CHEMICAL ENGINEERING TRANSACTIONS

VOL. 45, 2015

A publication of AIDIC
The Italian Association of Chemical Engineering
www.aidic.it/cet

Guest Editors: Petar Sabev Varbanov, Jiří Jaromír Klemeš, Sharifah Rafidah Wan Alwi, Jun Yow Yong, Xia Liu

ISBN 978-88-95608-36-5; **ISSN** 2283-9216 DOI: 10.3303/CET1545064

Understanding the Technological Substitution by Hybrid Modelling Practice: a Methodological Approach

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Various novel climate technologies and eco-innovations have already reached a mature state, but they diffuse slowly into the market. Due to this slow process the mitigation of climate change does not take the most effective path. In the literature general models for diffusion are given, but specific factors affecting the adoption of new technologies are not studied enough. Since the affecting factors are not explored, the technological substitution cannot be triggered purposefully. Therefore the aim of our research is to propose the model of technological substitution. The methodology used combines a white-box and black-box modelling approaches. As white-box model the system dynamics is used, and as the black-box artificial neural networks. Since each of these methodologies have got specific strength and weakness, by combining those methods comprehensive modelling tool is obtained. Due to our knowledge this is the first attempt to model the technological substitution process by hybrid modelling, which includes system dynamics and artificial neural networks. The obtained results show that the model can explain 89 % of the systems behaviour. Although the model was based on the one specific technological substitution process, its general application to other products and services is possible, since the developed model is fully outlined and can be used for further research of other processes.

1. Introduction

Various novel climate technologies and eco-innovations have already reached a mature state, but they diffuse slowly into the market. Due to this slow process the mitigation of climate change does not take the most effective path and convergence to the Green Energy strategy (Blumberga et al., 2014a) slows down. General models for diffusion are given by Bass (1969) on dynamics of market players and Rogers (2003) on overall dynamics in the market, but specific factors affecting the adoption of new technologies are not studied enough (Karakaya et al., 2014). Since the affecting factors are not explored, the technological substitution cannot be triggered purposefully.

Therefore the aim of our research is to propose novel model of technological substitution. In substitution theory, buyers' decisions are based on both a generic function and additional activities performed by the product (Porter, 1985). In many cases, when the substitution of a product is made by an eco-innovation, it performs the same generic function as the product being replaced; however, the product itself is very different. For example, the introduction of micro-fibre clothes for cleaning purposes of surfaces is eco-innovation (in its broader definition) since the clothes can substitute both conventional wipes and cleansing agents. Micro-fibre clothes have the same generic function as other wipes and an important addition property substitution of cleansing agents.

The novelty of the work is given by the developed methodology. This methodology used combines a white-box and black-box modelling approaches. As white-box model the system dynamics is used, and as the black-box artificial neural networks. Since each of these methodologies have got specific strength and weakness, by combining those methods comprehensive modelling tool is obtained. Due to our knowledge this is the first attempt to model the technological substitution process by hybrid modelling, which includes system dynamics and artificial neural networks. The model is tested for the case study of microfiber cloth diffusion in Latvia using goal framing theory by Lindenberg and Steg (2007). Although the model was based on the one specific technological substitution process, its general application to other products and

Please cite this article as: Timma L., Blumberga A., Blumberga D., 2015, Understanding the technological substitution by hybrid modelling practice: a methodological approach, Chemical Engineering Transactions, 45, 379-384 DOI:10.3303/CET1545064

services is possible, since the developed model is outlined and can be used for further research of other processes. This proposed methodology can be applied to trigger the diffusion processes of various energy saving technologies and practices, which in turn reduces overall pollution.

2. Methodology

This work combines white-box and black-box methods to develop model for technological substitution. The overall attitudes of consumers towards eco-innovation are tested based on the goal framing theory.

