Exploring the effects of domestic water management measures to water conservation attitudes using agent based modelling
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ABSTRACT
The urban water system’s sustainable evolution requires managing both water supply and water demand within a complete urban water cycle framework. Such an approach, however, requires tools to analyse and simulate the complete system including both physical and cultural environments. One of the main challenges, in this regard, is the design and development of tools able to simulate the society’s water demand behaviour and the way policy measures affect it. The effects of these policy measures are a function of personal attitudes that subsequently lead to the formation of people’s behaviours. This work focuses on the exploration of social impact theory on water conservation attitudes of urban households. A model is designed and implemented using agent based modelling. The developed model’s ability to represent social structure and mechanisms of social influences is tested against historical data from the 1988–1994 drought of Athens, Greece as a case study.

Key words | agent based modelling, social impact theory, urban water demand management, water conservation

INTRODUCTION
Integrated, system-level approaches to the urban water cycle, attempting to manage both supply and demand through a unified urban cycle management framework, have recently been emerging in the literature (including for example Rozos & Makropoulos 2013; Bach et al. 2014; Behzadian et al. 2014), but even these leave the water end-user essentially out of the simulation domain. A main challenge for including the water end-users in urban water modelling approaches is the need to model the water demand behaviour of a given household. Such approaches require tools to analyse and simulate the social dimension of the urban water system.

Domestic water demand behaviour is shaped jointly by households’ attitudes and society’s norms (Harlan et al. 2009). Complimentary to society’s norms, small – minority – groups may influence attitudes towards water saving (Hogg & Vaqunan 2011) just as early ‘environmentalists’ influenced pro-environmental behaviour (Fell et al. 2009). In correlation with these pro-environmental social changes, it can be deduced that an attitude change, from negative to positive, regarding water conservation is a product of influence of the early ‘water savers’, which comprise the minority attitude towards water conservation.

In this research, the social impact theory (Latane 1981) was selected to investigate the process of forming a positive water conservation attitude. This theory was introduced by Latane in 1981 and further developed by Nowak (Nowak et al. 1990), including Bahr and Passerini’s statistical mechanics (Bahr & Passerini 1998). This selection was based on the theory’s ability to investigate minority influence while taking also into consideration the effects of social norms and external influences. Additionally, in this work, social impact theory is combined with a network based approach, as suggested by Sobkowicz (2009), for simulating the
interactions relevant to water demand attitudes and to address the notion of social immediacy.

The main innovation of the presented work is the design of an agent based modelling (ABM) tool for integrating a complex network representing the links between the domestic water users of a city and social impact theory in order to simulate the imposed influences of society, policies, and other external forces to the domestic water users’ attitude. This feature goes beyond similar work such as Galan et al. (2009), which integrates ABM with an opinion diffusion model or Yuan et al. (2014), and Athanasiadis et al. (2005), which created ABMs that focus mainly on the effects of water price changes using water price and household income elasticities.

ABMs are able to address problems that concern emergence arising from interactions between a system’s individual components and their environment (Railsback & Grimm 2009). Additionally, ABM is a contemporary computational intelligence tool that is capable of capturing complex system characteristics of coupled socio-environmental systems (Filatova et al. 2015). The hypothesis, partly tested in this paper, is that this ability to capture emerging (bottom-up) behaviour, makes ABM an appropriate tool to simulate the dynamic interaction between the socio-economic and the water system and hence to provide the missing link in the modelling of the urban water system (Wheater et al. 2007; Koutiva & Makropoulos 2011).

The developed model is tested against historical data from the most recent severe drought event of 1988–1994 in Athens, Greece, as a case study. The effects of this drought event and the implemented policies are still observable on the water demand behaviour of the Athenians, as was concluded in a social research study published in 2016 (Koutiva et al. 2016). The proposed model attempts to depict Athens’ social structure and the mechanisms of social impact relevant to water conservation behaviour, focusing on the social interaction component of the water demand behaviour shaping mechanism.

MATERIAL AND METHODS

Agent based model description

The purpose, the variables and the processes of the designed model are explained in the following paragraphs, using the ‘ODD’ (Overview, Design concepts, and Details) protocol (Grimm et al. 2006) as a roadmap, as suggested in Polhill et al. (2008).

