complex nature of this condition including social a cultural conditions and economical aspects.
The authors have developed several simulation models reproducing human behavior in different frameworks (i.e. for country reconstruction operations, as well as, port security and safety) (Bruzzone et al. 2007). We have developed a set of Libraries, named IA-CGF (Intelligent Agents for Computer Generated Forces), in order to

simulate units (i.e. police, gangs, terrorist, etc.), as well as, non-conventional frameworks (i.e. food distribution and humanitarian support, disaster relief). Our goal is to use these libraries to address obesity problem world wide, and thus to provide theoretical support for decision makers most cost-effective approaches to curb obesity epidemic. This paper is aimed to test and validate BACCUS (Behavioral Advanced Characters and Complex System Unified Simulator) Model by reproducing two different scenarios, one related to Massachusetts State in the U.S. and second related to an Italian Region, by taking into account the mutual influence of different factors related to physiological and psychological issues, behavioral aspects and regional/ethnical/social/geographical and economical factors.

This kind of model may be also helpful to simulate and predict the impact of behavioral, social and economic interventions aimed to prevent further development of obesity epidemic and to curtail its costs. Therefore, BACCUS t could become a strategic tool for designing preventive strategies and decision as well as evaluating the impact of actions and countermeasures of public and private institutions and organizations on such a critical sector of the health care.

2. THE OBESITY EPIDEMIC AND CRITICAL FACTORS

The obesity is defined as a medical condition in which an excess proportion of body fat accumulates in human body; this causes various health problems. Obesity is most commonly defined in term of Body Mass Index or BMI.

A person is considered obese when he or she has 20% higher than their normal body weight. According to the World Health Organization (WHO) an overweight person has a BMI between 25 and 29.9, and obesity is marked at a BMI of 30 and above.

$$BMI = \frac{W}{H^2}$$

Where:

BMI Body Mass Index
W Weight [kg]
H Height [m]

Extreme form of obesity is termed as “morbid obesity” which means either a person is more than 100 pounds over normal weight, 50%-100% over normal weight, has a BMI of 40 or above, or is enough overweight to suffer from various health concerns. The main causes of obesity are related to:

- Diet or consumption of excessive calories
- Age: With age the human body’s power to metabolize food decreases, leading to gaining of weight.
- Gender: gender difference in obesity rate is disappearing. In general women have slightly a lower resting metabolic rate than men, more body fat and less muscle mass.
- Physical activity: Lack of physical activity increases energy storage and accumulation of fat and weight gain. .
- Genetics: genes play an important role in the prevalence of obesity. There is a good chance of 75% to be fat or slender if a person has biological parent who is obese or normal weight. This predisposition, however, is likely to be enhanced by eating habits and social factors during childhood.
- Psychological factors: eating habits and obesity run parallel and, similarly, potentiate factors and habits that lead to overeating. Many people tend to eat more when they are lonely, bored, sad, depressed or angry.
- Illness: some disorders like hypothyroidism, depression, and some rare diseases of the brain, which are mostly hormonal diseases, may lead to obesity.
- Medication: certain medications may be associated with weight gain.

Therefore, obesity is a multifactorial process that results from interactions among the individual health status, functional and social habits, social networks, education and other factors that cannot be predicted from a single variable (i.e. body mass) but requires nonlinear modeling of multiple variables and their interactions.

Mathematics and Statistics provide different modeling tools that can be used to measure and control obesity.

For example, a model predicting how the body composition changes in response to what it ate, developed by K. Hall at NIDDK (National Institutes of Diabetes and Kidney Diseases) (Hall et al. 2011).

This is a mathematic model of a human being that contains several variables (i.e. height, weight, food intake and composition, exercise). The model can predict what a person’s weight,dependent on their body size, food intake and exercise. However, the model is complicated: hundreds of equations; and new attempts are being made to simplify it to a single equation.

In addition, Dragone and Savorelli (2010) underlined the importance of psychological factors and of the ideal body weight concept. They analyzed obesity and anorexia together and demonstrated that increasing the ideal body weight is socially desirable. Therefore, if a majority of population is overweight, but an ideal body weight is low and therefore difficult to achieve, then increasing the ideal body weight may be socially desirable and would reduce social pressure. Their model is based on forward-looking agent depending on food consumption, health condition, and the conformity of body weight to an ideal

weight. So, the agent is aware of how food consumption affects body weight, and it explicitly takes this information into account when choosing how much to eat (Dragone & Savorelli 2010).
In this study we propose a model based on Intelligent Agents, that include the following characteristics of the study population:

- Social Status and employment status: in our sample, including 307 adults from Massachusetts, obese people are both employed or unemployed, while retirees have higher percentage of sever obesity (Figure 4).

