

Strategic Energy Planning of Residential Buildings in a Smart City: A System Dynamics Approach

Regular Paper

Giancarlo Caponio^{1*}, Vito Massaro¹, Giorgio Mossa¹ and Giovanni Mummolo¹

¹ Dipartimento di Meccanica Matematica e Management – Politecnico di Bari, Bari, Italy

*Corresponding author(s) E-mail: giancarlo.caponio@poliba.it

Received 06 May 2015; Accepted 14 October 2015

DOI: 10.5772/61768

© 2015 Author(s). Licensee InTech. This is an open access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/3.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Abstract

Buildings are the largest urban energy consumers, but their impact can be largely cut back by improving efficiency. Policy-making plays a crucial role in harmonizing national and local incentive schemes. The authors analyse variables related to energy consumption, then propose a simulation model based on System Dynamics applied to a medium-sized Italian city. The model allows the testing of “what-if” scenarios and analysis of the results of implementing energy efficiency policies. Results stress the importance of a holistic view of urban energy processes. Simulation trends provide essential information for the city’s future energy and carbon emission profiles, helping policy-makers to achieve their goal.

Keywords Local Energy Planning, Urban Carbon Footprint Reduction, Smart City, System Dynamics, Energy Efficiency Policies

1. Introduction

The problem of how to tackle increasing global energy consumption due to the rampant growth of the human population – mostly in the less developed countries [1] – is

one of the main challenges facing mankind today. At the same time, one of the most important factors of government policy is security of energy supply [2]. Therefore, concerns such as growing energy demands, limitations of fossil fuels, threats of carbon dioxide (CO₂) emission and, consequently, global warming have placed strategic energy planning at the top of the policy makers’ agenda [3].

Over time, the notion that cities play a key role in moving towards a sustainable development has become mainstreamed into policy-making and planning. This statement is particularly appropriate for the energy sector. According to the International Energy Agency [4], cities are responsible for about 75% of the overall primary energy consumption and for as much as 80% of global greenhouse gas (GHG) emissions. The United Nations [5] predicts that urbanization will reach 70% by 2050, implying an increase of 2.8 billion people in urban areas.

Consequently, energy-planning activities are shifting from a centralized approach to an integrated centralized-decentralized one. Centralized energy planning cannot take into account the variations in socio-economic and ecological factors on a regional scale; these factors have a direct impact on the success of a policy. Vice versa, decentralized planning pays attention to the peculiar needs of a

region [6]. Energy districts can be referred to as energy-autonomous areas, where renewable energy can be generated and stored locally. An analytical model for wind power plants' technical-economic optimization can be found in [7]. In particular, energy planning processes on a city scale are taking on an ever more decisive role [8, 9].

The European Commission is at the front line of energy-saving policies. As stated in the Energy Efficiency Plan 2011, energy efficiency is one of the best ways to tackle the growing hunger of energy. Thus, the EU countries are aiming for a 20% cut in their primary energy consumption by 2020. At the same time, starting in 2008, a group of European cities autonomously set an ambitious target in seeking to reduce their carbon footprint related to energy consumption by at least 20% by 2020, within the so-called Covenant of Mayors.

In the last decade the "concept" of a Smart City has been introduced to embrace urban factors in a common framework and to highlight the growing importance of ICT networks [10] in addressing cities' sustainability. The term "smart" has multiple meanings, such as instrumented, interconnected and intelligent [11]. Specifically, the adjective intelligent refers to the application of complex analytics, modelling processes and optimization to improve strategic and operational decisions [12].

There is a rising demand for tools to support decision makers in handling urban issues [13, 14]. These tools need to be accessible to a wide group of people dealing with sustainable urban issues, including energy-planning processes. Against this background, the main target group for this paper is decision makers at a national and local level. It could be profitable for them to have an in-depth understanding and a holistic view of urban energy processes. The result of a particular policy initiative or strategic plan is largely dependent on whether the decision maker truly understands the inner interactions and complexity of the system in which he is going to act.

Considering the size and complexity of systems that public decision makers must manage, the intuitive approach to policy design often falls short of, or is counter-productive to, desired outcomes [15]. Knowing how to think in terms of systems and interconnections is a critical step in effective policy design, policy implementation and consensus-building. In this regard, the paper aims to identify the macro-variables related to both thermal and electric energy consumption in the residential sector. Furthermore, a simulation model based on the System Dynamics approach is proposed. The model refers to Bari, a medium-sized city in the southeast of Italy and a leading partner of the "Res Novae" research project involving industry, research institutions and municipalities in the smart planning and management of energy. It allows local policy makers to test "what-if" scenarios analysing the expected results of implementing short-term and medium-term initiatives for energy savings.

2. Energy Efficiency in the Residential Sector

2.1 Energy Efficiency Policies in Italy

The Italian government has placed energy efficiency promotion as a priority of its national energy policies. European Directive 2002/91/CE (Energy Performance of Buildings Directive) has driven the impulse in improving energy efficiency in the buildings sector. The civil sector is one of those most responsible for final energy consumption and greenhouse gas emissions. This problem is particularly pronounced in Italy due to the obsolescence of building stock [16]. From 1997 to 2013, against a decrease in industry and transportation energy consumption, due to the global economic crisis, the civil sector maintained a constant growth (Figure 1) [17]. In particular, consumption related to heating, cooling and domestic hot water represented one fourth of the Italian primary energy consumption. In 2007, the Italian government launched an Energy Efficiency Action Plan, in which a series of measures and initiatives to increase energy performance in the civil sector was encouraged.

As an incentive to conserve energy, the Italian government has defined a list of energy-efficient home improvements that households can adopt, which will save them money on their next tax return. The tax credit repays 55% (65% from 2014) of the intervention cost.

Some examples of solutions to increase the energy-saving performance of residential buildings are:

- Building envelope improvements to reduce air leakage through the barrier between conditioned and unconditioned space. High-performance windows and extra insulation in walls, ceilings and floors are included.
- Solar collectors (flat-plate and evacuated-tube) installation for space heating and domestic hot water.
- Heating systems substitution (heat pump, with direct use also of geothermal energy for heating applications, condensing boilers or biomass heating system installation).

Previous energy-efficiency measures are from now on referred as initiative #1, #2 or #3, respectively.

2.2 Effects of Policies on Civil Sector in Apulia

The effects of initiatives vary considerably from one region to another in terms of average cost, average energy saving achieved and household penetration. The reasons are multiple: local weather, average income, obsolescence and typology of building stock and effectiveness of the information campaign (among households and heating system installers). In particular, the paper focuses attention on the Apulia region. The results achieved from 2009 to 2012 are summarized in Table 1 [16].