Purpose

In this work, an ABM was developed to simulate the effects of social influence on the urban household’s water conservation attitude. The urban population is simulated using agents representing households (called from now on household agents) whose social characteristics are sampled in order to represent the social conditions in place following the distribution of these characteristics as defined by censuses and other social studies. Every household agent’s water conservation attitude is assumed to be affected by those household agents who participate in its social network. This attitude is also influenced by water demand management measures such as water price changes and awareness raising campaigns as well as contacts from outside the local social network.

The model was implemented in NetLogo (Wilensky 1999), including the network extension for building the social network structure. The interaction of the household agents is addressed using complex network theory, as proposed by Sobkowicz (2009). Household agents are linked with each other randomly using NetLogo’s preferential attachment or small-world code (Wilensky 2005). The network is expanded by using the sum of the socio-demographic characteristics’ difference of the paired household agents as the strength of the social links, in order to simulate the effect of social immediacy (Sobkowicz 2009).

State variables

The low level parameters of the household agents (Grimm et al. 2006), their setup and descriptions are given in Annex I (available with the online version of this paper), categorised per household agent’s decision procedure where appropriate.

Agents’ procedures

Household agents’ social impact procedure allows them to rethink, every month, their water conservation attitude.
(positive or negative). During this procedure, the household agent’s water conservation attitude is affected by its own social network and external water policies. This effect (termed Social Impact, $I$) is estimated using the Theory of Social Impact, introduced by Latane in 1981 and further developed by Nowak et al. (1999), supported by Bahr & Passerini’s (1998) statistical mechanics. Equation (1) calculates Social Impact ($I$) as a function of pressure exerted by (a) each household agent’s social network and (b) by water demand management policies currently in effect.

$$I_i = -S_i b - O_i h - \sum_{j=1}^{n} \frac{S_j O_j}{d_{ij}^2}$$  \hspace{1cm} (1)

where,

$I_i$ is the exerted social impact on household agent $i$ who is a member of a social network of $n$ other agents ($j$)

$O_i$ (positive or negative) is the household agent’s attitude on water conservation ($-1$ or $+1$)

$S_i$ is the household agent’s strength of influence ($\geq 0$)

$b$ is the household agent’s attitude strength ($\geq 0$)

$h$ is the external influence $h = S_{PC} O_{PC} + S_{AC} O_{AC}$ where,

$S_{PC}$ is the strength of influence regarding water price changes information ($\geq 0$)

$O_{PC}$ is the information regarding water price changes (if water prices increase, then $O_{PC}$ is positive, if prices decrease then $O_{PC}$ is negative ($-1$ or $+1$), creating a positive or negative influence towards water conservation, respectively)

$S_{AC}$ is the strength of influence regarding awareness raising campaigns ($\geq 0$) with a value of zero corresponding to an absence of awareness raising campaigns

$O_{AC}$ is the awareness campaign’s attitude, which is always positive.

The summation term of Equation (1) estimates the influence of the social network of the household agent $i$ that includes $n$ other household agents $j$ with each member of the social network having a strength of influence $S_j$, an attitude $O_j$ and a social distance $d_{ij}$. Social distance measures the ease of communication between two individuals within a given population and is assumed to be related to the proximity of an agent’s socio-demographic characteristics to those of her peers. The magnitude of mutual interactions decreases with distance.

The probability that a particular agent $i$ will change her attitude due to social impact $I_i$ is calculated using Equation (2). This is based on the notion of ‘volatility’ of social impact, introduced by Bahr & Passerini (1998), as a measure of an individual’s susceptibility to change, amended by Kacperski & Holyst (1999) to include a degree of randomness in the (otherwise deterministic) pressure.

$$P_{\text{change}} = \frac{\exp(-I_i/T)}{\exp(-I_i/T) + \exp(I_i/T)}$$ \hspace{1cm} (2)

If $X < P_{\text{change}} \Rightarrow O_i(t + 1) = -O_i(t)$

If $X > P_{\text{change}} \Rightarrow O_i(t + 1) = O_i(t)$

where,

$P_{\text{change}}$ is the probability of an individual changing their attitude

$I_i$ is the exerted social impact

$X$ is a randomly selected number from a uniform distribution of $[0,1]$

$T$ is the average volatility or social temperature of social impact. Low values of $T$ mean that household agents’ attitudes are highly dependent on their social network’s attitudes, thus it is more probable that they will be affected by the social impact ($I_i$) exerted on them, whereas higher levels of $T$ reduce the power of $I_i$ in determining a household agent’s attitude.

The result of the overall procedure is either a positive or a negative attitude on the water conservation of household agent $i$ for the next month of the simulation. The model operates in a monthly time step, and its output is the number of agents with positive attitudes on water conservation per month. The following section presents an application of the proposed modelling framework for Athens during the 1990’s drought event.