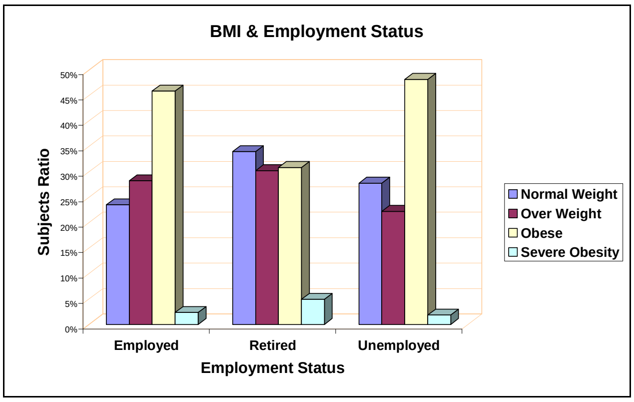

Figure 4. BMI & Employment Status

- Gender: women had higher average BMI in this sample (Figure 5).

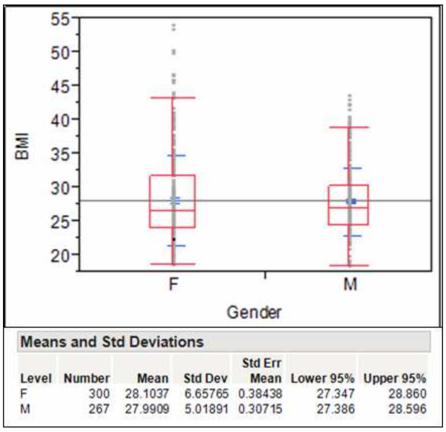

Figure 5. BMI & Gender

- Age: Our analysis shows that obesity is becoming more prevalent in younger people e; in fact on average, people younger than 39 years are more overweighed than elderly. The age range the most affected by obesity is between 40 and 70 years old (Figure 6).

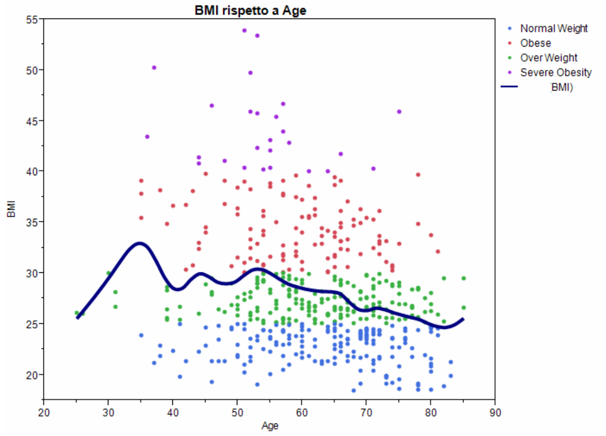

Figure 6. BMI & Age

- Ethnicity: majority (97%) subjects in our samples were not Hispanic or Latinos. However, there was a trend for suggesting that American Native and African American are more prone to obesity.
- Religion: no information about religion was collected in our sample. The model however includes this variable by considering statistics related to Ethnicity and Race on Massachusetts area.
- Education: the average duration of schooling was from 11 to 20 years (Figure7), but there was no clear trend in relation between obesity and education.

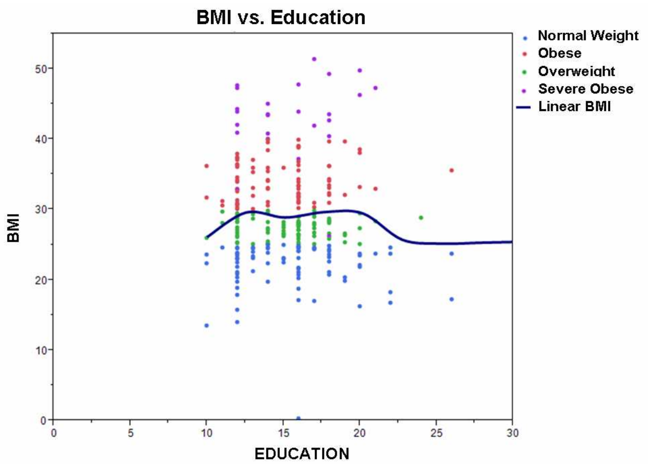

Figure 7. BMI and Education

Furthermore, the model considers other variables in order to simulate the social network, i.e. marital status, Figure 8 shows that majority of obese people are not married, which may indicate underlying social or/and psychological issues.