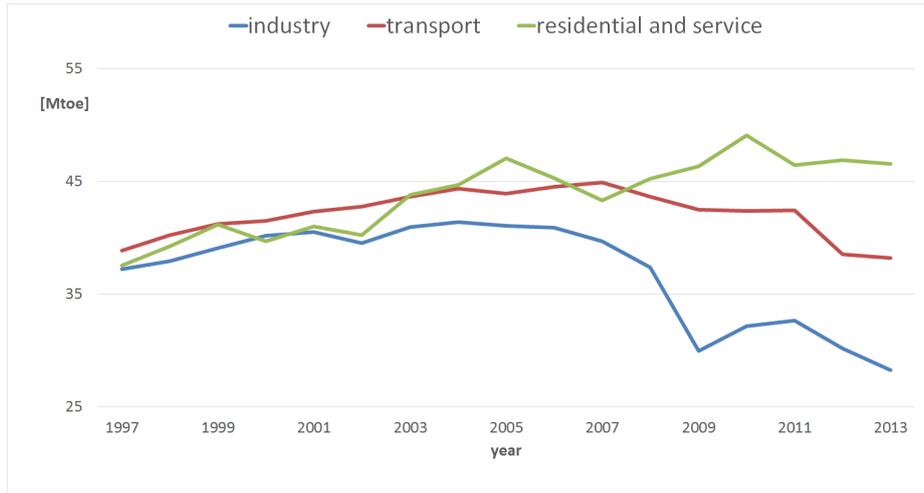


Figure 1. Final Energy Consumption by Sector in Italy from 1997 to 2013 (data from [17])

	nr [unit]	average cost [€]	average energy saved [kWh]
initiative #1	20,761	10,507	2,039
initiative #2	3,696	4,224	7,536
initiative #3	10,007	7,673	2,982

Table 1. Effects of Efficiency Initiatives in Apulia

3. Energy Planning Modelling by System Dynamics

3.1 Overview of the System Dynamics approach

The outcome of a specific policy initiative or strategic plan is largely dependent on whether the decision maker truly understands the inner interactions of the system in which he is going to act [13]. Thinking in terms of systems and interconnections is a critical step in effective policy design and then policy implementation. The concept of system thinking was introduced in the 1950s to help in understanding the behaviour of complex systems. It is an approach for problem solving by considering things as part of an overall system and acting on the entire system, rather than analysing every single part of the system individually [18, 19]. System Dynamics (SD) is a methodology based on system thinking [20]. It analyses problems dynamically and holistically, revealing the dynamic changes, feedback, delay and other processes of the complex system, by utilizing various control factors, e.g., feedback loops and time delays. SD modelling is suited to policy and decision makers because it assists them in understanding complex and dynamic behaviour over time.

Figure 2 shows the stages of SD methodology. The identification and definition of the problem is the first step in SD modelling. Determining where the problem stands and defining the objectives are two issues that should be clearly identified in the earliest stages. Thus, at this level, data and information, experiences and judgments are key factors. This follows the system conceptualization in which

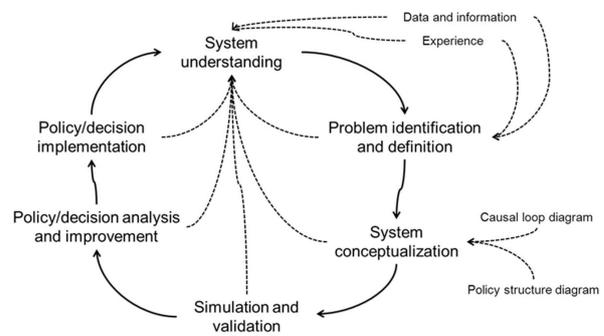


Figure 2. Stages of System Dynamics Methodology

boundaries, identification of causal relations and policy framework (through a qualitative analysis) are determined. To have an effective conceptualization, policy structure, causal loop and stock and flow diagrams are subsequently built. These diagrams help to provide a clear overview of the research subject, making clear from the model what is included and what is not. A causal loop diagram is a causal chart that shows how interrelated variables affect each other. It consists of nodes (variables) and their relationships (arrows) (see also Section 4.4). A stock-flow diagram includes stocks (levels), flows (rates), auxiliaries and connectors (see also Section 4.6). A stock (or "level variable") is an entity that is accumulated over time by inflows and depleted by outflows. It accumulates past events characterizing the state of the system. A stock typically has a certain value at each moment in time. Mathematically, a stock (S) can be seen as an integration of difference between inflow and outflow over a specified interval of time (Equation 1).

$$S_t = \int_{t_0}^t [\text{inflow}(t) - \text{outflow}(t)] dt + S(t_0) \quad (1)$$

A flow (or "rate") changes a stock over time. Flows can be divided into two types: inflows (adding to the stock) and

outflows (subtracting from the stock). Flows typically are measured over a certain interval of time. Mathematically, a flow can be seen as the derivative of the stock with respect to the time, which is its net rate of change (Equation 2).

$$F = \text{inflow} - \text{outflow}; F = \frac{dS}{dt} \quad (2)$$

The remaining variables are called “auxiliaries”. They help to calculate the flows or to communicate the steps in the calculation. Causal loop and stock-flow diagrams are the cornerstones in SD modelling. Finding the mathematical equations and simulation is the third stage of SD methodology. After testing the reliability and validity of the model, policy/decision analysis is carried out to evaluate the system simulation outcome and plan appropriate policies. Finally, a policy/decision will be implemented in the real world.

Each of the previous stages should enhance the overall perception of the system characteristics. Consequently each of them should basically have feedbacks for “system understanding”, making it the main part of SD [21]. The ultimate objective of SD is to improve the knowledge of the system through modelling and simulation. For further information on SD, interested readers are referred to [20, 21].

3.2 Short Review of the System Dynamics Research in Energy Planning

System dynamics modelling has been used for strategic energy planning and policy analysis for more than 30 years. The story begins with the World Models conducted in the early 1970s by a group of MIT researchers [22]. These models were developed to study the “predicament of mankind” - that is, the long term socioeconomic interactions that cause, and ultimately limit, the exponential growth of the world’s population and industrial output. In 1973, Roger Naill studied natural gas discovery and production, adopting a system dynamics approach. He concluded that the production of US natural gas will be depleted sometime in the late 20th or early 21st century. Afterwards, Naill developed several models, including COAL2, which dealt with US reliance on coal, and FOSSIL2, which dealt with fossil fuels’ effect on the US economy [23, 24].

In recent years, Chinese researchers have adopted system dynamics modelling to simulate the energy consumption and CO₂ emission trends for the City of Beijing from 2005 to 2030 [25]. They found that the key to carbon emission reduction activities for Beijing would be a change in energy structure, from carbon-rich fuel as coal to low-carbon fuel as natural gas. In addition to this study, in [26] a model for CO₂ emission reduction in a traditional industry region (Liaoning Province) is built. By using the system dynamics approach, the CO₂ emission trend from 2009 to 2030 is simulated and emission reduction policies are improved, in order to achieve the best possible performance. Widening the boundaries from city/regional scale to national, in

[27] a system dynamics model for evaluating renewable energy policies on dependency is proposed. The model considers the role of diversification on dependency and security of energy supply in Finland. The authors managed to foresee that, despite 7% electricity/heat consumption growth by 2020, dependency on imported sources would decrease between 1% and 7% on the defined scenarios.