Athens is the capital and the largest city of Greece. Water supply in the city of Athens has always been a major...
development issue. During the drought period of 1988–1994, Athens’ water runoff reached the lowest record ever, and remained for a long time so low (less than 50% of the long term average) that by the end of 1994 water reserves were barely enough to satisfy the demand of less than a year (Mamasis & Koutsoyiannis 2007). The main response to this drought pressure in terms of water demand management was the substantial increase in water prices, an average of 240% across all levels of consumption, and extensive water saving awareness campaigns in 1990, 1992 and 1993 (Kanakoudis 2008; EYDAP 2009).

The effect of these policy measures was an approximately 33% drop in domestic water demand, namely from an average volume of 150 litres per inhabitant per day in 1989 to 100 litres per inhabitant per day in 1993 (Mamasis & Koutsoyiannis 2007). Following the end of the drought period and the extension of the water supply network, water saving awareness raising campaigns were stopped and water consumption returned to 150 litres per inhabitant per day in 1997 and continued to increase, mainly due to the increase in living standards (EYDAP 2009).

It is evident, in retrospect, that awareness campaigns and the diffusion of information, in this case the risk of running out of water and the rise in water price, had a major impact on the water saving attitudes of the population of Athens (Koutiva et al. 2016). Evidently, when the drought was over and even though the prices remained at a higher level than pre drought, the consumption levels increased (Mamasis & Koutsoyiannis 2007; Kanakoudis 2008).

One important feature of this case study is that knowledge exists on the sequence of actions taken and the results achieved by the water demand management strategies employed. As such, it was selected as a case study that could test the potential of the proposed approach to re-create the social dynamics and provide insights as to the legitimacy of the conceptualisation and implementation of the proposed agent based model.

**Modelling social influence’s effect on water conservation attitudes in Athens**

The lack of information regarding the actual distribution of water conservation attitudes in Athens during the period in question necessitates the ‘translation’ of the decrease of water demand from 1991 to 1995 into possible distributions of attitudes across the population. As mentioned earlier, a positive water conservation attitude only increases the chances of water saving behaviour (Dolnicar & Hurlimann 2010). Thus, it was assumed that to achieve such a water demand decrease, part of the population needed to have acquired positive attitudes regarding water conservation. Of this element of the population, which became positively predisposed, influenced for example by awareness campaigns or by information regarding water price increases, some have actually implemented demand reductions, resulting in the actual reduction that can be observed in the data. In other words, it was assumed that having a positive attitude was a necessary but not sufficient condition to reduce one’s demand. This portion of the population was estimated by comparing the 1990’s projected mean values of water demand (theoretical series in Figure 1, Germanopoulos 1990) and the mean values of water demand from EYDAP’s datasets (EYDAP’s series in Figure 1, EYDAP 2009).

For the purposes of this work, it is assumed that the 1990’s projections represent the business-as-usual scenario (in other words they are a reasonable representation of the evolution of demand without the impact of the drought event and related awareness raising), while EYDAP’s datasets capture the effect of the implemented drought measures. We compare the mean values and standard deviations of these time series, following Linacre (1996), to calculate the minimum percentage of the total population that would need to have a positive water conservation attitude, for the observed conservation to have actually taken place (the results of this calculation are presented in Annex II, available with the online version of this paper). This minimum percentage is in effect a lower boundary of people needed to change attitudes for the observed demand reduction to have taken place (Figure 1). Clearly, more people than that could have indeed adopted a positive attitude – but have then failed to actually engage in demand reduction. Since this cannot be known on the basis of available data, we concentrate on identifying the boundary – which is a conservative estimate of the impact of the campaigns.

**Model’s experimental variables sensitivity analysis**

The designed model is assessed based on its capability to simulate the years when the awareness campaigns were
active. A sensitivity analysis of the proposed modelling framework’s experimental variables using the Monte Carlo Analysis Toolbox (Wagener 2004) was undertaken. This analysis provided an insight into the physical meaning of each variable and their effect on the model’s results. The sensitivity analysis led to the selection of a suitable set of values able to capture the estimated minimum percentage of population with positive attitudes in Athens (Figure 1 and Table 1). A total number of 930 household-agents are created as an aggregation of the approximately 930,000 households that existed in Athens in 1981. This approximation is in accordance with other applications of ABM in the water sector, with a scaling down ratio from 0.0001 to 0.1 (see for example the works of Galan et al. (2009), Becu et al. (2005), Athanasiadis et al. (2005) and Barthel et al. (2008)). Every 12 steps (≈1 year) 25 new household agents, representing 25,000 households, are created to demonstrate the population increase (ELSTAT 2012).