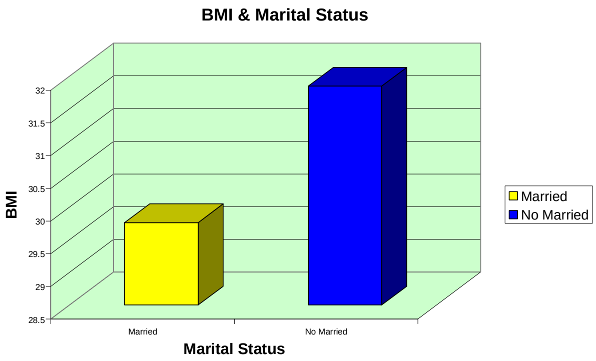

Figure 8. BMI and Marital Status

The data collection and analysis has involved many other parameters in order to verify correlations with BMI trend. In particular among the others:

- Previous Tobacco Use and Current Tobacco Use and the related quantitative variable (i.e. Tobacco Pack Years)
- Previous Alcohol Use and current Alcohol Use and the related quantitative variable (Alcohol Dose/Week)
- Family History: related to cancer, heart disease, hypertension, diabetes, Stroke; for instance by considering Bother Decease number it's interesting the result: people with more than one brother decease, have on average a higher BMI (see figure below):

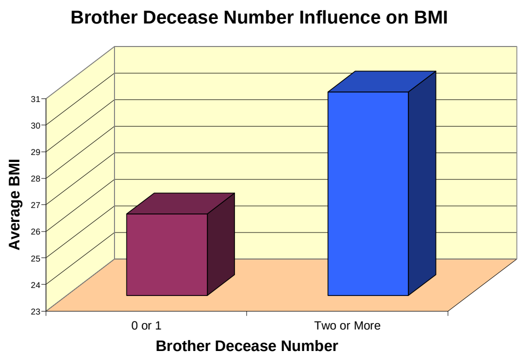

Figure 9. BMI and Brother Decease Number

- Patient Medical History in term of cancer, heart disease, hypertension, diabetes, Stroke and Falls
- Medications (Antiplatelets, Anticoagulant, Antihyperlipidemic, Antiparkinsonian, Statins, Estrogen, ACE Inhibitors, ARBS, Beta Blockers, Diuretics, CA ++, glucose mg/dL, Insulin, Cholesterol mg/dL, triglycerides mg/dL, hemoglobin A1C%, heart rate, systolic and diastolic blood pressure at baseline)
- Other parameters: walking speed and brain volumes measure by on magnetic resonance imaging (MRI) global intracranial volume(ICV), gray matter volume (GM), white matter volume (WM),l cerebrospinal fluid volume (CSF) and white matter hyperintensities volume (WMHs).

These analyses are based on the studies conducted in the Syncope and Falls in the Elderly (SAFE) laboratory at the Beth Israel Deaconess Medical Center. These data were collected during different five studies including clinical tests and questionnaires from patients. All the data were reviewed and validated for for consistency, missing and outlying values. The analytical approach included the following steps:

1. Distribution, Variance, Standard Deviation and Average Value for each variable to identify possible outliers
2. Estimating BMI respect each variable of interest
3. Multivariate regression analysis

Even we have found correlations between BMI and each involved variable (i.e. education, age, gender etc.), it is difficult to define a linear correlation combining all these variables. This is due to the fact that BMI is influenced by too many factors interacting with each other, that are related to human behavior and stochastic elements. Therefore, it is important to introduce a simulation approach to investigate obesity phenomenon the effects of different cultural and social factors on the trend of this epidemic. .