4. Conceptual Model

4.1 Study area

The city of Bari is located in the southeast of Italy. Bari is the capital city of the Apulia region and is the second most important economic centre of mainland Southern Italy. The city itself has a population of about 323,000 as of 2013 (Italian National Institute of Statistics - ISTAT), over 116 square kilometres, but is located at the centre of a large metropolitan area containing approximately one million inhabitants. In its Sustainable Energy Action Plan (SEAP) [28], an ambitious goal is stated: a minimum CO₂ emission reduction target of 35% compared with that of 2002, by 2020. The buildings sector is responsible for more than 60% of urban emission, mostly due to the residential and tertiary sectors [28]. Therefore, the sustainable buildings sector is one of the focus areas. Some initiatives for promoting energy efficiency are suggested (e.g., replacing of incandescent light bulbs with compact fluorescent lamps, upgrading to a high-efficiency boiler, the construction of nearly zero emission new buildings and the implementation of an “energy cadastre”).

4.2 Problem Formulation

Two main forms of energy consumption can be identified and modelled: (i) electric energy consumption; and (ii) thermal energy consumption.

There is a strong relationship between energy consumption and economic growth. Many studies [29-33] relate energy consumption to economic factors such as per GDP or household income. Another relevant element is weather variation. Figures 3 and 4 describe the change trends of the energy usage and the average temperature respectively in summer and winter, with reference to the city of Bari. Consumption energy data are from the ISTAT database [34]; rough climate data have been taken from [35].

These figures demonstrate that there exists a strong relationship between per capita energy usage and external temperatures during the same time period. More specifically, when the summer temperature increases or decreases, the electric energy usage consumed by the resident will increase or decrease respectively. Due to the specific location, the temperature in the summer is very high. Thus the residents need to use air conditioners in their apartments. Conversely, in the winter, the heating consumes less energy when the temperature increases. Winter temperature variations are related to per capita natural gas con-

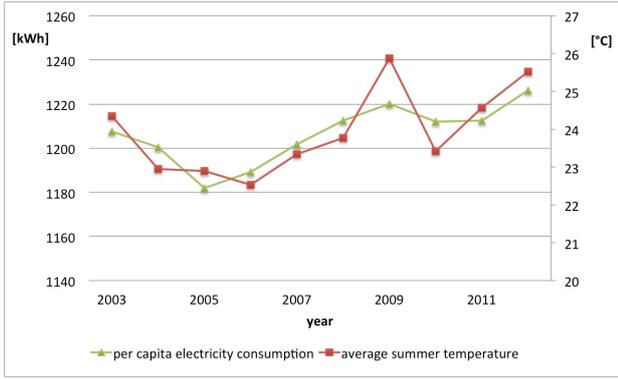


Figure 3. Per Capita Electricity Consumption and Average Summer Temperature Trends from 2003 to 2012

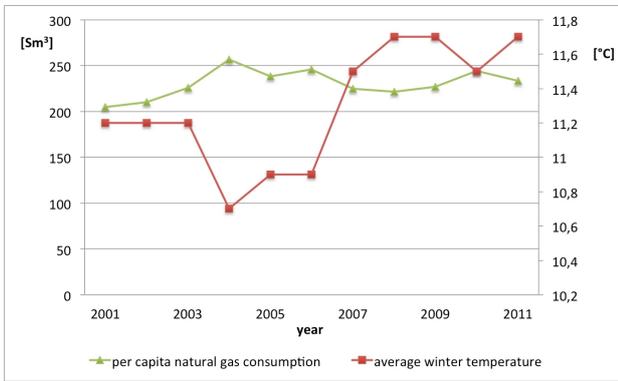


Figure 4. Per Capita Natural Gas Consumption and Average Winter Temperature Trends from 2001 to 2011

sumption, since it is the fuel most used for heating (for 95% of the Apulia population, according to [16]).

According to these considerations, per capita electric energy consumption (i) will be modelled as a function of per capita income and average summer temperature and per capita natural gas consumption (ii) is modelled as a function of per capita income and average winter temperature. The statistical technique of multiple linear regression analysis is used to derive the equations.

Formally, parts (i) and (ii) are modelled by Equation (3) and Equation (4), respectively.

$$PEC_t = \alpha_0 + \alpha_1 \cdot AI_t + \alpha_2 \cdot AST_t \quad t = 2001, 2002, \dots, 2011 \quad (3)$$

$$PNGC_t = \beta_0 + \beta_1 \cdot AI_t + \beta_2 \cdot AWT_t \quad t = 2001, 2002, \dots, 2011 \quad (4)$$

where the independent variables are:

- *PEC* : per capita electricity consumption [kWh/person]
- *PNGC* : per capita natural gas consumption [Sm³/person]

and the dependent variables are:

- *AI* : average per capita income [€/person]
- *AST* : average summer temperature [°C]

- *AWT* : average winter temperature [°C]

4.2.1 Estimation of Parameters

The authors have modelled the two relationships by fitting a linear equation to 11 observed data (2001-2011). Average per-capita income data have been taken from the Ministry of Economy and Finances database [36].

The independent variables that contribute to the regression with a significance level less than 95% are withdrawn. Tables 2a and 2b show the estimation of the coefficients for each predictor variable in Equation 3 and Equation 4.

	(a)			(b)		
	α_0	α_1	α_2	β_0	β_1	β_2
Value	985.598	0.007	5.871	833.352	0.030	-83.930
SE	30.330	0.002	1.710	53.614	0.003	6.927
<i>t</i>	32.495	3.615	3.433	15.543	11.077	-12.117
<i>P</i>	0.000	0.009	0.011	0.000	0.000	0.000
	$R^2_{adj}=0.896$		$d=1.867$	$R^2_{adj}=0.963$		$d=2.601$
			$VIF=1.895$			$VIF=3.993$

Table 2. Coefficient Estimates and Regression Statistics for Equation 3 (a) and Equation 4 (b)

For each coefficient information about standard errors (SE), *t* values (computed under the null hypothesis that the true population value of each regression coefficient individually is zero) and the estimated *P* values are given. Values of $P \leq 0.05$ contribute to the regression with a significance level of at least 95%. The quality of the regression is described by the three parameters below: the R^2 adjusted (R^2_{adj}) expresses the goodness of fit of the regression equation; the Durbin-Watson *d* statistic is a test for detecting autocorrelation; the *VIF* factor expresses the extent of inter-correlation, for detecting multi-collinearity. For more details, the readers can refer to [37]. In Table 2, for both (3) and (4) a high value of R^2_{adj} is observed (considering the area of application) as well as a significant *t* ratio, together with a moderate *VIF*, denoting moderate multi-collinearity (as a rule of thumb, if the *VIF* exceeds 10, the variables are said to be highly collinear [38, 37]). Tabulated upper (d_U) and lower (d_L) critical values for the Durbin-Watson *d* statistic with $n=11$ (observations) and $k=2$ (dependent variables) are 1.604 and 0.658 respectively. As shown in Table 2, for both Equations (3) and (4), $d > d_U$, which means that there is no statistical evidence that the error terms are positively autocorrelated [39]. Moreover, there is no indication of spurious regression in (3) and (4) because the Durbin-Watson *d* statistic is larger than the R^2 statistic [37].