2.1 Focus group and goal framing theory

As focus group for this research the consumers in Latvia was targeted. The survey was conducted in order to test the motivation for technological substation. The survey included various questions, which aim to describe goal frames for decisions made by consumers (Steg et al., 2014). These goal frames includes gain, normative and hedonic Gain goal deals with the financial and material gains, as well as saving in time and effort, normative goal deals with the environmental concerns and the necessity to make “the right” choice, hedonic goal deals with the ease of use and introduction of new products and social acceptance and support (Lindenberg and Steg , 2007).

2.2 White-box modelling

As white-box modelling system dynamics was used, since this tool incorporates nonlinearities, feedbacks and delay in the studies system (Forrester, 1958). System dynamics is white-box modelling approach, since all interconnections of elements are outlined and given by differential mathematical equations (Sterman, 2000). Another important property of system dynamics is that this tool is used to explore the nature of system with interlinked elements, where general system’s behaviour not the point’s predictions are of interest (Barlas, 1996).To create system dynamics model following main elements should be used: stocks, flows, auxiliaries, and connectors. Stocks represent state conditions in the system, flows handles the rate of change for inflows and outflows, auxiliaries are exogenous parameters affecting the system and connectors transmits information among variables (Blumberga et al., 2014b).
All stocks are given by following differential equations:

$$Stock_t = \int Flow_{(t,t-dt)} dt + Stock_{(t-dt)} \tag{1}$$

where $Stock_t$ is the stock at time t; $Flow_{(t,t-dt)}$ is the flow rate in the time period from $(t-dt)$ to t; dt is the time interval of equation span; $Stock_{(t-dt)}$ is the initial stock. The relations between the variable in the stock-flow diagram can be given by causal loop diagram, see Figure 1.

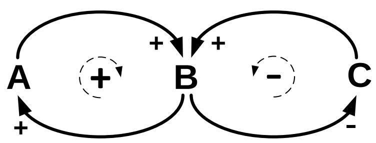

Figure 1: Representation of causal loop diagram

‘Causal’ refers to the cause-and-effect relationship while ‘loop’ denotes the closed chain of cause and effect creating the feedback. In this case A affects B and both of these elements expect changes in the same direction (either positive or negative) and B affects C and both of these elements expect changes in the opposite direction (one positive and second negative or opposite is true). This modelling approach is used to explore aspects of policy, for example, in the field of social acceptance of “green” electricity by Tziogas and Georgiadis (2013), in the field of waste management for biowaste by Pubule et al. (2015), for portable waste batteries by Blumberga et al. (2015) and in the field of biofuels by Barisa et al. (2015).

2.3 Black-box modelling

As black-box modelling artificial neural networks (ANN) was used, because it obtains the mathematical relations for relatively small, incomplete and noisy date sets (Dreyfus, 2005). In contrast to system dynamics, ANN are black-box modelling tool, where for the defined inputs the corresponding outputs are obtained, by the user has limited possibility to interfere with the internal structure of this model. On the other side, similarly, to system dynamics all elements in ANN are interconnected and there are possibility to incorporate delays and feedback. The graphical representation of ANN is given in Figure 2, where the neuron receives inputs signals; these signals are weighted and transferred.

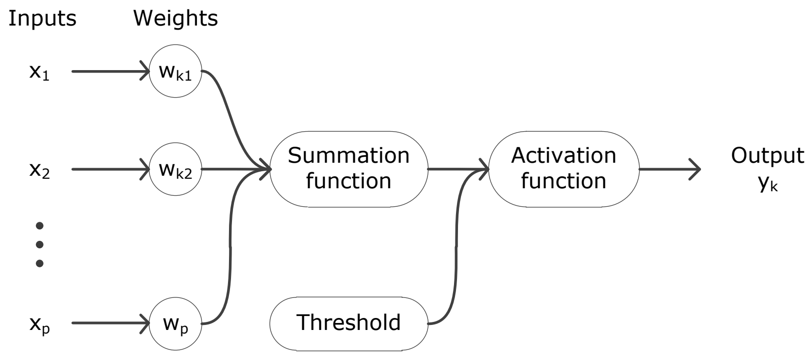

Figure 2: Graphical representation of artificial neural network with main elements