3. THE SIMULATION MODEL FOR OBESITY EPIDEMIC

We propose a model based on Intelligent Agents driving people acting and moving in the area in order to simulate the Obesity epidemic evolution in a specific region and scenario. This model is based on a stochastic discrete event simulation. The simulator, named BACCUS, allows to simulate the population behaviour and to reproduce different scenarios and geographical areas. The goal is to reproduce the scenario of Massachusetts, with particular focus on Boston Area in order to test the simulator and compare its results with the real data, and then compare these results with a region in Italy.
The input data are provided by statistical analysis developed at the SAFE Lab that was combined with statistics by the World Health Organization.
The simulator allows to generate over 600.000 agents based on statistical distributions of social and cultural characteristics, and then it allows to generate a social network including families relationships, friendships and working relationships. These links are generated based on compatibility algorithms and social algorithms allowing to compare the agents based on their social and cultural characteristics in order to measure a level of compatibility; if this level overcomes a predefined threshold the connection link is generated (Giribone & Bruzzone 1999).
The BACCUS model, is defined as a IA-CGF framework that takes into account population behaviour and obesity factors. IA-CGF is an innovative solution

provided by DIPTEM Genoa University and MAST srl, and it includes behavioural libraries for Non-Conventional Frameworks (i.e. disaster relief, humanitarian support, natural disasters etc.) to reproduce human behaviour in town or regions (Bruzzone et al. 2008). These models were designed to study evolution of obesity epidemic (Avalle et al. 1999), analyzing urban disorders (Bruzzone et al. 2006) and country reconstruction (Bruzzone & Massei 2010).
The IA-CGF Libraries include the following Human Factors (Figure 10):

- Physiological Characteristics
- Social Factors
- Political Factors
- Ethnical and Tribal Factors
- Religious Factors
- Cultural Factors

The BACCUS model provides the following functionalities:

- To generate the population
- To generate the families
- To generate the social network
- To visualize zones characteristics and statistics
- To visualize the operative status of agents
- To set up population characteristics
- To provide report on specific parameters

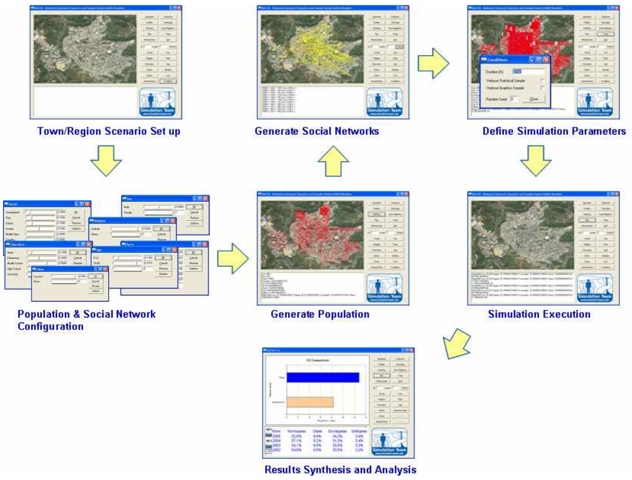

Figure 10. Model Functionalities and Key Elements

The population is grouped in zones and is characterized by different parameters (social, religious, ethnic).
Based on these parameters the population is generated randomly respecting original statistics on the geographic region, but even considering the different groups characteristics with their specific structure (i.e. some ethnic group have different social status statistics respect other one living in the same region); this process generates the people agents; in addition inside the region it is possible to define Zones as objects that have affinities with the main factors and so the people agents are distributed geographically in term of living and working locations in consistency with their affinities; it is possible to overlap zones with different affinities in order to represent inconsistent mixes of different groups of the population.
Daily regimen of an individual is defined as well. Each e individual operates through the whole day by getting up, going work, working, having lunch, having relax, doing exercise, having diner, sleeping.
The model includes relationships among obesity and people's behavior based on data collected and analyzed at the SAFE Lab. In particular the following aspects are included in the model:
- Children, having an obese parent, increases the risk of by 30%.
- Not-married, being single increases the risk of obesity.
- BMI decreases at advanced age (>70 years).
- Obese people tend to have obese friends.
- Exercise: regular exercise three times a week for 40 minutes negatively correlates with BMI.
- Alcohol: moderate to severe alcohol consumption increase the risk of obesity.
- Morbidity and mortality: obesity people have higher morbidity and mortality.

The authors propose to implement two different scenarios in BACCUS model in order to test and validate it. In fact dealing with human modeling the verification and validation of the simulator, as well as data validation, collection and analysis is critical in order to test hypotheses about the conceptual model of behavior leading to obesity epidemic.