4.2.2 Calculation of Local Emission Factor for Electricity

Following the guidelines on how to carry out SEAP by the European Commission [40], IPCC emission factors in line with the IPCC principles are used. However, in order to

calculate the CO₂ emissions to be attributed to electricity consumption, a local emission factor for electricity is calculated by using the equation below (Equation 5):

$$EFE_t = \frac{[(TCE_t - LPE_t) \cdot NEEFE_t + CO_2LTE_t]}{TCE_t} \quad t = 2001, 2002, \dots, 2011 \quad (5)$$

where the variables are:

- *EFE* = local emission factor for electricity [gCO₂/kWh_e]
- *TCE* = total electricity consumption in the province of Bari [kWh]
- *LPE* = total electricity production in the province of Bari [kWh]
- *NEEFE* = Italian emission factor for electricity [gCO₂/kWh_e]
- *CO₂LTE* = CO₂ emission due to the local production of electricity [gCO₂/kWh_e]

The authors have made the following assumptions:

- a constant growth of total electricity consumption, according to the Italian grid operator for electricity transmission (TERNA GROUP) forecasts [41].
- a growth less than linear of the total photovoltaic power installed (the Italian government stopped the feed-in tariff in 2013).
- a power regression decay of the national emission factor [42].
- the energy from biomass and wind power is not accounted for because their potential in the province of Bari is negligible.

4.3 The Framework of Local Energy-Saving Policies

In Italy, national subsidies have a different impact in terms of costs and energy saved, depending on local conditions (weather, number of sunlight hours, know-how, building stock's conditions) [16]. In addition to national subsidies (see Section 2.1), local government could also use jointly, as a further incentive, those measures that allow it to achieve its objectives quickly and with an efficient use of money. This financial help could integrate national subsidies in a non-selective manner, or focus on the option with the lowest [€/MWh] ratio to save money *ceteris paribus*. From Table 1, it is clear that the installation of solar panels gives the best results in the Apulia region, of which the municipality of Bari is the capital.

Therefore, two different policies are considered:

1. A 5% annual increment of tax credit for each initiative;
2. A 5% annual increment for initiative #1 and #3; an immediate incentive of 35% for initiative #2 to cover the whole cost.

Policies 1 and 2 are named respectively "Alternative 1" and "Alternative 2".

To define household behaviour in relation to the level of incentive, some considerations are necessary: population response is assumed to vary according to the demand curve with the level of incentives. Moving towards an incentive that repays the whole intervention cost, the number of households undertaking initiatives rapidly increases. Thus, the exponential function has been chosen as the most convenient for this task.

Moreover, the policies' effectiveness largely depends on the information campaign. For this purpose, three different scenarios are evaluated: a positive (or optimistic), negative (or pessimistic) and neutral (or middle-of-the-road) scenario. Historical trends are used to determine all constants [16, 17].

4.4 The Causal Loop Diagram

A causal loop diagram is a causal chart that shows how interrelated variables affect each other [18]. Among a number of variables within the subsystems of energy efficiency initiatives, only main variables that are related to the proposed model are included in this diagram (Figure 5). The main advantage of this kind of analysis is to understand the feedback structure of each variable related to the energy efficiency.

The diagram consists of nodes (variables) and their relationships (arrows). The arrows are labelled + or - depending on whether the causal influence is positive or negative. The + sign represents a cause-and-effect relationship, in which the two variables change in the same direction [37]. In Figure 5, the arrow between population and electricity consumption means that an increase in population causes an increase in electricity consumption. It also means that a decrease in the first causes a decrease in the second. The - sign marks the tip of the arrow, when the two variables change in the opposite direction. In Figure 5 the energy efficiency measures opposite natural gas consumption.

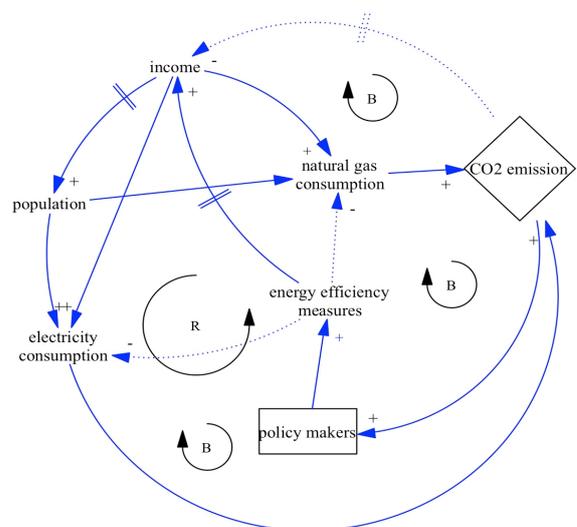


Figure 5. Causal Loop Diagram

According to Figure 5, four causal loops can be recognized:

- Population → (+) electricity (natural gas) consumption → (+) CO₂ emission → (+) policy makers → (+) energy efficiency measures → (+) income → (+) population;
- Income → (+) electricity (natural gas) consumption → (+) CO₂ emission → (-) income;
- Electricity (natural gas) consumption → (+) CO₂ emission → (+) policy makers → (+) energy efficiency measures → (-) electricity (natural gas) consumption;
- Population → (+) electricity (natural gas) consumption → (+) CO₂ emission → (-) income → (+) population.

Loop 1 is an example of a positive feedback. It describes a situation in which the system reinvests in itself, to make itself grow over time [37]. It tends to make the system grow bigger over time. In Figure 5, the positive loop is marked with an R, which stands for “reinforce”.

Loops 2, 3 and 4 are examples of negative feedback. They wear down the system over time. In Figure 5, negative loops are marked with a B, which stands for “balance”.

The arrows marked with a double line represent a delay in the causality. For example, an increase in energy-efficient measures will cause an increase in average income because of job creation [25]. However, this effect is not simultaneous. It occurs only after a period.

4.5 Bull's Eye Diagram

A bull's-eye diagram is a concise way to portray the system boundary of the model [43]. According to the degree of modelling, variables are written in from the centre to the external surfaces. Omitted variables are placed outside the outer ring. A bull's eye diagram of the proposed model is shown in Figure 6. Endogenous variables subjected to a thorough modelling are placed in the innermost part; the variables are then subjected to a superficial modelling. Exogenous variables are placed in the outer ring. Exogenous variables are placed in the outer ring.