As proposed by Nikolic et al. (2012), Latin hypercube sampling was used to sample the multidimensional parameter space and create experiments for exploring the sensitivity of the proposed model’s experimental variables. 100 value sets were selected and experiments were created. These experiments were repeated 10 times each to decrease the influence of outliers to the average result. The mean output of the ten repetitions of each of the 100 sampled parameter sets was used for the sensitivity analysis of the proposed modelling platform. The experimental parameters are (presented in Annex 1):

1. percentage of initial population with positive attitudes (ipa)
2. percentage of external positive influence (epa)

Table 1 Most identifiable value ranges for the experimental variables

<table>
<thead>
<tr>
<th>Experimental variable</th>
<th>Selected constraint</th>
</tr>
</thead>
<tbody>
<tr>
<td>External positive influence (×100%)</td>
<td>0.6–0.8</td>
</tr>
<tr>
<td>Initial positive attitude (×100%)</td>
<td>0.3–0.4</td>
</tr>
<tr>
<td>Volatility of Social Impact (T)</td>
<td>10–40</td>
</tr>
<tr>
<td>Mean strength of influence</td>
<td>0–30</td>
</tr>
<tr>
<td>Mean strength of influence regarding awareness raising campaigns</td>
<td>60–80</td>
</tr>
<tr>
<td>Mean strength of influence regarding water price changes</td>
<td>0–20</td>
</tr>
</tbody>
</table>

Figure 1 Comparison of EYDAP mean domestic water demand (L/p/d) (EYDAP 2009) and 1990’s projected theoretical mean domestic water demand (L/p/d) (Germanopoulos 1990) to estimate the minimum percentage of population with positive attitudes regarding water.
3. volatility of social impact (T)
4. mean strength of influence (S)
5. mean strength of influence regarding awareness raising campaigns (S_{AC})
6. mean strength of influence regarding water price changes (S_{PC}).

As suggested earlier, the main goal of the work presented here was to capture the effect of the campaigns on the society’s water conservation attitude. Thus the modelling framework’s results need to match or exceed the required minimum of positive attitudes estimated earlier and presented in Table 1 and Figure 1.

In addition, the mean of absolute percentage errors between the required minima and the modelled percentage of positive attitudes is used as a measure that shows the deviation of the modelled results (Equation (3)). This is done in order to select experimental variables’ value sets able to produce results larger than the required minima while resulting in small sum of percentage errors and hence value sets that create the lowest discrepancy between the data and the modelled results.

\[
\text{MAPE}(\text{pars}_k) = \frac{\sum_{\text{December}}^{\text{January}} (\text{E}_{PO,i} - \text{M}_{PO}(\text{pars}_k)/\text{E}_{PO,i})}{N}
\]

\[(3)\]

where,

- \(k\) denotes the parameter set under investigation (\(\geq 0\))
- \(i\) denotes the result of the \(i\)-th month (1, 72)
- \(N\) denotes the total number of months
- \(j\) denotes the monthly interval that also calculates the total number of months (e.g. \(j = \text{months} 12\) to 30, total number of months = 18)
- \(\text{M}_{PO}\) corresponds to the model’s results for the \(i\)-th month
- \(\text{E}_{PO}\) corresponds to the required minimum of positive attitudes for that \(i\)-th month
- \(\text{pars}_k\) corresponds to the respective \(k\)-th parameter set, as selected from the Latin hypercube sampling process.

The Monte Carlo Analysis Toolbox (Wagener 2004) was used to identify the value ranges of the experimental variables that affect the output, and their results may be estimated with some degree of certainty. In order to do that, identifiability plots were created for the MAPE objective function and for the number of times that the percentage of the positive attitude distribution within the population was less than the required minima. This process led to the identification of the value ranges within which the parameters are most identifiable (Table 1).

The type of complex network, scale-free or small-world, depends on the ability of the complex network structure to simulate the evolution of change in water conservation attitudes in the case under investigation. Yet, it has been identified that different social networks follow different complex network structures depending on their intrinsic characteristics (Nikolic et al. 2012). Additionally, attitude change depends, as well, on the notion of immediacy (McPherson et al. 2001), where someone is influenced more by those social network connections with the same social characteristics. The ability of the scale-free network to be built dynamically, by incorporating a preferential attachment strategy (Nikolic & Kasmire 2002), makes this structure preferable in this particular case. The network structure is built dynamically so as to incorporate new agent households representing population increase rates. These new agents are connected to those existing agent households that already are connected with more agent households than their peers.