After weighting, the input signal undergoes an aggregation and non-linear activation. Under conditions when the aggregation signal exceeds a threshold value, the neuron generates an output signal, which is output signal (Yeung et al., 2010). The mathematical model of the basic ANN structure is as follows:

$$u_k = \sum_{i=1}^{n} w_{ki} x_i = w_{k1}x_1 + w_{k2}x_2 + ... + w_{kn}x_n \tag{2}$$

Where x_i *(i=1,2,…,n)* are the input signals from *n* external neurons transmitted to the neuron *k* and w_{ki} is the weight between the *i*-th external input and the neuron *k*. The output from the summation function is u_k. This modelling approach is used to study the production of citric acid by Kana et al. (2012), the formation of bubble point pressure in crude oil by Cuptasanti et al. (2013), the degradation of organic pollutants in water by Capocelli et al. (2014a) and the capability of hydrodynamic cavitation by Capocelli et al. (2014b).

2.4 Hybrid or grey-box modelling

The both of these presented modelling approaches are combined to obtain comprehensive modelling tool, since previous researches where technological substitution was modelled using only system dynamics in combination with statistical data analysis tools yielded relativity low explained variance, for example, study by Bariss et al. (2015) explained 13 % of motivation for energy efficiency and Tonglet et al. (2004) 33 % of motivation for waste recycling.

The general advantages of combined and mixed modelling tools in environmental engineering are discussed by Timma et al. (2015), where improved reliability of the model and requirements for fewer observations are pointed out. The general layout of proposed methodology is given in Figure 3.

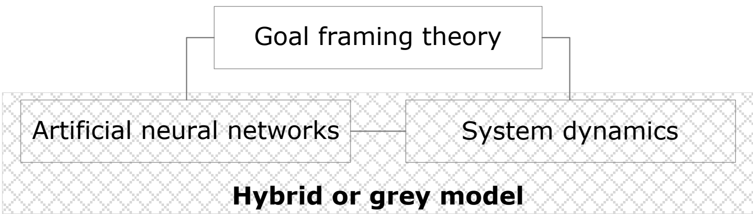

Figure 3: General layout of proposed methodology

The proposed methodology links goal framing theory with artificial neural networks (ANN) and system dynamics models, thus creating hybrid or grey model. The outputs from ANN will be feed to the system dynamics model. The ANN describes the goal framing theory by mapping the respondents answers from the survey to their behaviour, the system dynamics model is used to outline the broader effects of the consumer’ s behaviour, such as societal transitions and technological substitution in the society. As the measure for ANN fit the coefficient of determination and mean squared error was used.

3. Results and discussion

The structure of ANN is defined experimentally by testing five different training algorithms. The fit of the ANN is expressed by the coefficient of determination; see Figure 4.