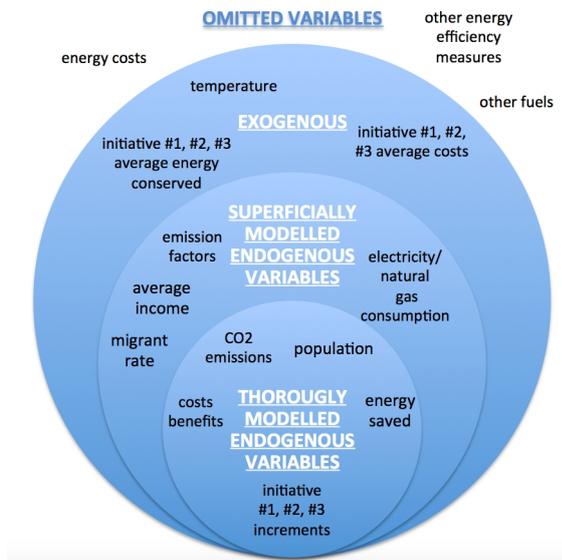


Figure 6. Bull's-Eye Diagram

4.6 Stock-Flow Diagrams

A stock-flow diagram is the core of the model. It consists of the process of quantification and materialization of the causal loop diagram. According to these considerations, the model is built using VENSIM software ® (Figure 7). It is composed of 47 variables: seven level variables, nine rate variables and 31 auxiliary variables. The parameters and simultaneous differential equations in the stock-flow diagram are defined, formalizing the considerations in the previous paragraph.

In the model, six sub-models can be identified:

- Socio-Economic sub-model (Figure 7). Taking into account weather conditions, total population and household economic conditions, the objective of this sub-model is to estimate per capita energy consumption (both electrical and thermal) over years.
- Initiative #1, #2 and #3 sub-models (Figure 8). These three sub-models estimate energy conserved and costs associated with each initiative.
- Local Emission Factor (EF) for electricity sub-model (Figure 9). This sub-model estimates the local EF for electricity, according to the previous considerations (see 4.2).
- Benefit-costs sub-model (Figure 10). Taking into account the monetary quantification of CO₂ avoided emissions, through the shadow price, as benefit and overall costs related to the policy initiatives, it allocates an annual budget to the three different energy saving initiatives and determines the amount of the incentive fund.

5. Simulation

As a first step, the possible trends of CO₂ emission saved from 2010 to 2020 in the city of Bari have been simulated under the condition “without local policy makers’ intervention”. As the smallest time constant in the model is one year, the time stamp used in the simulations is 1/8 year. According to [44], the time stamp should be between 1/4 and 1/10 of the smallest time constant in the model. Furthermore, the Euler integration method is preferred to “second-order Runge Kutta”. The Runge Kutta method gives a more accurate estimate, paying the price of extra time to perform the calculations. Considering that the proposed model is not a forecasting model but a learning model designed for general understanding, the authors have chosen the less time-consuming method.

Simulation results from 2010 to 2014 are compared with energy consumption actual data for the validation of the model. In this case, real temperature data are employed. In 2011, the winter was warmer than average, resulting in less consumption of natural gas for heating (Figures 12 and 15). This caused a peak in the percentage reduction of CO₂ emissions (Figures 11 and 14). In order to assess whether the model fit to the actual data or not, the Mean Absolute

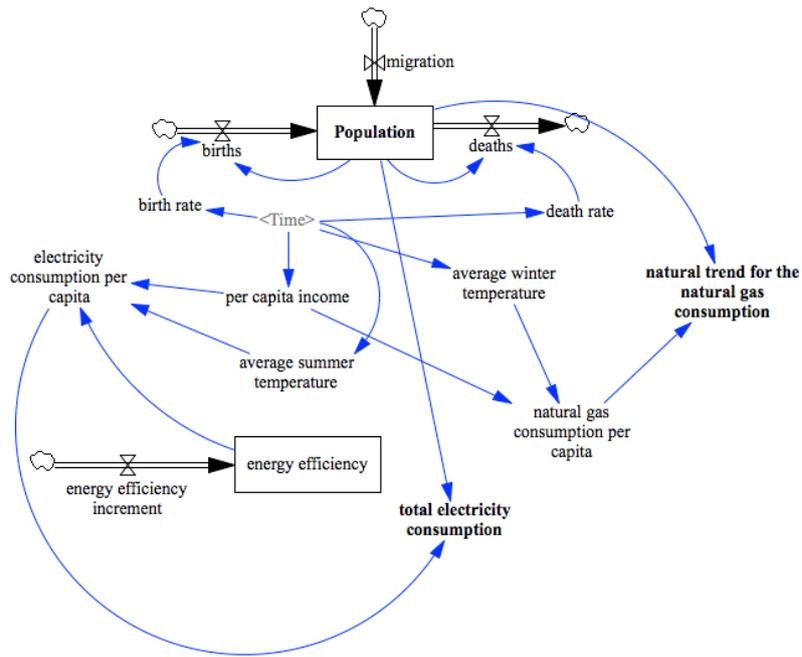


Figure 7. Socio-Economic Sub-model

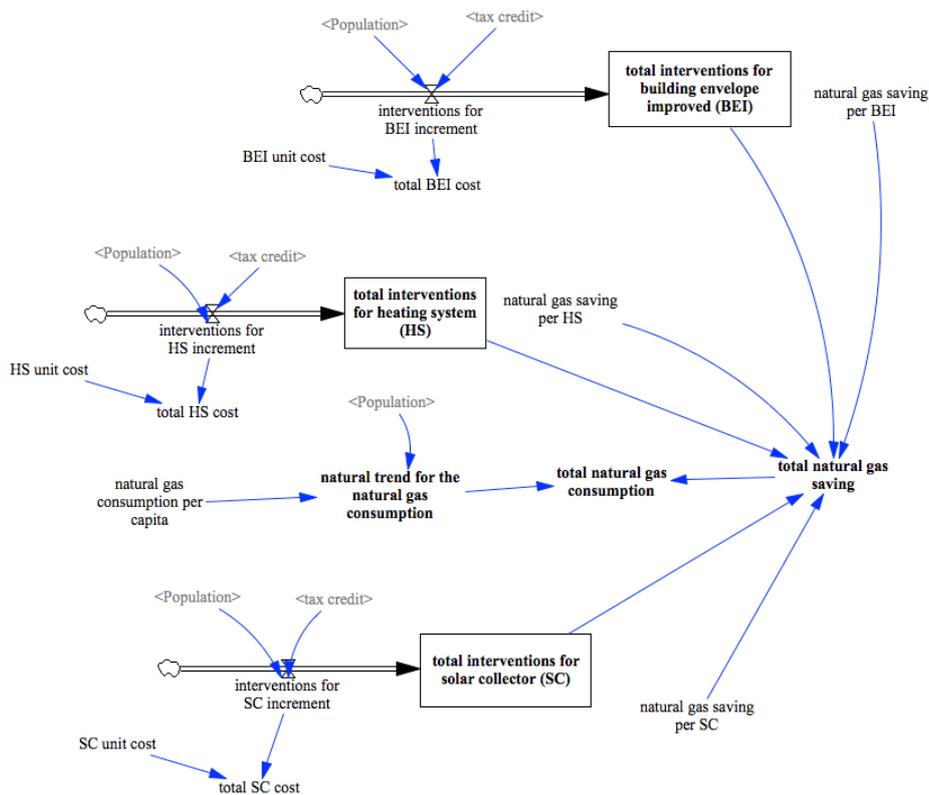


Figure 8. Initiatives #1, #2 and #3 Sub-models

Percent Error (MAPE) statistic has been calculated for variables under validation (i.e., per capita energy consumptions). The result shows that their fitting degree is more than 0.93, indicating that the model successfully replicates real-life data.