4. COMPARATIVE RESULTS ANALYSIS

The model results are based on two different scenarios: an Italian Town including about 40.000 people (Figure 11) and Boston Area scenario including over 600.000 agents (Figure 12), with obesity distribution collected by the SAFE lab studies. Target functions include the different obesity classes and the average BMI:

– Normal Weight
– Overweight
– Obese
– Average BMI

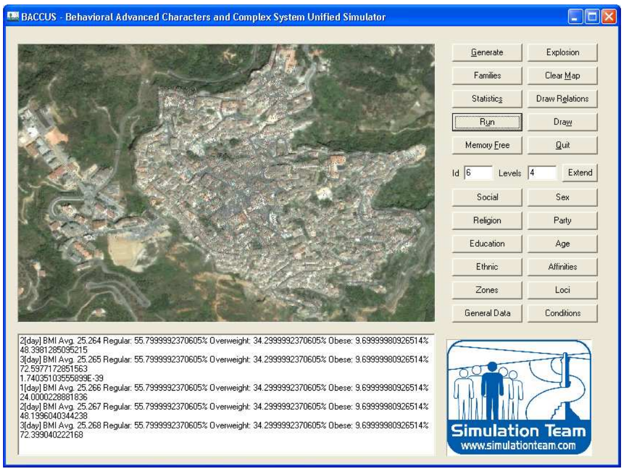

Figura 11. BACCUS Model Interface: Italian Town

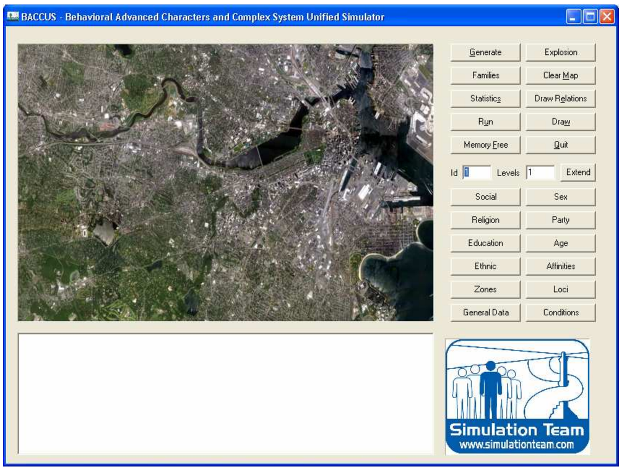

Figure 12. BACCUS Model Interface: Boston Area Scenario

The VV&A (Verification, Validation & Accreditation) of BACCUS is based analysis of MSpE (Mean Square pure Error analysis) as measure of the variance of the target functions among replicated runs over the same boundary conditions; by this approach it becomes possible to identify the number of replications and the simulation duration able to guarantee a desired level of precision; MSpE values in correspondence of these experimental parameters determines the amplitude of the related confidence band:

$$MSpE^m(t,n_0)=\frac{\sum_{i=1}^{n_0}\left[Sr_i^m(t)-\frac{1}{n_0}\sum_{j=1}^{n_0}Sr_j^m(t)\right]^2}{n_0}$$

$$CBA^m(t,n_0,\alpha)=\pm t_{\alpha,n_0}\sqrt{MSpE^m(t,n_0)}$$

t — simulation time

m — m-th target function estimated by the simulator

no — number of replications with same boundary conditions and different random seeds

$Srk^m_k(t)$ — m-th target function value at t time of the k-th replicated simulation

$MspE^m(t,n_o,\alpha)$ — Mean Square pure Error at t time and with no replications for the m-th target function

α — percentile

$CBA^m(t,n_o,\alpha)$ — Confidence Band Amplitude at t time, with no Replications for the m-th target function

In fact the MSpE allows to quantify the experimental error due to influence of the stochastic components. In the figure below it is reported the result for the first scenario: the variance of all the target function reach steady state situation over a reasonable number of replications and over a time duration for about a one year period . This confirms that simulator provides consistent results, when a situation is a stable with capability to define the confidence band for estimating the obesity target functions.