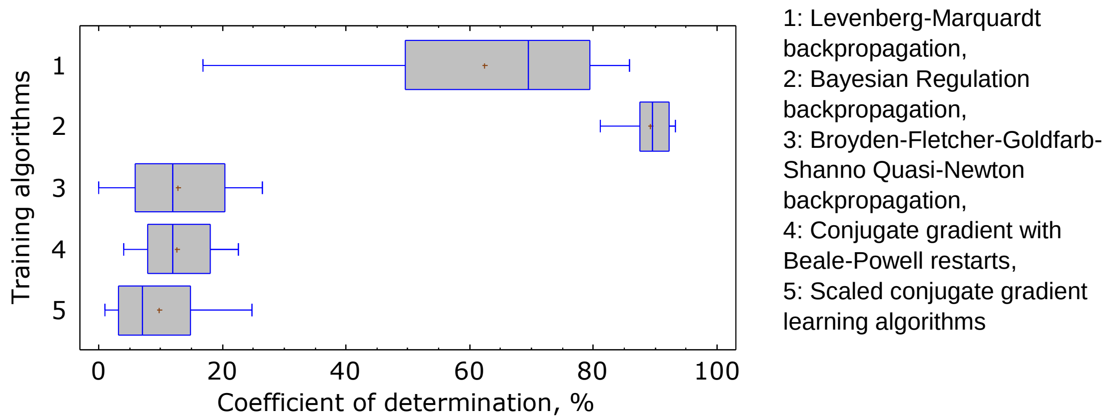

Figure 4: Testing of best-fit for the learning algorithms with the value of the coefficient of determination

As given by the Figure 4 the training algorithms of Bayesian Regulation backprogagation shows the best fit and more stable learning properties of the ANN. The statistics for the coefficient of determination for this learning algorithm is above 81.20 % with an average of 89.17 %, the standard deviation of 3.44 and the coefficient of variation is 3.85 %. Next best preforming algorithm is found to be Levenberg-Marquardt backpropagation with average of 62.36 %, standard deviation of 22.46 and the coefficient of variation of 36.02 %. As the second measure of fit the mean square error was used, see Figure 5.

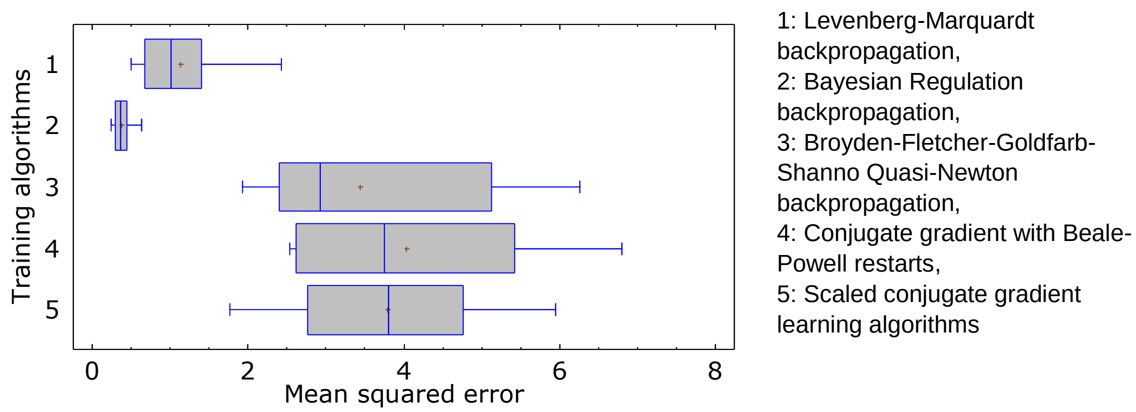

Figure 5: Testing of best-fit for the learning algorithms with the value of mean square error

For the mean squared error the similar trends are observed as for the coefficient of determination: the Bayesian Regulation backpropagation learning algorithm shows the best statistics and more stable performance of the ANN. The average mean squared error for this algorithm was $3.81 \cdot 10^{-2}$ with standard deviation of $1.09 \cdot 10^{-2}$ and coefficient of variation of 28.73 %. Based on the trend given in Figure 4 and Figure 5 the Bayesian Regulation backpropagation algorithm was chosen for further study. System dynamics model follows the following causal loop diagram, see Figure 6.

As for system dynamics part, the model developed by Vigants et al. (2015) will be modified by the integration of developed ANN network. The behavior explained by developed ANN and comparison with other works are given in Table 1; the model using ANN explained the most variance in the comparison with the works by Bariss et al. (2015), Tonglet et al. (2004) and Vigants et al. (2015) where statistical data analysis methods such as logistic regression, factor analysis and reliability analysis was done.