The simulation process under the condition “without local policy makers’ intervention” is named “Baseline or Business as Usual”. The baseline simulation trends are shown in Figures 11-16 and compared with simulation trends under different alternatives.

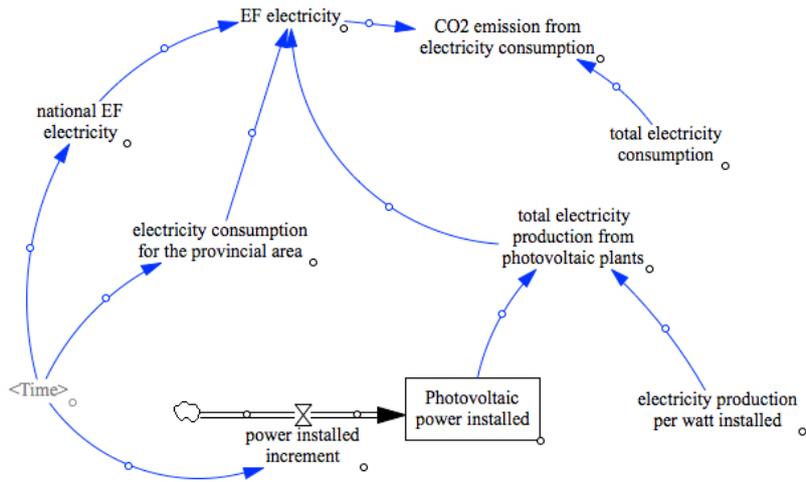


Figure 9. Local Emission Factor Sub-model

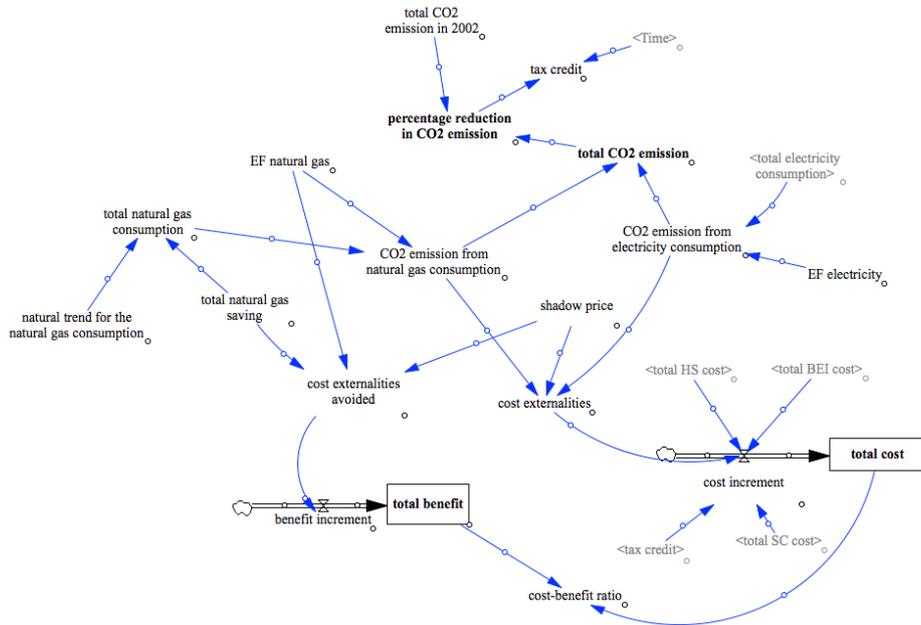


Figure 10. Benefit-costs Sub-model

The household advantages consist only of the tax credit, as expected for state aids. With the lack of further policy adjustments, buildings implementing energy efficiency initiatives will remain constant. Considering a slight increase in average income and temperature, the simulation shows a flattening in the residential total energy consumption, although per capita natural gas and electricity consumption grow. This is mostly due to the dwindling population. In these conditions, only a 26% cut is possible in the emission of carbon dioxide, compared with the 2002 level. Private individuals are not adequately supported, hence only a few of them will autonomously contribute towards implementing energy efficiency measures.

The framework of local energy policies was then implemented in the model (see Section 4.3). The results are shown

in Figures 11-16. Figures 11-13 refer to Alternative 1 simulation trends; Figures 14-16 refer to Alternative 2 simulation trends.

Providing indiscriminate incentives (Alternative 1), a 27% to 31% emissions reduction could be gained (Figure 11). Costs associated with the optimistic scenario are four times greater than those deriving from the pessimistic scenario (Figure 13). However, they are at a level in line with the incentives fund set aside in Bari's SEAP (around 40 [M€]) [28]. The population still decreases, although in a less clear way. The benefit-cost ratio, defined as the monetary quantification of CO₂ avoided emissions, through the shadow price, divided by total costs (intervention costs and those related to CO₂ emissions), gives the best results in the middle scenario. This means that local policy makers are

operating in a non-optimal way, because the intervention costs are much greater than the benefits obtainable from the energy saved.