**RESULTS AND DISCUSSION**

A Latin hypercube sampling was performed in the selected value ranges of the experimental variables. The model was run 10 times for each of the selected experimental variable sets, and the resulted percentages of positive attitudes were transformed to mean domestic monthly water demand (Figure 2). This transformation was based on the earlier assumption that water demand per person is normally distributed. 1989’s actual – from EYDAP’s datasets – water demand per person is used as a baseline to calculate water demand decrease during 1990–1995. Based on the normal distribution’s properties, the difference between two normal distributions has a mean equal to the difference of the means and a standard deviation equal to the square root of the sum of the variances, of the two normal distributions. The water decrease in Athens’ households from 1990 to 1995 equals the difference between the normally distributed water demand of 1989 \((\mu = 150, \sigma =\)
21) and households’ water demand from 1990 to 1995 (the results of this calculation are presented in Annex III, available with the online version of this paper). Water decrease is assigned to households performing a Latin hypercube sampling of 100 values of mean monthly water decrease in litres per person per day, using the normal distribution of water decrease as presented in Annex III. The results of the presented agent-based model give the percentage coverage of the water conserving households. The remaining household population, with negative attitudes on water conservation, acquires a mean monthly domestic water demand equal to that of 1989 (150 litres per person per day).

Figure 2 also illustrates the comparison between the simulated water demand and the mean monthly domestic water demand given by EYDAP’s datasets (EYDAP 2009). Figure 2 demonstrates that the results from the ABM are able to follow the changes of water consumption related to the effects of awareness raising campaigns. The model results fit best the requested data in 1991, 1993 and 1994, which are the years when the effects of the awareness campaigns were observable. This means that the proposed modelling framework was able to represent the effect of these campaigns to the population’s attitude regarding water conservation.

The Athens model demonstrates that it is possible, even with a small number of data available, to simulate the effect of awareness campaigns on urban households’ water conservation attitude.

CONCLUSIONS

Simulating water demand behaviour is challenging and usually addressed by developing water demand scenarios. This paper presented an agent-based model for simulating the effects of social influence on water conservation attitudes. ABM has been identified as a promising tool for simulating society’s dynamics and thus provides a modelling tool for exploring diverse water management decisions and strategies including, for example, water demand management (Athanasiadis et al. 2005; Galan et al. 2009; Koutiva & Makropoulos 2011), flood management (Wheater et al. 2007) and catchment management (Becu et al. 2005; Barthel et al. 2008).

In this work, the authors focused on an empirical entry point towards the decision making process for conserving water: the positive attitude towards water conservation.
Whilst this entry point is important, a positive attitude does not always lead to an actual water saving behaviour (Dolnicar & Hurlimann 2010) but it does imply a positive attitude towards water conservation. Furthermore, three of the main innovations of this work are:

(a) the integration of social impact theory, complex network theory and statistical physics on social dynamics using ABM technology to represent the dynamics of social influence on water conservation attitudes;
(b) the integration of water price changes as an external force of influence to change one's water conservation attitude contrary to either the use of econometric functions for translating water price changes to water demand (Athanasiadis et al. 2005) or the exclusion of water prices changes from behavioural rules (Gala’n et al. 2009) because water price is inelastic (Arbués et al. 2005); and
(c) the use of sensitivity analysis for exploring the state space of the model’s experimental variables, selecting reasonable – informed – parameters and thus providing a more transparent way for setting up such models.

The developed ABM performed well, being tested using the 1988–1994 drought of Athens, Greece, as a case study and the outputs of the modelling platform fitted well to the required levels of water conservation acceptance. The showcased model forms part of a comprehensive ABM tool, called Urban Water Agents’ Behaviour (UWAB), which integrates the rules and procedures presented here and goes one step further, translating water conservation attitudes to water demand behaviour in response to water demand management measures (Koutiva & Makropoulos 2016). UWAB is linked to a source-to-tap urban modelling tool, the Urban Water Optioneering Tool (UWOT) (Makropoulos et al. 2008; Rozos & Makropoulos 2013), to calculate the evolution of domestic water demand, rendering the different water demand behaviours into actual volumes of water (Koutiva & Makropoulos 2016).

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