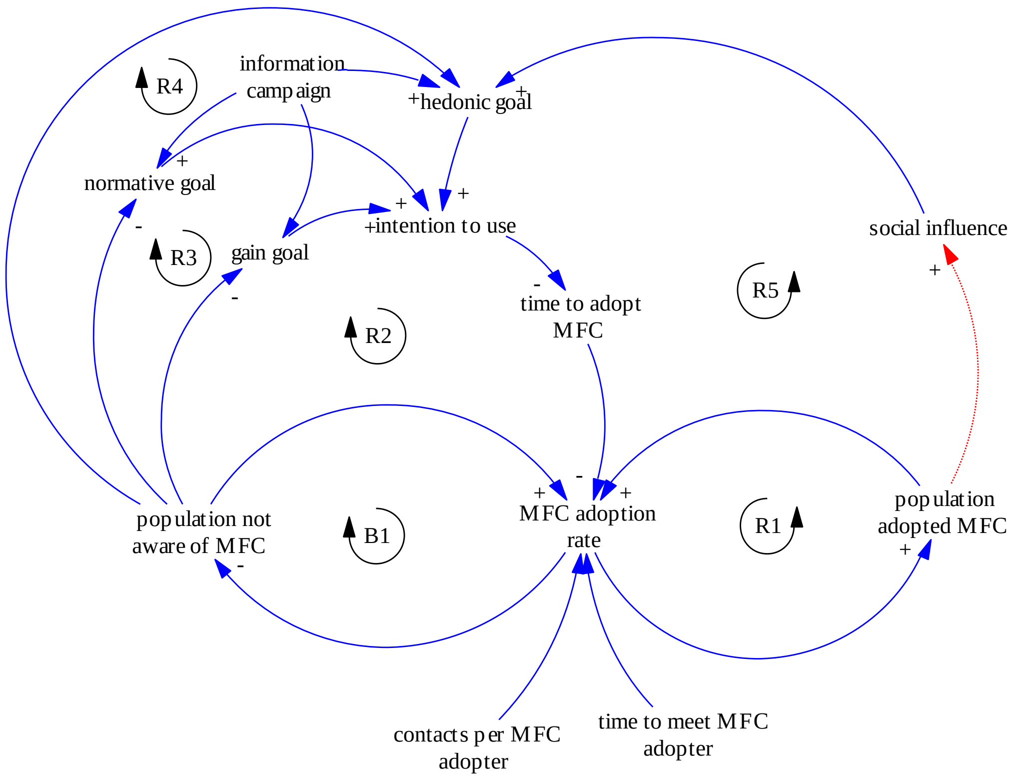

Figure 6: Causal loop diagram for the model (MFC – microfiber cloth) authors' work under review

Table 1: Behaviour explained by the various studies using different method

Study on	Behaviour explained	Method use	Reference
Energy efficiency motivation	13 %	Statistical data analysis	Bariss et al. (2015)
Waste recycling motivation	33 %	Statistical data analysis	Tonglet et al. (2004)
Innovation diffusion	34 %	Statistical data analysis and system dynamics	Authors' work under review
Technological substitution	89 %	Artificial neural networks and system dynamics	Current work

As given in Table 1, 89 % of behavior is explained in the case when Bayesian Regulation backprogagation training algorithm is used for ANN. Afterwards the outputs from ANN will be feed to the system dynamics model. While the ANN describes the goal framing theory by mapping the respondents answers, the system dynamics model is used to outline the broader effects of the consumer's behaviour, such as societal transitions and technological substitution in the society.

4. Conclusions

The works presents the methodology where white-box and black-box modelling approaches are combined to model technological substitution. As white-box model the system dynamics is used, and as the black-box artificial neural networks. The obtained results show that the model can explain 89 % of the systems behaviour.

Although the model was based on the one specific technological substitution process, its general application to other products and services is possible, since the developed model is fully outlined and can be used for further research of other processes.

Acknowledgements

The work has been supported by National Research Program "Energy efficient and low-carbon solutions for a secure, sustainable and climate variability reducing energy supply (LATENERGI)".

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