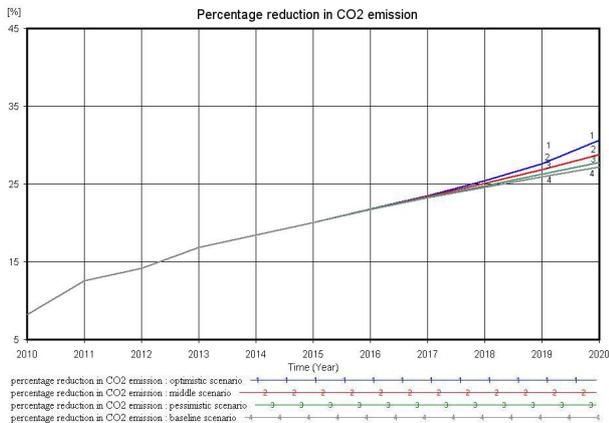


Figure 11. CO₂ Reduction - Alternative 1

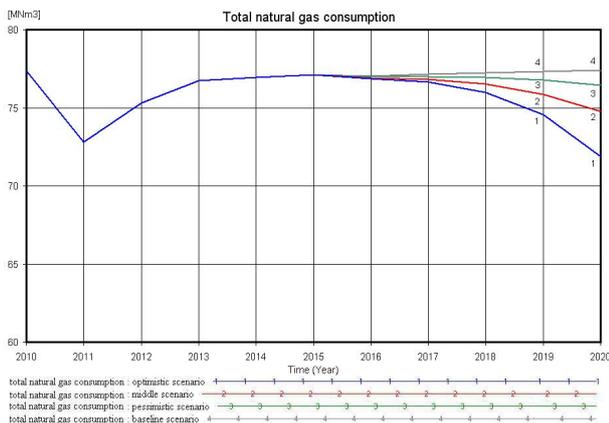


Figure 12. Total Natural Gas Consumption - Alternative 1

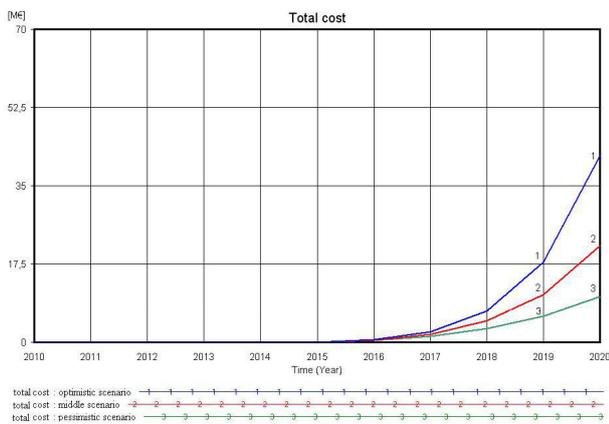


Figure 13. Overall Costs - Alternative 1

Results obtained with Alternative 1 have been improved with the Alternative 2 policy. The simulation results (Figures 14-16) show the effectiveness of this policy. The overall carbon footprint in the residential sector is estimat-

ed to decrease to around 400,000 tons of CO₂, with a 37.4% cut in the optimistic case (Figures 14-15). At the same time, costs increase to 65 M€ (Figure 16), but the benefit-cost ratio reaches its best value. The population remains almost constant.

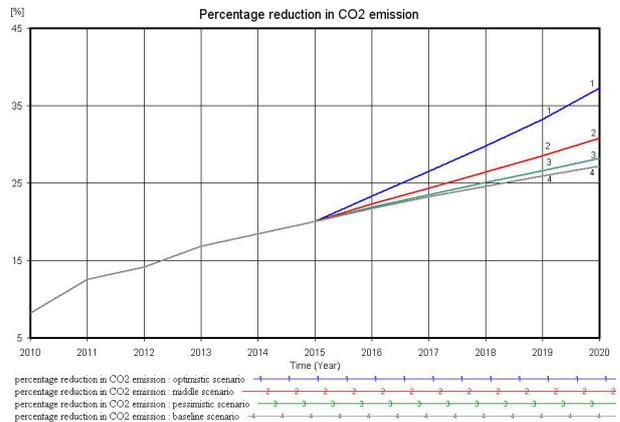


Figure 14. CO₂ Reduction - Alternative 2

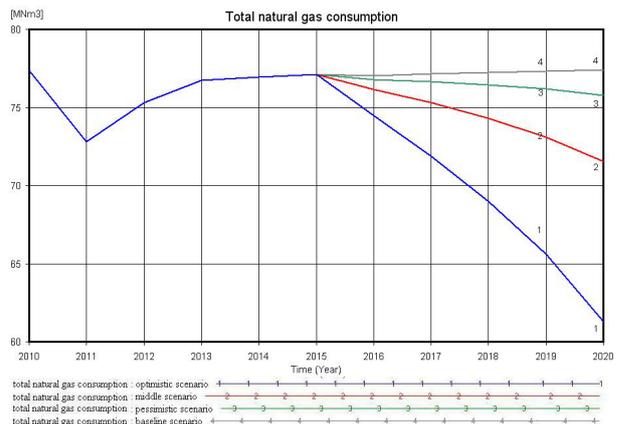


Figure 15. Total Natural Gas Consumption - Alternative 2



Figure 16. Overall Costs - Alternative 2

6. Conclusion

The proposed SD model is shown to be effective at simulating and improving the local energy planning policies in

the residential building sector. After identifying the key indicators (per capita energy consumption, average income, temperature), the paper tests different possible sets of decisions (policy framework) under different assumptions about the uncertainties related to household behaviour. The model has been applied to a full-scale case study concerning Bari, a medium-sized city in the southeast of Italy.

In the best-case scenario (optimistic scenario under Alternative 2), policy makers could significantly reduce energy consumption towards the SEAP objectives. Investment in increasing the public awareness of citizens by communication and education campaigns is highly recommended, since these would exert a beneficial impact on the penetration index of energy efficiency initiatives and, consequently, on the carbon footprint of the city.

Future research will be oriented towards investigating the effects of further energy policies enlarging the portfolio of initiatives, e.g., implementing a Building Management System (BMS), replacing old appliances with more energy-efficient versions, improving lighting efficiency, installing small wind turbines towards energy self-sufficiency and extending the model to public buildings.

7. Acknowledgements

The paper has been written within the framework of the project PON04a2_E “Smart Energy Master per il governo energetico del territorio - SINERGREEN - RES NOVAE”. The project is supported by the Italian University and Research National Ministry research and competitiveness programme, which Italy is developing to promote “Smart Cities, Communities and Social Innovation”.