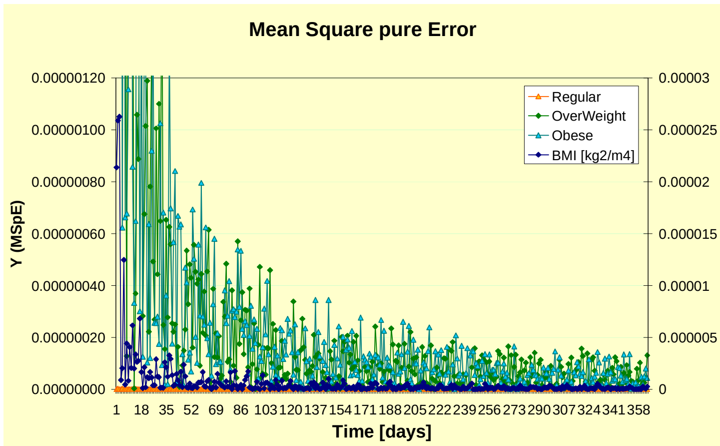

Figure 13. BACCUS VV&A based on Dynamic Analysis of Mean Square pure Error on Population Obesity Classes in Italian Scenario

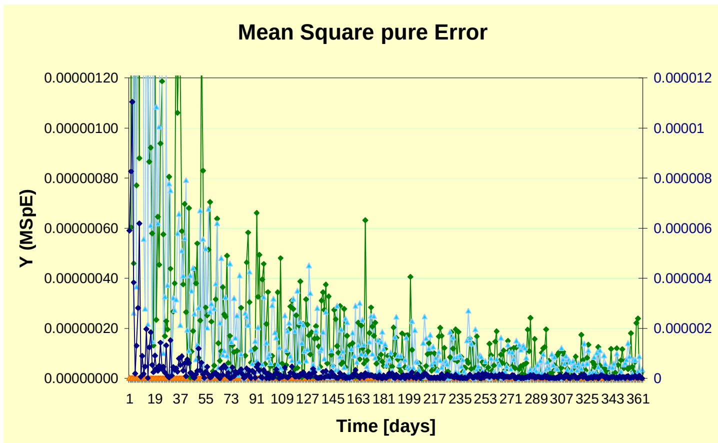

Figura 14. BACCUS VV&A based on Dynamic Analysis of Mean Square pure Error on Population Obesity Classes in Boston Scenario

Figure 13 and Figure 14 show the Mean Square pure Error trend for both the scenarios in Italy and in Boston. In the first one the experimental error is correctly evaluable after about 120 replications, while in the second one the optimal number of replication is about 199.

At the end of the Simulation a report is available to analyze how the obesity evolves day by day:

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6[day] BMI Avg. 22.793 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
7[day] BMI Avg. 22.794 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
8[day] BMI Avg. 22.795 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
9[day] BMI Avg. 22.796 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
10[day] BMI Avg. 22.797 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
11[day] BMI Avg. 22.798 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
12[day] BMI Avg. 22.799 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
13[day] BMI Avg. 22.8 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
14[day] BMI Avg. 22.801 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
15[day] BMI Avg. 22.802 Regular: 14.7000007629395% Overweight: 55.5999984741211% Obese: 29.7000007629395%
16[day] BMI Avg. 22.803 Regular: 14.2999992370605% Overweight: 56% Obese: 29.7000007629395%
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Figure 15. Extract from Simulation Final Report

Considering the two scenarios and replicating the simulation for more years the results indicate that the trends of obesity growing in Italy follow the USA Obesity Trend, but more slowly. These preliminary results indicate that it is possible to simulate and validate trends in population behavior related to obesity, and to prospectively predict its impact on the society around the globe.

5. CONCLUSIONS

This study proposed an agent based model to analyze and to evaluate the obesity trend in different scenarios around the globe. In particular we compared and evaluated two scenarios in order to test and calibrate the simulation model. Our model is designed to reproduce population behaviour in order to evaluate how social and cultural conditions impact on obesity epidemics. It was developed an extension of the IA-CGF intelligent agents developed by Simulation Team to represent the behaviour of the population and the critical factors related to obesity epidemics. The use of these agents and simulation allows to investigate large scale health care problems, and represent an important opportunity to for prediction and early interventions. The obesity epidemic represents a very important and interesting application framework that could be very useful to consolidate research in this area of modeling and simulation related to Medicine and Health Care.

In addition the research highlighted the critical aspects related to collecting, mining and filtering the data to define the conceptual models related to such complex problems as well as to support parameter fine tuning and simulator VV&A (Verification, Validation and Accreditation).

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