8. References

- [1] United Nations. The World Population Situation in 2014. A Concise Report. New York; 2014.
- [2] Brown MH, Rewey C, Gagliano T. Energy Security. National Conference of State Legislatures. Washington, DC; 2001.
- [3] Kleinpeter M. Energy Planning and Policy. John Wiley and Sons; 1995.
- [4] International Energy Agency (IEA). World Energy Outlook. International Press; 2013.
- [5] United Nations. United Nations Environment Programme. In Proceedings of Regional Seas Visioning Workshop, pp. 1–25. 3–4 July 2014, Geneva (Switzerland). Available from http://www.unep.org/regionalseas/globalmeetings/Visioning_Workshop/Scenario-new.pdf [Accessed: 22-02-2015].
- [6] Hiremath RB, Shikha S, Ravindranath NH. Decentralized energy planning; modeling and application - a review. *Renewable and Sustainable Energy Reviews*. 1997; 11(5): 729–752.
- [7] Fortunato B, Mummolo G. Technical-economic optimization of a wind power plant by means of a stochastic analytical model. *Energy Conversion and Management*. 1997; 8(38): 813–827.
- [8] Løken E. Use of multicriteria decision analysis methods for energy planning problems. *Renewable and Sustainable Energy Reviews*. 1997; 11(7): 1584–1595.
- [9] Caponio G. Energy Strategic Planning of a Smart City by Dynamic Simulation. In Di Sciascio E, Castorani A, Andria G, Nuzzo S, Guerrieri CD, Monno G, Camarda P. PHD Students Research Programs, pp. 157–162. Gangemi Editore; 2014.
- [10] Caragliu A, del Bo P, Nijkamp P. Smart Cities in Europe. *Journal of Urban Technology*. 2011; 18(2): 65–82.
- [11] Harrison C, Eckam B, Hamilton R, Hartswick P, Kalagnanam J, Paraszcak J, Williams P. Foundations for Smart Cities. *IBM Journal of Research and Development*. 2010; 54(4): 1–16.
- [12] Chourabi H, Nam T, Walker S, Gil-Garcia JR, Mellouli S, Nahon K, Pardo TA, Scholl HJ. Understanding smart cities: An integrative framework. In Proceedings of the 45th Hawaii International Conference on System Science, IEEE, pp. 2289–2297. 4–7 January 2012, Maui, HI, USA.
- [13] Brailsfor S, Churilov L, Dangerfield B. Discrete-Event Simulation and System Dynamics for Management Decision Making. *Wiley Series in Operations Research and Management Science*; 2014.
- [14] Caponio G, Digiesi S, Mossa G, Mummolo G, Verriello R. Minimizing Carbon-Footprint of Municipal Waste Separate Collection Systems. In Cortes P, Maeso GE, Escudero-Santana A., Enhancing Synergies in a Collaborative Environment, pp. 351–359. Springer; 2015.
- [15] Radzicki MJ, Taylor AR. Introduction to System Dynamics. US Department of Energy; 1997. Available from: <http://www.systemdynamics.org/DL-IntroSysDyn/> [Accessed 20-01-2015].
- [16] Italian National Agency for New Technologies, Energy and Sustainable Economic Development. Available from <http://www.acs.enea.it/rapporti/> [Accessed: 11-11-2014].
- [17] Italian Ministry of Economic Development - Department for energy. National Energy Balance (BEN). 1997-2013. Available from <http://dgerm.sviluppoeconomico.gov.it/dgerm/> [Accessed: 25-12-2014].
- [18] Sushill AA. System dynamics: a practical approach for management problems. Wiley Eastern Ltd; 1993.
- [19] Russell LA. Systems thinking for curious managers. Triarchy Press; 2010.

- [20] Forrester JW. *Urban Dynamics*. The MIT Press, Cambridge; 1969.
- [21] Forrester JW. *World Dynamics*. Wright-Allen Press, Cambridge; 1971.
- [22] Donnella H, Dennis L, Jørgen R and William W. *The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind*, New York: Universe Books; 1972.
- [23] Naill RF. A system dynamics model for national energy policy planning. *System Dynamics Review*. 1992; 8(1): 1–19.
- [24] Radzicki MJ, Taylor AR. *Origin of system dynamics: Jay W. Forrester and the history of system dynamics*. US Department of Energy's Introduction to System Dynamics; 2008.
- [25] Feng YY, Chen SQ, Zhang LX. System dynamics modeling for urban energy consumption and CO₂ emissions: A case study of Beijing, China. *Ecological Modelling*. 2012; 252(1): 44–52.
- [26] Li F, Dong S, Li Z, Li Y, Li S, Wan Y. The improvement of CO₂ emission reduction policies based on system dynamics method in traditional industrial region with large CO₂ emission. *Energy Policy*. 2012; 51: 683–695.
- [27] Aslani A, Helo P, Naaranoja M. Role of renewable energy policies in energy dependency in Finland: System dynamics approach. *Applied Energy*. 2014;113: 758–765.
- [28] Comune di Bari, 2010. *Lo sviluppo di un'economia low carbon. Piano d'azione energia sostenibile/Sustainable Energy Action Plan (SEAP)*. Available from: <http://www.comune.bari.it> [Accessed 05-12-2015].
- [29] Brans J, Macharis C, Kunsch PL, Chevalier A, Schwaninger M. Combining multicriteria decision aid and system dynamics for the control of socio-economic processes. *An iterative real-time procedure*. *European Journal of Operational Research*. 1998; 109(2): 428–441.
- [30] Jumbe CBL. Cointegration and causality between electricity consumption and GDP: empirical evidence from Malawi. *Energy Economics*. 2004; 26(1): 61–68.
- [31] Mozumber P, Marathe A. Causality relationship between electricity consumption and GDP in Bangladesh. *Energy Policy*. 2007; 35(1): 395–402.
- [32] Chen ST, Kuo H, Chen CC. The relationship between GDP and electricity consumption in 10 Asian countries. *Energy Policy*. 2007; 35(4): 2611–2621.
- [33] Naryan PK, Smyth R. Multivariate granger causality between electricity consumption, exports and GDP: Evidence from a panel of Middle Eastern countries. *Energy Policy*. 2009; 37(1): 229–236.
- [34] Italian National Institute of Statistics. Available from <http://dati.istat.it/?lang=en> [Accessed 10-10-2014].
- [35] Tutiempo Network, SL. Available from <http://en.tutiempo.net/climate/ws-162700.html> [Accessed 12-12-2014].
- [36] Ministero delle Finanze. Available from http://www1.finanze.gov.it/dipartimentopolitichefiscali/fiscalilocale/distribuz_addirpef/lista.htm?r=1&pagina=puglia.htm&pr=BA [Accessed 31-10-2014].
- [37] Gujarati DN. *Basic Econometrics*. 4th ed. McGraw-Hill, New York; 2004.
- [38] Myers RH. *Classical and Modern Regression with Applications*. Boston, Duxbury; 1986.
- [39] Fleming MC, Nellis JG. *Principles of Applied Statistics: An Integrated Approach Using MINITAB and Excel*. 2nd ed. Thompson Learning, London; 2000.
- [40] European Commission. *How to develop a Sustainable Energy Action Plan (SEAP) – Guidebook*. Luxembourg: Publications Office of the European Union. 2010. Available from http://www.covenantofmayors.eu/IMG/pdf/seap_guidelines_en-2.pdf [Accessed: 24-07-2014].
- [41] Terna Rete Italia. *Previsioni della domanda elettrica in Italia e del fabbisogno di potenza necessario anni 2014 – 2024*. Available from <http://www.terna.it/LinkClick.aspx?fileticket=MidHqjXTZuo%3D&tabid=375&mid=434> [Accessed: 20-01-2015].
- [42] SINAnet database [Internet]. Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA). Available from <http://www.sinanet.isprambiente.it/it/sia-ispra/serie-storiche-emissioni/fattori-di-emissione-per-la-produzione-ed-il-consumo-di-energia-elettrica-in-italia/view> [Accessed: 11-11-2014].
- [43] Ford A. *Modeling the Environment*. 1st ed. Island Press; 1999.
- [44] Sterman JD. *Business Dynamics: System Thinking and Modeling for a Complex World*. USA: McGraw-Hill, Indianapolis; 2000.